BACHELOR THESIS

Industrial Engineering and Management

DECISION SUPPORT TOOL FOR TRANSPORTATION PLANNING AT NIJHOF-WASSINK

by:

Katina Aparicio Pezino

University Supervisors
Prof. Dr.ir. Martijn Mes
Dr. Patricia Rogetzer
External Supervisor
Frank Wageman

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Management Summary

This thesis aims to support the Dry Bulk Logistics (DBL) planning department of Nijhof-Wassink, by developing a decisions-support tool to assist planners in assigning trailers to customer orders.

Currently, the trailer-to-order assignments are done manually, depending on the planners' judgment. However, due to the high volume of daily orders and the numerous factors that have to be taken into account, this task is very time consuming. To address this, a tool consisting of a cost-based heuristic was proposed, aiming to help planners make faster and more informed decisions. The tool was designed to mimic the logic that planners follow when assigning trailers to orders. A heuristic approach was chosen because the problem involves multiple operational constraints, and flexibility, speed, and ease of implementation are more valuable than pursuing mathematically optimal solutions.

The heuristic first prioritizes the orders by delivery deadline, looks for available trailers near the customer's pickup location, checks cleaning requirements, and selects the most cost-efficient option. Additionally, the tool also gives information on expected task duration and legal driving time, which could help planners assess the feasibility of each assignment in real-world conditions. The tool then suggests consistent and feasible trailer assignments based on cost, distance, cleaning requirements, and legal driving constraints.

To evaluate the performance of the decision support tool under realistic planning conditions, a simulation was conducted using historical order data. The simulation aimed to replicate how the model would perform in practice if it is used to assign trailers on a daily basis.

The tool is designed to generate a ranked list of the top five trailer options for each order, allowing planners to choose among several feasible alternatives while considering real-world factors not explicitly modeled. However, for the purpose of the simulation, it is assumed that the planner would always select the top-ranked option (the trailer assignment with the lowest total cost).

The output of the simulation indicates that the heuristic is able to perform well under controlled scenarios. The heuristic output was compared against a Last Recently Used (LRU) benchmark, which consists on assigning trailers based on idle time. The heuristic outperformed the benchmark, obtaining on average 50% less cost per assignment, and being able to deliver the orders 22.3% faster.

Therefore, it is recommended for the company to consider implementing this model as a support tool for planners. As it provides cost-efficient assignments in a reasonable amount of time, and could help reducing planning time and complexity, improve consistency and decrease operational costs, by showing options that may not have been considered. Apart from this, this approach allows the planners to have the final decision, for them to account for external factors not captured in the model.

Preface

Dear reader,

This thesis represents six months of hard work, learning, and personal growth. At the beginning of this journey, I was faced with a challenge unlike any I had encountered before. There were moments when I doubted whether I would be able to solve the problem on time. However, through persistence, dedication, and many hours of effort, I learned that even the most complex problems can be overcome, with time, patience, and determination.

I am very proud of the final result and grateful for the opportunity to conclude my bachelor's degree with a project that pushed me both technically and personally.

I would like to thank my parents for their constant support and encouragement throughout my studies. I also want to thank my friends, who have been a great source of support and made this journey more enjoyable.

A special thank you to the company Nijhof-Wassink, for allowing me to carry out my thesis with them, and to my company supervisor, Frank Wageman, for his guidance throughout the process.

I am also very grateful to my first supervisor, Martijn Mes, for his patience and invaluable feedback. His expertise and guidance helped shape this thesis and supported me at every stage of the process. I am also sincerely grateful to my second supervisor, Patricia Rogetzer, for her helpful feedback that improved the quality and clarity of this work.

Thank you for reading.

Contents

Chapter 1: Introduction

This chapter introduces the company Nijhof-Wassink, where the research was conducted. Section 1.1 gives an explanation of what the company does and the industry in which it operates. Section 1.2 introduces the problem. Section 1.3 presents the structure of the report, the type of research and the data gathering method.

1.1 Background and Context

Nijhof-Wassink is a family-owned transportation and logistics company founded in 1967, employing 1,750 people across the Netherlands (head office), Belgium, Germany, Hungary, and Poland. It is a leading organization in the European logistics sector, specializing in the transport of bulk goods for the chemical, food, and feed industries. Its fleet transports both liquid and dry goods, prioritizing safety, efficiency, and cost-effectiveness (Nijhof-Wassink, 2025).

Transportation planning in this company requires efficient management of trucks, trailers, and drivers while complying with strict cleaning and product compatibility protocols. Currently, this process heavily relies on the planner's expertise, which can lead to inefficiencies, time-consuming decision making, and significant workload.

This research focuses on the Dry Bulk Logistics (DBL) department, which transports products for the chemical and petrochemical industry, such as clean granulates and powders, including polyvinyl chloride (PVC), polyethylene (PE); polypropylene (PP) and polyethylene terephthalate (PET), among others (Nijhof-Wassink, 2025).

1.2 Problem Identification

Currently, the decisions involved in the planning of orders are based on the knowledge and experience of the planners. They are responsible for assigning trucks, trailers, drivers, cleaning stations, and routes to each order, making decisions based on what they believe is the most adequate and what has worked well in the past. However, due to the complexity of the planning task and the numerous variables involved, this approach is increasingly inefficient. Manual planning increases the risk of errors, such as overlooking important constraints, which can lead to a suboptimal assignment. In addition, it is a time-consuming and difficult task to perform, and complicated to train new staff.

This problem mainly affects the planners, since they have to retain a lot of information and consider a lot of factors when assigning the resources. The company is also influenced because the manual process is labor-intensive and prone to errors that reduce operational efficiency. Additionally, clients may be also affected, especially when planning mistakes lead to delays in delivery.

The reliance on human expertise has become more problematic in recent years, as the volume of orders and resources has increased significantly. Therefore, if the current planning approach is not addressed, the workload for the planners will continue to increase, along with the risk of errors and operational costs.

Problem Cluster

A problem cluster is a structured method that is used to visualize the problems and their connections. In this case, it was created to understand the causes and effects of the problems in the DBL planning department. The process begins by identifying a specific action problem and following a backward approach, questioning its underlying causes, by asking *why does this happen?* leading to a deeper layer of causes, until a core problem is reached. This approach ensures that the core problem is addressed instead of just the consequences (Heerkens et al., 2017).

Figure 1.1 shows the problem cluster. The problems included in the cluster were identified after conducting an exploratory analysis based on interviews, conversations, and observations with employees of Nijhof-Wassink.

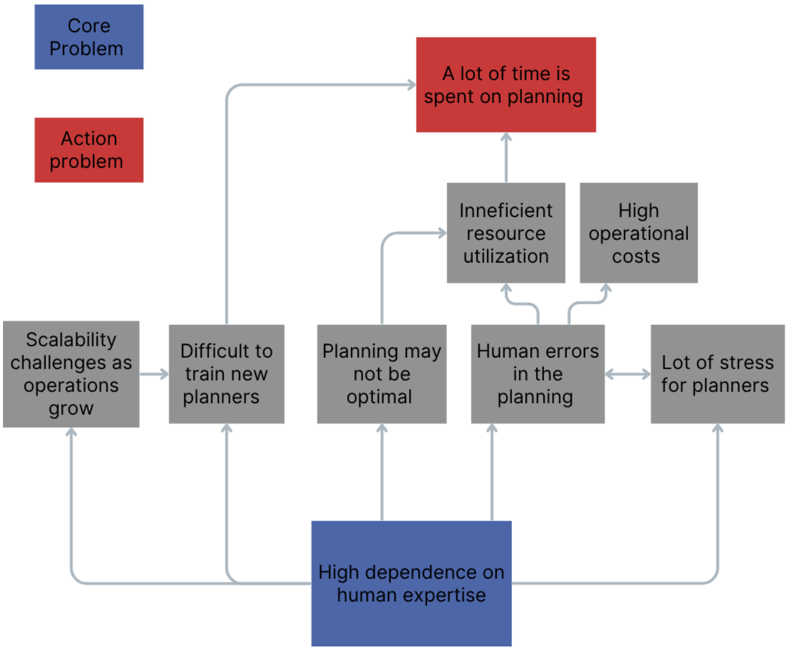


Figure 1.1: Problem cluster

Action Problem

Among the consequences of this core problem, a lot of time spent on planning was selected as the action problem (shown in a red box) in Figure 1.1, as it represents a critical challenge that impacts the operational efficiency. According to Heerkens et al. (2017), an action problem is a discrepancy between the norm (how a situation should be) and the reality (how the situation currently is).

Core Problem

In the problem cluster, the core problem is shown in a blue box. The core problem was chosen based on Heerkens et al. (2017), who state that a core problem does not have a cause in itself, and it can be influenced. The core problem identified is the high dependence on human expertise. This is an issue because planning requires specialized knowledge that is not codified, forcing planners to rely on intuition and personal experience. This makes it difficult to train new planners due to the great amount of information they must acquire. Additionally, the complexity of the planning (because of the wide range of factors that have to be taken into account) increases the likelihood of human errors, leading to stress for the planners.

This reliance on human expertise limits the company's scalability, as it becomes more challenging to manage the increasing number of variables. In addition, it can lead to suboptimal planning outcomes, since there is no systematic way to evaluate whether decisions lead to the best outcomes or if better alternatives exist. Suboptimal planning results in an inefficient use of resources, such as underutilized trucks and trailers, unnecessary waiting times, and an unbalanced workload distribution, among others. In addition to that, planners have to dedicate significant time to repetitive manual assignments instead of focusing on more complex tasks.

Gap Between Norm and Reality

Reality

Currently the resources are allocated based on the intuition and experience of the planners, which means that each planner has to manually evaluate each order and assign the resources that they believe are the most appropriate. However, due to the complexity of the task, this process is slow and time consuming, which affects the efficiency and the speed of decision-making.

Norm

The desired situation is a more efficient and standardized planning process that supports planners in making consistent and efficient decisions. This will reduce the dependency on individual expertise, and decrease the time required to allocate the resources.

1.3 Problem Solving Approach

For this thesis, the Managerial Problem Solving Method (MPSM) is used. According to Heerkens et al. (2017), the MPSM is a systematic problem-solving approach consisting of seven phases. The first phase, *Problem definition* is addressed in Section 1.2. Phase two *Problem solving approach* is described in this section. Phase three *Problem analysis*, consists of a descriptive and exploratory analysis that describes the current planning process and the factors that are taken into account when assigning the resources, this is addressed in Chapter 2. In Phase four, *Solution generation*, a literature review is conducted in order to explore existing approaches that support the planning process. The goal of this phase is to investigate how similar problems were addressed in a related context, and to identify successful strategies and potential solutions that could be adapted and implemented in this study, this phase is addressed in Chapter 3. Phase five is *Decision making*, where one of the possible solutions that were found in phase four is selected, and the necessary information is gathered in order to adapt it to the company's context. This phase is discussed in Chapter 4. Chapter 5 shows the results of the model, forming the basis of Phase six, *Evaluation*. Chapter 6 is the continuation of phase six, and it focuses on testing the performance of the model that was developed using historical data, and comparing it to a benchmark approach. Finally, phase seven *Conclusions and Recommendations*, is presented in Chapter 7. This chapter summarizes the findings, presents the limitations, and provides suggestions for practical application and future improvements.

Research Questions

In order to guide this research, the following research questions were formulated:

Main Research Question

How can the trailer assignment process at Nijhof-Wassink be enhanced to support planners in their decision-making and reduce the time spent on planning?

Sub-research Questions

To answer the main research question, several sub-questions have been formulated. Each sub-question will be addressed in a specific chapter, aligned with its corresponding MPSM phase.

2. **Chapter 2 — Problem Analysis:** This chapter presents a qualitative, descriptive and exploratory analysis that aims to understand the current planning process. The data will be gathered through interviews with planners and the manager, as well as observations and walkthroughs. The question that will be addressed in this chapter is the following:

    - **RQ2:** How is the current planning process designed and operationalized?

3. **Chapter 3 — Literature review:** This chapter reviews the existing literature. Academic databases such as Scopus will be used to gather relevant information. The purpose of this chapter is to find valid and reliable approaches that have been applied in a similar context. The question addressed in this chapter is:

    - **RQ3:** What approaches have been developed to support planning decisions for trailer assignment in the transportation and logistics sector?

4. **Chapter 4 — Solution Approach:** This chapter presents the design of the solution that aims to support trailer-order assignment. Based on literature insights and company-specific constraints.

    - **RQ4:** How can a solution be designed and developed in order to support the planning process at Nijhof-Wassink?

5. **Chapter 5 — Results:** This chapter shows the results of the model.

    - **RQ5:** What is the output of the model?

6. **Chapter 6 — Evaluation:** This chapter evaluates the model through an experimental setup using realistic data and analyzes the results.

    - **RQ6:** How well does the model perform when tested with realistic planning data?

7. **Chapter 7 — Conclusions and Recommendations:** This chapter presents the findings of this study, and gives recommendations for improving and applying the model in practice.

Research Design

Type of Research

This study follows an applied research approach that aims to enhance the planning process by supporting planners in assigning resources. This research is descriptive because a detailed and structured analysis of the current situation and context is done, providing an understanding of the current planning process. It is also exploratory, because it examines approaches from the literature on transportation planning and resource allocation, with the goal of identifying approaches that can be adapted and implemented in the context of this study.

Research Subjects

The research subjects were selected based on their involvement in the planning process. They consist of both organizational stakeholders and relevant research subjects within the company. The key subjects are as follows:

1. Nijhof-Wassink, the transportation and logistics company, since it is the environment in which the problem occurs and for whom the solution is directed.
2. The planners from the DBL department, since they are responsible for assigning the resources.
3. Customer related information, including destination patterns, and demand frequency. Although customers are not directly involved as participants, their data is relevant for understanding planning decisions.
4. Historical data that shows the trips performed, the products that were carried, and the cleaning stations that were assigned.

Operationalization of Key Variables

The key variables in this research are selected based on the main factors that planners consider when assigning new orders to vehicles. Variables are defined and measured in the following way:

- Distance: This refers to the total distance that a trailer must travel in order to fulfill a new order, starting from its last unloading location. It includes the distance from the previous unloading location to a cleaning station (if required), then to the loading location of the new order, and finally to the unloading location of that new order
- Cost: According to Liu et al. (2022) transportation costs are mainly affected by the length of routes traveled. Well-planned vehicle routes can significantly reduce transportation costs. In the context of this study, the cost will be approximately calculated based on distance and cleaning requirements

- Time: Aghazadeh et al. (2024) define time as the deterministic average travel time between locations. In this study, time accounts for the time elapsed when the trailer starts moving towards the customer pickup location until the order is delivered. Time is calculated by using the distance divided by the average speed of the vehicles on road, plus the time it took to load/unload or clean the trailer. Fixed values are used for loading, unloading, and cleaning times, making the overall time calculation deterministic

- Product compatibility: Each product has a corresponding and unique *ProductCode*. If a trailer is assigned to an order with a different *ProductCode* than the product it previously carried, then cleaning is required

- Trailer status: The status and location of a trailer depend on the last action it performed. For example, after delivering a load, the trailer may be empty until it is assigned a new load. According to Yang et al. (2016), an empty trailer typically exists in the time between two loaded trailer tasks, meaning trailers often travel empty from one delivery to the next pickup location.

Data Gathering Method

The research uses qualitative and quantitative data collection methods. The qualitative approach includes observations, interviews and walkthroughs. Through this approach, an insight on how planners assign the resources and the reasoning behind their decisions is obtained. It also allows capturing implicit knowledge that is not documented. Quantitative data is collected by analyzing the historical planning data of the company. The data analysis will be conducted in Excel and Python. The company's historical data includes information on trailers, trucks, product movements, cleaning station visits and customer pick-up and delivery locations. This secondary data is fundamental for identifying patterns and understanding the assignment of resources. Additional secondary data from published documents that aim to solve a similar problem is used.

Limitations of the Research Design

1. The model is validated in a simulated environment, not in the real world.

2. The focus is on trailer-to-order assignment, excluding individual drivers and trucks.

3. A full vehicle routing problem is not considered, only the decision on the next location of a vehicle is included, based on its current location, and the orders that have to be fulfilled.

4. The time constraint of 10 weeks, limits the model to account for every possible scenario.

Reliability and Validity

According to Cooper and Schindler (2014) validity refers to the extent in which the research measures what it is intended to measure. In this study, validity concerns whether the results accurately reflect the operational realities of planning decisions. The two types of validity that are considered are internal and external validity.

- Internal validity refers to the degree of confidence that the causal relationships identified in the study are trustworthy and not influenced by other factors or variables. In this context, external events, data entry errors, or operational changes during the period of data collection can affect the validity of the conclusions.

- External validity is concerned with the ability of findings and conclusions to be generalized to persons, settings, and times (Cooper & Schindler, 2014).

Since this research is based on historical data, internal validity may be compromised if past decisions were affected by external factors that are not documented (such as weather conditions, traffic jams, driver's availability, among others).

Reliability refers to the accuracy and consistency of the analysis. It is concerned with the extent in which the study produces stable and consistent results when repeated. The data used in this research is structured and consistently formatted in Excel and processed using Python, which helps to ensure that the same results will be obtained if the analysis is repeated. However, the reliability of this study can be compromised by possible data entry errors or missing data from the historical data set, which may affect the accuracy and consistency of the results.

Theoretical Perspective

Vehicle assignment is a significant challenge in the logistics and transportation sector. And an effective assignment can result in savings in cost, time and resources (Liu et al., 2022). Therefore, together with vehicle routing, they have been widely studied in the field of operations research. The most common formulation is the Vehicle Routing Problem (VRP), which involves designing a set of minimum-cost vehicle routes, originating and terminating at a central depot, for a fleet of vehicles that service a set of customers with known demands, and where each customer is serviced exactly once (Solomon, 1987). While the classical VRP assumes that a vehicle serves multiple customers in a single route, this study involves a different structure. First, each job consists of a predefined pickup and delivery location, which is specified by the customer, forming a fixed origin-destination (O-D) pair. Additionally, the orders handled by the company are full-truck-load (FTL) delivery, which means that each trailer can only serve one order at a time for only one customer, and the order must be fulfilled before the trailer can pick up another order. Additionally, the orders have time windows, and the customers impose delivery deadlines constraints. While traditional VRP assumes that vehicles return to a central depot after completing their routes, this assumption does not fully apply to the operational context of this project, where vehicles often remain in the field for extended periods. For this study, instead of constructing complete multi-stop routes, the approach focuses on proposing potential trailer-to-order assignments, with the aim of supporting planners in allocating resources while respecting operational constraints.

According to Miguel et al. (2019) decision support systems (DSS) are designed to facilitate decision making. These systems are not intended to automate the entire process, but to provide data that supports and facilitates planners' tasks, allowing them to make the final decision and consider external factors. For example, in a study conducted by Trottier and Cordeau (2019), an optimization-based decision support tool was made, to improve the routing and scheduling decision process and to help the tactical and strategic planning for a vessel company. The tool was able to create good schedules that could be used in daily operations, and it also led to an optimized asset allocation.

When facing complex, real-world problems, in a dynamic and time sensitive environment, using exact methods like mixed integer linear programming becomes impractical because the optimal solution cannot be obtained within a reasonable amount of time (Liu et al., 2022). According to Trottier and Cordeau (2019), unlike mathematical approaches, heuristics provide the necessary flexibility to incorporate the features of real-life situations. Heuristics provide good solutions quickly that are more suitable for real world operational decision-making. Therefore, this research aims to adopt a heuristic approach for the assignment of resources.

Deliverables

The deliverable of this thesis consists of a report that provides a clear analysis of the problem, a literature study and a decision support tool, aimed at assisting planners in their daily workflow, by proposing trailer-to-order assignments based on cost, feasibility, and operational constraints. Additionally, an interactive dashboard that visualizes the output of the model is presented as a prototype and inspiration for future implementation, showing how the results of the tool could be integrated into the company's planning environment.

Chapter 2: Problem Analysis

This chapter provides an analysis of the current planning process in the DBL department of Nijhof-Wassink. Understanding the current process is essential to identify the steps involved, the logic behind the decisions, the stakeholders and the factors that have an impact on the daily operations. This chapter begins with a stakeholder analysis in Section 2.1. Section 2.2 explains the current planning process and the actors involved. Section 2.3 describes the factors that are taken into account when planners schedule an order. Section 2.4 provides an overview of the current situation. And Section 2.5 explains the logic that planners follow when assigning an order. This chapter answers the question *"How is the current planning process designed and operationalized?"*

2.1 Stakeholder Analysis

The planning process of the DBL department of Nijhof-Wassink involves multiple stakeholders, who play an important role in ensuring that the orders are processed and executed efficiently. The key stakeholders include the customers, sales department, customer service, planning department, cleaning stations, and drivers. These stakeholders play an equally important role in supporting the planning and execution of orders.

1. **Customers**: In this sector, customers are the initiators of the process. They operate through a tendering process and make contracts for the transportation of their products, (see Section 2.2 for more information)

2. **Sales department:** This department is responsible for calculating the prices of the lanes at a competitive price during the tender process. Prices are determined based on distance, type of product, required services (specific cleaning requirements), and expected transport volumes

3. **Customer service:** Customers communicate specific handling instructions, product characteristics, and any cleaning requirements through this department

4. **Planning department:** This department is responsible for the tactical allocation of resources to fulfill the orders. This involves assigning drivers, trucks, trailers, and cleaning stations

5. **Cleaning stations:** Cleaning stations play an essential role in preparing the trailers for the next load

6. **Drivers:** They are responsible for transporting the orders as planned

2.2 Overview of the Current Planning Process

The planning system at Nijhof-Wassink consists of multiple steps executed manually, involving several departments and stakeholders. It is important to understand the process before an order is placed, which involves the sales and customer service departments. As mentioned in Section 2.1, customers typically operate through a tendering process. A tender is a formal and structured process through which entities invite potential suppliers to submit proposals for transporting products across specific routes (referred to as ”lanes”). In response to the tender, the transportation company submits a bid. The bid states how the company intends to meet the requirements stated in the tender document and at what price. Based on the bids received, the customer evaluates the proposals and selects the supplier that aligns the best to their needs, in terms of cost efficiency, and service quality.

If Nijhof-Wassink is chosen as the desired company, a contract, (usually long-term) is established. An agreement is made for a specified lane, therefore it is possible that the same customer has several agreements with the company. These agreements typically define a total volume to be transported over a certain period, and contain information such as the details of the customer, origin (loading location), destination, type of product, load, schedules and costs, and service expectations over a specific period.

Once the contract is established, the customer service department becomes the main point of contact with the customer. The customer provides detailed product handling requests and cleaning requirements. This department ensures that the information is correct before placing the order.

Once the necessary information is obtained, the order is redirected to the planning department and added to the list of orders that have to be planned. From that list the planners choose the order with the nearest delivery deadline. Planners are then responsible for assigning the necessary resources to fulfill the order, (see Figure 2.5 for more information regarding the planning process). It is important to note that each order in DBL is a full truckload, which means that each trailer can carry at most one product from exactly one customer, as the trailer has one compartment and the products cannot be mixed.

Planners typically work with a short planning horizon of two to three days in advance but are also responsible for making in-day adjustments to accommodate delays because of unexpected disruptions, such as traffic jams or weather conditions. The planning team uses specialized software to support the manual assignment of resources. This system provides planners with visibility of vehicle location, estimated arrival times, driver rest periods, and potential delays. However, despite the support of this software, the decision-making process still relies fully on the intuition and experience of the planners. For instance, if a trailer requires cleaning before loading an order, planners are also responsible for assigning cleaning stations and specifying the necessary procedure.

Once planning decisions are made, the designed routes and tasks are communicated to the drivers through an onboard computer system. Through this system, drivers can communicate with the planners, report any issues or delays, they can also receive instructions and view their assigned routes. Throughout the process, planners remain in constant communication with drivers to monitor progress and make real-time adjustments if necessary.

Figure 2.1 provides a geographical visualization of the customer locations as well as the cleaning facilities. Loading locations are marked in green, unloading in red and cleaning facilities in yellow, and the size of each marker reflects the frequency of use for that location. As can be seen, the customer locations are spread across the Netherlands, Belgium, Germany, Poland, Denmark, and France, with greater activity concentrated in the Netherlands, Germany, and Belgium. This spatial overview is important for understanding the geographic scope of planning decisions.

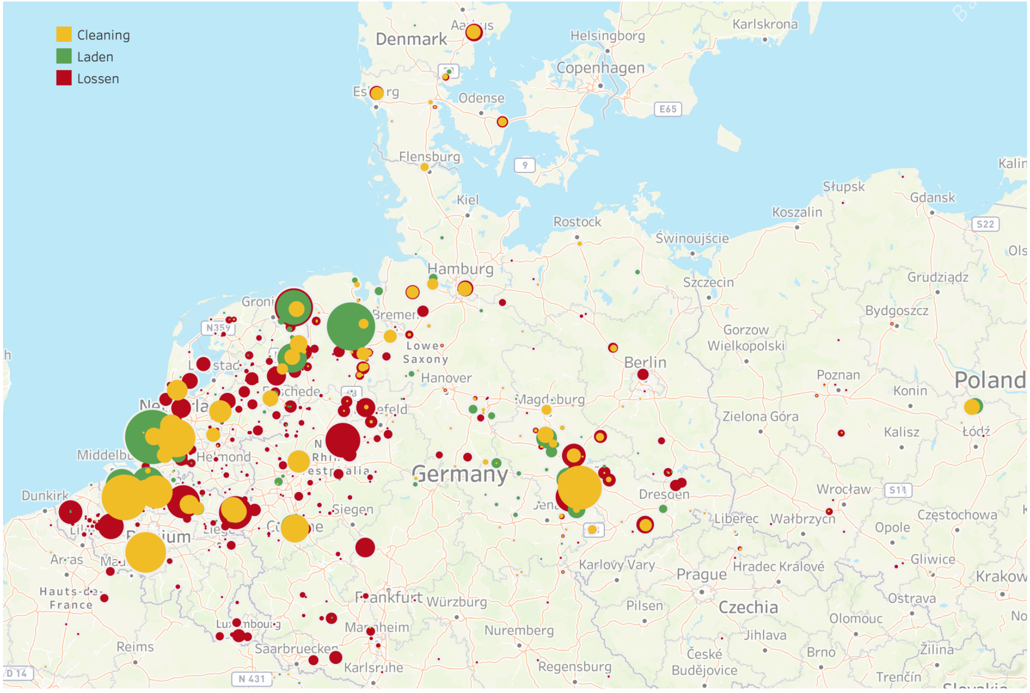


Figure 2.1: Geographical visualization

Overall, while the current system allows planners to manage daily operations effectively, it is manual and reliant on experience. The software does not offer automatic recommendations for vehicle assignments or cleaning requirements, which means that the process is entirely manual. These limitations create a potential risk for inefficiencies and limit the ability to scale or optimize the planning process. Section 2.3 presents the specific factors that planners consider when assigning orders, offering a deeper insight into the complexity of their decision-making process.

2.3 Factors Taken Into Account when Assigning an Order

When planners assign a new order, they take into account several factors that directly impact the efficiency and effectiveness of the process. These factors help ensure on-time deliveries, optimal resource usage, and smooth operations. By considering these factors, planners can make informed decisions that will minimize the risks of future changes and therefore maximize overall performance. These factors are the following:

1) **Location:** When assigning an order, the planners look for the nearest available truck and trailer to the loading location of the customer, in order to minimize travel time, empty kilometers and maximize efficiency

2) **Time window:** Customers often impose time windows for loading and unloading. These time constraints must be considered to maintain a smooth flow of operations, ensure customer satisfaction, and avoid delays. However, in many cases, the time windows offer some flexibility. Planners can inform customers of a late delivery, and in most cases this is accepted

3) **Product constraints:** There are certain products that cannot be transported in trailers that previously carried incompatible loads, due to risk of contamination. In some cases, even after cleaning, specific customers prohibit certain previous products to prevent any chance of residue affecting the new load. Failure to comply with these requirements may result in the customer's rejection of the entire shipment. In this study, these specific product constraints are not considered. In practice, such rules are not fully standardized and collecting the necessary information would require significant time and input from experts. For simplicity, it is assumed that any trailer can carry any product, as long as a cleaning is performed if the previous product carried is not exactly the same as the next order's product (*ProductCode*), as mentioned in 1.3

4) **Balancing vehicle distribution:** In order to avoid the accumulation of vehicles in a single area, the planners try to distribute the vehicles evenly across different regions. This balance ensures vehicle availability where needed, minimizes waiting times, and reduces the cost of repositioning empty trailers and trucks. Therefore, planners must maintain this balance without compromising operational efficiency

5) **Scheduling loading and unloading time slots:** Some customers require transportation companies to pre-book time slots for loading and unloading to prevent congestion at their facilities, minimize downtime and improve efficiency. Therefore, planners are also responsible for securing these slots in advance, often before knowing the exact vehicle or driver assignment. This constraint influences resource planning and requires flexibility to align the confirmed slot with available equipment and drivers. However, due to the complexity of this task, this will not be taken into account in this study

6) **Fleet:** The trailers from the DBL department are of the same type and have the capacity to fulfill different types of customer orders

7) **Cleaning requirements:** After every load, the trailer requires a cleaning. The cleaning requirements of the trailer are a critical factor in the planning process, as they determine trailer availability and impact the sequence in which orders can be scheduled. An analysis of the historical data showed that in approximately 70% of the cases, a trailer required a cleaning before loading the next order (see Figure 2.2)

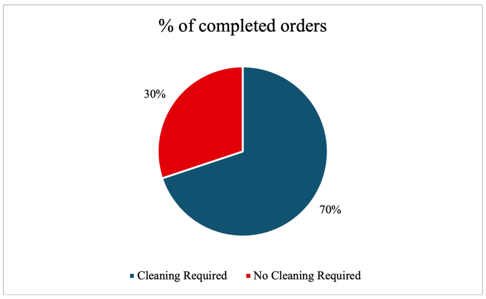


Figure 2.2: Frequency of cleaning

The type of cleaning needed depends on the previous loaded product and the next product that will be loaded. It usually takes around 1-2 hours to clean the trailer, however, the duration depends on the cleaning type needed:

- *Rinsing:* The normal cleaning procedure is rinsing. The trailers that are rinsed receive a certificate, often the EFTCO Cleaning Document (ECD) issued by the European Federation of Tank Cleaning Organisations (EFTCO), which allows them to be loaded at the customer's facilities. During this process, the trailer interior and the hoses are rinsed with water by cleaning agents. The interior is then dried with hot air to prevent moisture
- *Wiping:* In some cases, instead of a thorough rinsing, manual wiping is carried out. The driver issues a handwritten certificate, stating that the trailer has been swept and is ready for the next load. This procedure is usually applied when transporting compliant products, such as whey powder after plastic granules
- *Special cleaning requirements*: Some customers require additional cleaning, such as a combination of ECD and polymer cleaning (PICS). And in certain cases, customers require that the cleaning is performed with drinking water and/or food-approved detergents

8) **Drivers:** Even if vehicles and trailers are available, without drivers who are legally allowed to drive, orders cannot be executed. Therefore, drivers are a crucial factor in the planning process, as their availability and legal constraints determine transport capacity and scheduling flexibility. And planners must carefully balance driver schedules and rest periods to maintain operational continuity

   - *Driver's availability:* When scheduling an order, planners must consider the driver's availability, as not all drivers work the same schedule. The drivers from Nijhof-Wassink have different availabilities, for example, some drivers work for two weeks in a row and then rest for one week, while others only work certain days of the week. This variability must be carefully managed to ensure that drivers are always available to fulfill the orders from the customers

- *Returning to home base:* there are several depots where trailers are parked, these depots are located in the Netherlands (Coevorden, Rijssen, Rotterdam and Bleskensgraaf), Belgium (Antwerp, Zelzate, Kallo) and Germany (Barleben), and they are usually the starting and ending point for drivers. If a driver has to return to home base on that day or soon, planners must schedule orders that facilitate this return within the driver's legal working hours and operational constraints
- *Rest constraints:* According to the European Parliament and of the Council (Regulation (EC) No 561/2006), companies must comply with certain rules for drivers, with the aim of improving road safety and ensuring adequate working conditions. These regulations state that:
  - A driver is allowed to drive for 9 hours a day, with an exemption of twice a week where it can be extended to 10 hours
  - A driver can work a maximum of 56 hours per week, and within a two-week period, the driver is not allowed to drive more than 90 hours
  - The daily rest period of the driver should be at least 11 hours, with an exemption of reducing it to 9 hours at most 3 times a week. The daily rest can be split into 3 hours rest followed by 9-hour rest to make a total of 12 hours daily rest
  - After a driving period of 4h 30 minutes, a driver should take a break of 45 minutes
  - The weekly rest is 45 continuous hours, which can be reduced every second week to 24 hours

This working time of a truck driver includes the activities related to transport, such as driving, loading and unloading, cleaning, technical maintenance, monitoring load control and administrative procedures (European Parliament and Council, 2006).

External Factors that Influence the Planning

The planning process is also influenced by several external factors that are outside the control of the planners, but still impact the decision-making process, and adds complexity to the resource allocation task. Although these factors are not explicitly considered in the proposed solution, it is important to acknowledge their role in the current planning environment. These factors include:

- **Weather conditions:** adverse weather can affect delivery schedules, vehicle performance, and safety, requiring adjustments to planned routes or causing delays
- **Traffic conditions:** unexpected traffic congestion, accidents or road closures can impact the estimated arrival time and may require to reschedule the orders or reroute the vehicles

- **Drivers' last minute changes:** events like driver sickness, personal emergencies, or other unplanned absences can affect the planning process, and planners have to assign alternative drivers to fulfill the orders
- **Technical issues:** system or equipment malfunctions can lead to delays or disruptions in the planning process

2.4 Current Situation

To get a better understanding of the current situation of the company, an analysis of historical data was performed to see the number of orders that are handled per day and the variation in demand across months and different days of the week. Figure 2.3 shows the daily volume of orders over a six-month period. The data shows fluctuations in demand, with notable peaks on certain dates (for example, higher volumes at the end of November and lower demand around the Christmas holidays). These peaks could reflect customer-specific cycles or operational constraints. These patterns help to understand the variation of the workload and to create effective planning techniques to handle busy periods.

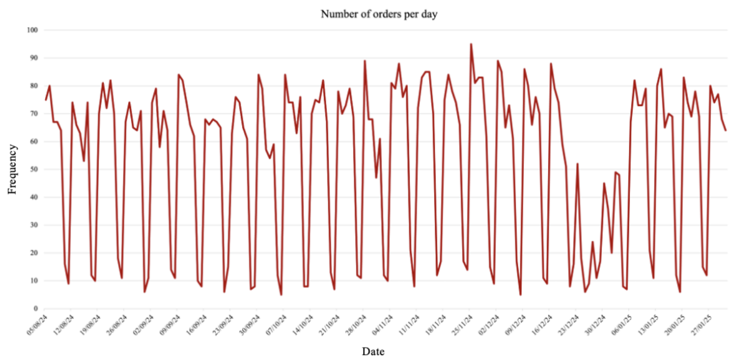


Figure 2.3: Orders handled per day

To further investigate patterns, the number of orders were aggregated by day of the week for each month, as seen in Figure 2.4. This allows to identify consistent trends, in this case, the busiest days are Mondays, while Saturday and Sunday show the lowest activity. These insights reveal a predictable workload distribution that planners may implicitly take into account during decision making. Additionally, the data shows that there is an overall month stability, since the order volumes across the months from August to January are relatively consistent on weekdays. As previously mentioned, December shows lower volumes, typically due to the holiday season.

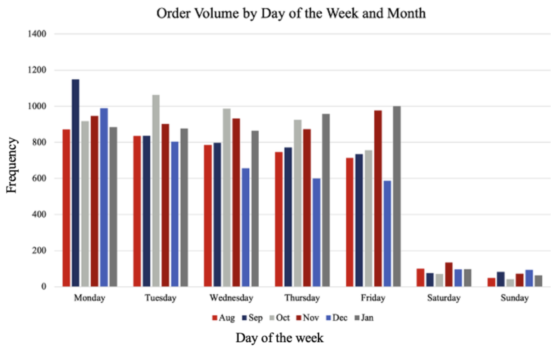


Figure 2.4: Orders per day of the week and month

2.5 Operational Decision-making in Planning

After describing the overall planning process in Section 2.2, the stakeholders in Section 2.1, the factors involved in Section 2.3, and the current situation in Section 2.4, this section focuses on the operational decision-making steps that planners take when they receive an order.

The planning process begins by identifying drivers who need to return to their home base on that particular day. Each driver is assigned to one of the eight depots owned by the company mentioned in Section 2.3. Planners prioritize assigning suitable orders to these drivers to facilitate their return journey to their home base on time. This helps optimize vehicle usage, minimize empty kilometres and maintain driver satisfaction.

After assigning these drivers, the planners focus on the remaining orders. The orders are prioritized based on their delivery deadlines, prioritizing the ones with the closest deadline. Planners then assess the type of product to be transported and verify any specific restrictions or compatibility requirements. Afterwards, the planners look for available trailers located near the loading location of the customer, to minimize repositioning time and empty kilometres. If multiple vehicles are close to the customer's facility, the one that requires the least complex cleaning process is prioritized, to reduce costs and downtime. However, when cleaning is required, the selection also considers the total distance (from the trailer's current location to the cleaning station, and from the cleaning station to the customer's loading facility). This ensures that a trailer requiring a larger detour for cleaning does not take priority over a more suitable option. A cleaning station is selected based on its combined proximity, and the necessary cleaning procedure is specified.

After the orders of that day have been assigned, the route is communicated to the driver. As mentioned in Section 2.2, planners are constantly communicating with the drivers via onboard computer systems. While the initial assignments are typically made two to three days in advance, planners can update the schedule and provide new instructions throughout the day if incidents, delays or unexpected changes occur. This real-time feedback allows planners to make adjustments to the schedule if needed, maintaining operational flexibility.

Additionally, as mentioned in Section 2.2, some customers require transportation companies to reserve specific loading or unloading time slots at their facilities. These slots usually have to be booked with some time in advance, before the assignment of vehicles and drivers is finalized. This requires planners to later align the available resources with the pre-booked time slots, adding further complexity to the planning process.

In some cases, if an order falls outside the company's network lanes, and fulfilling the order would require too many empty kilometres, planners may choose to outsource the order to external carriers. There are certain orders that are directly outsourced and known in advance, but there are other orders, where the outsourcing decision is made during planning, once the planners have a better overview of trailer availability and fleet dispersion. However, this is not always possible.

In general, the planning process at Nijhof-Wassink follows a structured and flexible approach that allows planners to assign resources and respond to changes effectively. Figure 2.5 shows the sequence of actions and decision points involved in the planning process.

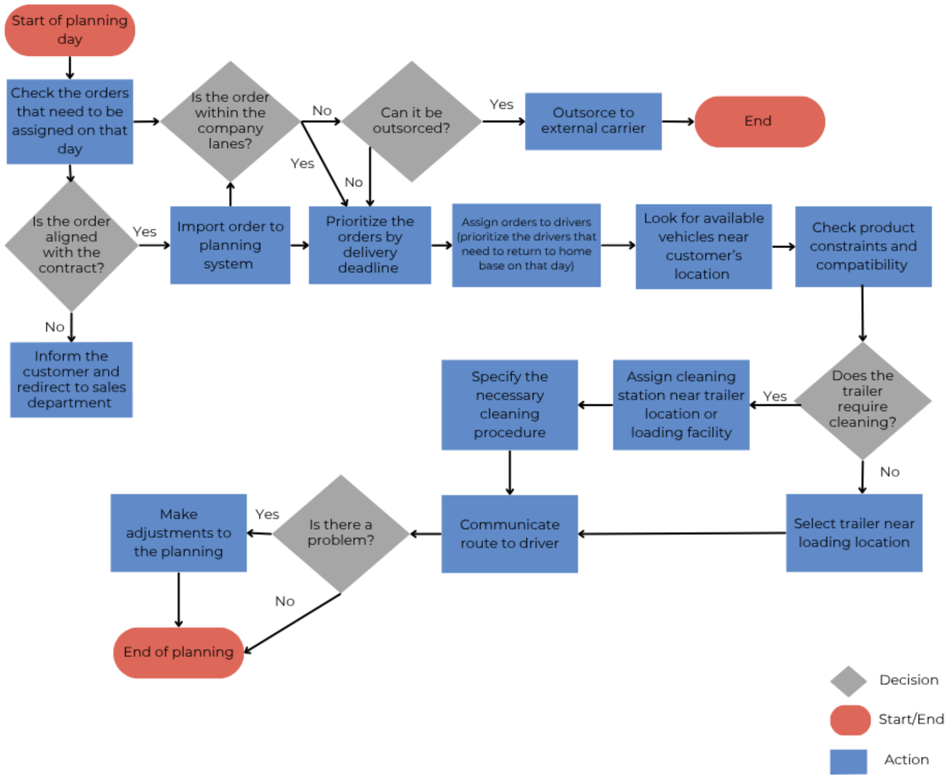


Figure 2.5: Current Planning Process for Assigning an Order

Summary

In this chapter, the stakeholders involved in the planning process (customers, sales department, customer service, planning department, cleaning stations, drivers) were introduced. The current planning process was described and the factors that influence the planning, such as product constraints, vehicle availability, cleaning requirements, were presented, since they add complexity to the decision making process. Lastly, the decision-making process that planners follow when assigning an order was explained. Overall, this chapter shows the manual and experience-driven nature of the current planning system, as well as the complexity of assigning the orders. The following chapter will explore solution approaches that can support the planning process.

Chapter 3: Literature Review

This chapter reviews the existing literature relevant to trailer allocation and resource-constrained assignment in transportation logistics. The review is guided by the research question:*What approaches have been developed to support planning decisions for trailer allocation in the transportation and logistics sector?*.

This chapter begins by presenting the problem of trailer assignment as a sub-problem of transportation planning in Section 3.1. It then presents classical problems in transportation logistics such as the Vehicle Routing Problem (VRP) and Pickup and Delivery Problem (PDP), and it also highlights their differences with the problem faced in this study. Section 3.2 shows how the literature addresses similar problems, and it categorizes them by methodological approaches, analyzing how different models incorporate real-world constraints. Finally, this section presents a comparative synthesis of the reviewed methods.

3.1 Classification of the Problem

The problem addressed in this thesis can be defined as a Trailer Allocation Problem (TAP) in full-truckload logistics (Kalantari et al., 2023). This implies the assignment of a limited number of trailers to transportation orders with fixed pickup and delivery locations, respecting operational restrictions like product compatibility, cleaning requirements, availability, and legal driving times as mentioned in Section 2.3

Although TAP shares characteristics with classical problems like the Vehicle Routing Problem (VRP) and Pickup and Delivery Problem with Time Windows (PDPTW), it is fundamentally different. The VRP models look to construct an optimal route departing from a central depot (Dantzig & Ramser, 1959), while the PDPTW consists of pickup and delivery pairs within time windows using a single vehicle (Tchoupo et al., 2017). In contrast, TAP focuses on assigning the available resources (trailers) instead of routing them to multiple clients. TAP can also be considered a special case within the Dynamic Fleet Management Problem (DFMP) framework, which involves the assignment of vehicles through time and space in response to transportation orders that evolve dynamically. This problem is characterized by reusable resources (like trailers) that need to be reassigned after completing a task, taking into account restrictions like time windows, availability, and operational restrictions (Carvalho & Powell, 2000).

In comparison to general routing problems, DFMP prioritizes real-time decision-making, with the objective of maintaining flexibility and availability of the fleet over time (Carvalho & Powell, 2000). In this thesis, TAP will be addressed as a resource-constrained assignment problem, where demand is deterministic and known in advance, but where trailer assignment must align with operational constraints. Recent studies such as Kalantari et al. (2023) have addressed TAP through advanced optimization and learning techniques. However, the TAP addressed in this thesis is focused on the specific constraints in the context of Nijhof-Wassink.

3.2 Operational Constraints Addressed in Literature

Building on the discussion of the trailer assignment problem in Section 3.1, this section focuses on how different approaches, including heuristics, metaheuristics, and mathematical models, address key operational constraints relevant to this context, such as product compatibility, cleaning requirements, time windows, and trailer availability.

Heuristics

Heuristic are most commonly used in practice for trailer assignment due to their simplicity, speed and ease of interpretation. These methods often mirror the actual decision logic used by human planners, making them highly applicable in operational settings. And they are frequently applied when the goal is not necessarily optimality, but feasibility and clarity under real-world constraints. Some studies that have applied heuristics in similar contexts include: Yang et al. (2016) who proposed a two-stage heuristic that manages trailer repositioning while minimizing time windows violations. Gifford et al. (2018) presented a matching model that respects the product compatibility constraints and manages cleaning requirements between deliveries. This operational scenario reflects similar challenges present in this thesis, particularly regarding trailer preparation between orders and the need to model activities such as cleaning within the planning horizon.

These studies emphasize that real-world feasibility not only depends on route distance or cost, but on the integration of practical, legal and safety constraints directly into the assignment logic. The key strength of heuristics lies in offering transparent and flexible decision making that can be adapted to planner judgment, which is critical in the company setting.

Metaheuristics

According to Dokeroglu et al. (2019) metaheuristics describe higher-level heuristics and are used to find solutions to a wide range of optimization problems. The advantage of using this approach to solve complex problems is that they can obtain the optimal solution even for large problems (Dokeroglu et al., 2019). While they are generally more computationally intensive than heuristics, they offer improved performance in highly constrained settings. Some examples found in the literature that have applied metaheuristics to solve vehicle allocation and assignment problems are Trottier and Cordeau (2019) who developed a tabu search-based decision support system for trailer planning that integrates cleaning times, product compatibility and time windows. Giovanni et al. (2017) who combined tabu search and intra-route optimization for trailer-to-order matching under complex constraints. Wu et al. (2022) applied a Particle Swarm Intelligence (PSI) with local search to address constraints such as distribution time, loading rate and heterogeneous fleet capacity. Additionally, Derigs et al. (2011) developed a metaheuristic framework that incorporates EU driving and rest time regulations through a rule-based feasibility check embedded within a local search procedure. However, metaheuristics often suffer from poor interpretability and may be difficult to tune or explain to users without a technical background.

Mathematical Optimization

Optimization methods such as linear programming and mixed-integer programming (MIP) have been used to obtain exact solutions for well-structured problems. Some examples of studies that have used optimization models include Velarde-Cantú et al. (2023), who proposed a Mixed-Integer Linear programming (MILP) framework to minimize transportation costs in a trailer-truck coordination setting. Similarly, Aggarwal and Kumar (2019) applied a MILP model to a VRP with time windows, optimizing fleet size and cost efficiency under strict delivery constraints.

Although these models guarantee optimality, they require larger computational times and they typically assume full data availability and stable problem definitions. Additionally, the features of real-life situations are harder to incorporate in these methods (Trottier & Cordeau, 2019). Therefore, it can be said that in contexts where decisions have to be made quickly and where situations change dynamically, optimization models may be too computationally intensive for practical use (Liu et al., 2022).

Learning-based Approaches

Learning-based models, particularly the ones that involve reinforcement learning (RL), offer adaptive tools for decision making for trailer assignment in complex logistics settings. These methods are typically trained in simulation environments, where the model learns a policy that prescribes optimal decisions across a wide range of scenarios. Once trained, the policy is applied in real time to support dynamic decision making. However, the flexibility and strong performance they offer usually comes at the cost of transparency, data requirements, and implementation complexity.

Examples of studies that have applied this approach to solve similar problems to the one present in this study include Kalantari et al. (2023), who developed a deep reinforcement learning framework that combines bipartite graph assignment (BGA) with an attention-based deep reinforcement learning aiming to optimize trailer-truck-order matching under dynamic conditions. Similarly, Jung and Yang (2023) introduced a reinforcement learning-based trailer assignment model to assign trailers under uncertainty.

Although reinforcement learning has proven to perform well in structured, high-volume contexts, their reliance on large datasets, limited interpretability, and high infrastructure costs makes it less practical in manual, decentralized planning settings like the one studied in this thesis.

Approach Comparison

Approach	Advantages	Disadvantages
Heuristics	Fast, transparent, flexible; easy to understand and modify	May not result in optimal solutions
Metaheuristics	High-quality solutions; adaptable to many situations	Longer run times; harder to interpret (compared to heuristics)
Optimization (LP/MIP)	Theoretical optimality; strong for small-scale deterministic problems	Scalability issues; rigid assumptions; impractical under volatile or uncertain data
Learning-based	Adaptive to new data and real-time changes	Requires large datasets; poor explainability

Table 3.1: Approach comparison

It can be said that no single approach universally outperforms the others. Instead, the choice depends on the planning environment. Metaheuristics, optimization, and learning-based models provide high-performance results under stable, data-rich conditions. In contrast, heuristics offer a balance of feasibility, adaptability and usability, particularly in settings requiring quick decisions and transparency.

This thesis builds on that insight, and since the current planning environment looks for transparent, fast, and feasible decision support, the chosen approach is a heuristic that offers interpretable trailer assignment suggestions, explicitly accounting for real-life settings.

In doing so, this research contributes to the literature on trailer assignment and helps bridge the gap between theoretical logistics optimization and decision support in real-world transportation systems, where operational constraints must be considered.

Chapter 4: Decision Making

This chapter aims to answer the RQ4: *Which solution approach is most suitable to support the planning process in the company's context?*

In Section 4.1 the reasoning behind the chosen approach is given. Section 4.2 describes the company-specific constraints that the solution should take into account. Section 4.3 explains the logic behind the heuristic. Section 4.4 states the assumptions that are incorporated in the model. Section 4.5 presents the model in a mathematical formulation, with its sets, parameters, decision variables, objective function, and constraints. Section 4.6 presents the algorithm, and Section 4.7 ultimately summarizes the key points discussed in this chapter.

4.1 Solution Choice

As mentioned in Section 3.2, modeling approaches, such as heuristics, metaheuristics, optimization and learning-based models offer different trade-offs between optimality, transparency, flexibility, and computational demands. Although advanced models like MILP and reinforcement learning offer theoretical guarantees, Section 3.2 states that they usually require large datasets, infrastructure, and computational resources that are not available in the context of this company.

Additionally, the planning process at Nijhof-Wassink is time-sensitive, which means that planners need to generate trailer assignments quickly. Given this need for fast computation, human-in-the-loop decision making, and the need for operational flexibility, heuristics were seen as the most suitable choice, since they can provide fast, interpretable, and flexible solutions while considering practical limitations like product compatibility, trailer availability, cleaning specifications, and legal working hour limits (Trottier & Cordeau, 2019). Therefore, this thesis proposes a heuristic that aims to mirror the reasoning used by planners, offering a transparent and usable decision support tool that bridges the gap between real-world constraints and computational planning.

4.2 Company-Specific Constraints

Although resource allocation problems have been widely addressed in the literature, many academic approaches are either too generalized or do not fully adjust to the daily operations of Nijhof-Wassink. In contrast, this study focuses on a practical and implementable solution that takes into account the main limitations observed in the planning environment of the company:

- **Full-truckload:** The orders can not be consolidated. Each trailer is assigned to a single pickup-delivery task
- **Legal driving time:** Drivers have a working limit of nine hours per day. Therefore, all planned activities, including driving, cleaning, loading and unloading, need to be feasible within that limit

- **Cleaning requirements:** Some trailers must be cleaned between orders, depending on the previous product carried and the next order to be carried. The cleaning stations are geographically dispersed and require time and cost.

Although there are approaches in the literature that also cover these constraints, they often use complex optimization frameworks. In contrast, the planning process of Nijhof-Wassink requires a solution that is fast, transparent, and easy to adapt, while considering these practical constraints. This motivated the development of a heuristic model tailored specifically to the company, with the goal of reflecting the operational logic used by the planners, and offering implementable recommendations without requiring complex computational effort or training.

4.3 High-Level Overview of the Heuristic

As mentioned in Section 4.1 the proposed solution is a cost-based heuristic specifically designed to support trailer to order assignment. The heuristic follows a structured process. First, all orders are sorted by delivery deadline. For each order, the model evaluates all trailers that are geographically in the proximity and available. Trailers are then scored based on a cost function that takes two factors into account: the empty-leg distance (the kilometers the trailer travels without carrying any cargo) and extra cleaning cost, if needed (see Section 4.5 for more details). The top scoring assignments are chosen and displayed to the planners. A visual overview of the heuristic logic is shown in Figure 4.1 and a detailed algorithm is shown in Section 4.6.

It is important to note that the model also evaluates the feasibility of delivery within the legal working hours of the drivers. Trailers that require more time than what corresponds to its order type are flagged as potentially infeasible. Each order is classified according to its type, and the corresponding working hours that should take (e.g., A-A: 9 hours, A-B: 18 hours, A-C: 27 hours, etc.), this is based on the number of days between pickup and delivery: A-A if it is picked up and delivered on the same day, A-B if it is picked up today and delivered the next day, A-C if it is picked up today and delivered two days later, and so on. However, if these time is exceeded, these options are not automatically discarded. Instead, the model assumes that the driver will stop working after nine hours and resume the remaining travel time the next working day. Because of this, if the delivery occurs later than what it was estimated, it is marked as late. For simplicity, the model evaluates delivery feasibility based on working days, not exact delivery timestamps.

This approach allows the planners to make the final decision without discarding the option. The reason for this is because in the company's practical environment, these constraints are often addressed flexibly. For example, planners can communicate with the customers to inform them of a later arrival when necessary, therefore the model treats time windows as soft constraints. Also, as mentioned in Section 2.3, drivers are allowed to increase their driving hours by up to 10 hours twice a week, which provides extra flexibility for operations. In addition, by presenting rather than enforcing this information, planners can have the flexibility to evaluate operational options such as coupling and decoupling the trailers, which occur in practice but are outside the scope of the model presented in this thesis.

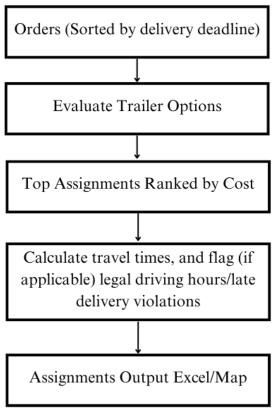


Figure 4.1: Overview of Trailer Assignment Workflow

4.4 Model Assumptions

Based on the workflow shown in Figure 4.1, the following assumptions were made in order to simplify the real-world operations and to create a feasible decision-support model:

- Truck-trailer combinations are fixed: trailers remain coupled to the same truck, decoupling strategies are outside the scope
- Homogeneous fleet: all trailers are identical in capability and cost, no trailer-specific constraints are modeled
- Static demand: all customer orders are known at the start of the planning day. No dynamic or real-time order changes are considered
- Stochastic or unforeseen disruptions: although in practice planners can adjust the schedules in case of real-time disruptions like traffic or breakdowns, the proposed model assumes a deterministic environment. The traveling times and trailer availability are based on average speeds and expected timing, and unforeseen disruptions are not incorporated. This simplification is done to maintain the model tractable and focused on the structural planning logic
- Loading, unloading and cleaning durations are fixed and do not vary by product type, customer, or location. These standardized times are applied uniformly across all orders
- Legal working time limits are 9 hours per day and are enforced in the model. Violations are reported for analysis purposes
- No split deliveries: Each order must be fulfilled entirely by one trailer within one delivery window
- Trailer location: The location of the trailer at the start of the day is taken as its last delivery location.

These assumptions are commonly made in heuristics to maintain tractability and focus on the core decision logic (Trottier & Cordeau, 2019). They form the basis for the model formulation presented in Section 4.5, which introduces the formal mathematical representation of the problem and guides the design of the heuristic algorithm.

4.5 Mathematical Model

Sets

- O: Set of orders
- T: Set of trailers
- C: Set of cleaning locations
- D: Set of all planning days, $date_o \in D$ [1]

Parameters

- l_o^p: Pickup location of order o
- l_o^d: Delivery location of order o
- $dist_{t,o}^p$: Distance from trailer t current location to pickup location of order o
- $dist_{t,c}$: Distance from trailer t current location to cleaning station c
- $dist_{c,o}^p$: Distance from cleaning station c to pickup location of order o
- $dist_o^{p,d}$: Distance from pickup location to delivery location of order o
- κ_c: Fixed cleaning cost at station c [2]
- $cleanTime$: Time required to clean a trailer (hours)
- speed: Average trailer travel speed (km/h)
- $loadTime_o$: Loading time for order o
- $unloadTime_o$: Unloading time for order o
- γ: Cost per kilometer traveled
- $\delta_{t,o} \in \{0, 1\}$: 1 if trailer t requires cleaning before order o, 0 otherwise
- $date_o$: Scheduled day of order o
- $maxWorkTime_o$: Legal working hour limit for order o (based on its type)
- a_t: Date on which trailer t becomes available for assignment

[1] Each order $o \in O$ consists of a loading and unloading task. Optional cleaning tasks may be inserted between previous unloading and next loading order depending on product compatibility.

[2] The closest cleaning station is selected based on the trailer's position

Decision Variables

- $x_{t,o} \in \{0, 1\}$: 1 if trailer t is assigned to order o, 0 otherwise
- $y_{t,c,o} \in \{0, 1\}$: 1 if trailer t is assigned to cleaning station c, before order o, 0 otherwise

Auxiliary Variables

- $\delta_{t,o} \in \{0, 1\}$: Indicator variable, 1 if trailer t requires cleaning before being assigned to order o, based on product compatibility with the previous product carried by trailer t.
- $u_o \in \{0, 1\}$: 1 if order o is not assigned to any trailer, 0 otherwise (because no trailer is available)

Objective Function

The total cost of assigning trailer t to order o is based on empty-leg travel distance and whether cleaning is required due to product incompatibility:

- If no cleaning is needed ($\delta_{t,o} = 0$), the cost consists only of the distance from the trailer's current location to the pickup location.
- If cleaning is required ($y_{t,c,o} = 1$), the cost includes:
  - Travel distance from the trailer's current location to the selected cleaning station
  - Travel distance from the cleaning station to the pickup location
  - Fixed cleaning cost at the selected station

This can be represented as:

$$\min \sum_{t \in T} \sum_{o \in O} x_{t,o} \cdot \left[\sum_{c \in C} y_{t,c,o} \cdot \left(\gamma \cdot \left(\text{dist}_{t,c} + \text{dist}^{p}_{c,o} \right) + \kappa_c \right) + (1 - \delta_{t,o}) \cdot \gamma \cdot \text{dist}^{p}_{t,o} \right] \tag{4.1}$$

This equation minimizes the cost where the trailer is empty, therefore the distance from the pickup location to the delivery location is not included, because these costs are covered by the customer.

Although cost is the main optimization criterion, total time per assignment (including cleaning, travel, loading, and unloading) is also calculated for feasibility checking and analysis purposes. However, it is not directly minimized in the objective.

Constraints

The following constraints control trailer-to-order assignments in the model:

1. **Cleaning requirement:** if there is a product incompatibility (previous product is not the same as the next product), the trailer requires a cleaning, therefore, a cleaning must be scheduled, and exactly one cleaning station is selected if a cleaning si required:
$$c_{t,o} \geq \delta_{t,o} \cdot x_{t,o} \quad \forall t, o$$
$$\sum_{c \in C} y_{t,c,o} = \delta_{t,o} \quad \forall t \in T,\ o \in O$$

2. **One-to-One Assignment:**

   Each trailer can be assigned to at most one order per day. Each order must be assigned to exactly one trailer, unless no trailer is available due to feasibility constraints.
$$\sum_{\substack{o \in O: \\ date_o = d}} x_{t,o} \leq 1 \quad \forall t \in T, \forall d \in D$$
$$\sum_{t \in T} x_{t,o} + u_o \leq 1 \quad \forall o \in O$$

   Where:

   - O_d is the set of orders available on day d
   - $u_o \in \{0, 1\}$: 1 if order o is unassigned

3. **Availability Constraint:** Trailer t can only be assigned to order o if it is available on or before the scheduled date of the order
$$x_{t,o} = 0 \quad \text{if } a_t > date_o$$

4. **Working Time (Soft constraint):** This constraint is used for post-assignment feasibility checking. The *TotalTime* is the time trailer t needs to complete order o, including travel time, cleaning, loading and unloading. This value is calculated and compared with the legal driving limit for the order type. While not enforced as a hard constraint, legal violations are tracked:
$$\begin{aligned} \text{TotalTime}_{t,o} = y_{t,c,o} \cdot & \left(\text{cleanTime} + \frac{\text{dist}_{t,c} + \text{dist}^{p}_{c,o}}{\text{speed}} \right) \\ & + (1 - \delta_{t,o}) \cdot \left(\frac{\text{dist}^{p}_{t,o}}{\text{speed}} \right) \\ & + \frac{\text{dist}^{p,d}_{o}}{\text{speed}} + \text{loadTime}_o + \text{unloadTime}_o \end{aligned} \tag{4.2}$$
$$\text{If } TotalTime_{t,o} > maxWorkTime_o \Rightarrow \text{Legal violation flagged}$$

The trailer's working time is evaluated independently for each order, not taking into account previous or future assignments. This simplification is based on the fact that each trailer is assigned to at most one order per day, and transport often lasts multiple days. Therefore, the total time required for each assignment can be evaluated per order and compared against the legal daily working limit without accumulating hours across orders.

4.6 Algorithm

This section presents the cost-based heuristic algorithm developed to generate feasible trailer to order assignments. This algorithm follows the logic presented in Section 4.3. It assigns trailers to orders, minimizing the total cost and making sure that it complies with the operational constraints. The orders are processed by urgency (according to its delivery date). For each order, the algorithm evaluates all available trailers and calculates the cost of the trip. It also checks if cleaning is required, (in case there is a product incompatibility), if this is the case, the trailer is directed to a feasible cleaning station, and the respective cleaning cost and detour cost as well as the corresponding cleaning times are calculated. Then it is assessed whether if the trailer will be able to arrive to the customer's delivery location at the estimated day, in case it is it is marked as *on time* (feasible), and *late* (violation) otherwise. Additionally, each assignment is evaluated according to the legal driving limits that are assigned to the order depending on its type (as mentioned in Section 4.3, if the order exceeds this time it is flagged). Finally, the top five lowest-cost trailer to order assignments are proposed, this is the principal idea of the decision-support tool, to provide planners with five assignments so they have several options to choose from.

Algorithm 1: Cost-Based Trailer Assignment Heuristic

Input: Orders O, Trailers T, Cleaning Locations C;
Parameters: cost per km, speed, legal work limits, loading, unloading and cleaning times
Output: Suggested trailer assignments with cost and feasibility status

Initialize `assignments` $\leftarrow \emptyset$;
Sort O by delivery date (urgency) ;
foreach *order* $o \in O$ **do**
  Identify trailers near pickup location $\rightarrow$ `sorted_trailers` ;
  foreach *trailer* $t \in$ *`sorted_trailers`* **do**
    if $y_{t,c,o} = 1$ *(product incompatible)* **then**
      Find feasible cleaning station ;
      Add cleaning time and cost κ_c ;
      Calculate the distance from trailer's current location to cleaning and from cleaning to pickup location ($dist_{t,c} + dist^{p}_{c,o}$);
    else
      Use direct travel time and cost ($\text{dist}^{p}_{t,o}$)
    Calculate total time: travel + cleaning + loading + delivery + unloading ;
    Estimate arrival time at pickup ;
    Check pickup window feasibility ;
    if *total time* $\leq$ *legal daily working limit* **then**
      Set *status* $\leftarrow$ Feasible ;
    else
      Set *status* $\leftarrow$ Violation ;
    Record $(t, cost_{t,o}, cleaning, status)$ in assignment list for o ;
  Select top 5 lowest-cost trailer assignments to order o ;
  Add to `assignments` ;
return *`assignments`*

4.7 Summary

This chapter addressed the research question: *Which solution approach is most suitable to support the planning process in the company's context?* by presenting a cost-based heuristic model. It presented the model's assumptions, mathematical formulation, and decision logic. And an algorithm was designed to generate cost-efficient trailer assignments.

Chapter 5: Results

This chapter presents the results produced by the proposed heuristic. The goal of this chapter is to show how the model behaves. The research question addressed in this chapter is: *What is the output of the model?* To see how the model behaves, the model was tested on a single planning day, drawn from historical data (January 28th, 2025). This test allowed for a detailed examination of the decision logic of the model, offering a transparent view of how trailers are assigned to orders. Section 5.1 presents the assumptions and the parameters that were used to test the model, Section 5.2 presents the output of the model. Section 5.3 presents general observations that are further addressed in Chapter 6, and lastly, Section 5.4 presents a summary of the chapter.

5.1 Experimental Assumptions

In addition to the assumptions mentioned in Section 4.4, the following assumptions were made to test the heuristic. These same assumptions and parameters were also used to evaluate the model and compare it with the benchmark in Chapter 6.

- **Legal driving time:** The model applies a maximum driving limit of 9 hours per day, (this is a simplification of EU driving regulations (European Parliament and Council, 2006), mentioned in Section 2.3). Each order is categorized according to its type, (e.g., A-A: 9 hours, A-B: 18 hours, A-C: 27 hours, etc.), based on the number of days between pickup and delivery, as explained in Section 4.3. This classification defines the total time expected to complete the order, including driving, loading, unloading, and cleaning. If the required time exceeds the expected limit for its type, the order is marked as a *legal violation* but it is not disqualified. It is important to note that the model always ensures that no driver can drive for more than 9 hours per day. For example, if an order takes 10 hours to complete, the driver will work 9 hours on day one and 1 hour on day 2. This means that the order is still executed, but takes longer than its classification would suggest

- **Informative constraints:** The preferred delivery dates were treated as informative rather than hard constraints. If an assignment exceeded the ideal delivery window, it was still included in the output but marked as *on time violation*. These flags allow planners to make informed decisions without prematurely excluding feasible options. This approach reflects real-world planning flexibility, since drivers can legally extend their driving time to 10 hours twice a week, as explained in Section 2.3, and planners often coordinate with customers in case of delays. By flagging these assignments rather than discarding them, the model supports human decision making, allowing planners to consider specific priorities and context-specific factors without eliminating potentially viable (though imperfect) options

- **Trailer Starting Locations:** The last known unloading location for each trailer prior to the experiment day is used to establish its present location

- **Cleaning Availability:** It is assumed that the cleaning stations are always available, with no capacity limits.

- **Cost Estimation:** Based on Section 4.5 the costs were calculated using a γ value (cost per km traveled) of €1.2 per kilometer and a fixed cleaning cost of €150. It is important to note that these values are realistic but fictitious, they were selected to reflect typical industry estimates, while ensuring confidentiality. The same applies to all other operational parameters used in this study. These values were selected in consultation with the company to simulate reasonable planning conditions without revealing sensitive data.

- **Shared Parameters:** Travel and handling calculations were based on fixed parameters, which are presented in Table 5.1.

Parameter	Value
Cleaning time	1.0 hour
Loading time	1.0 hour
Unloading time	1.5 hours
Average speed	80 km/h
Cost per kilometer	€ 1.20
Cleaning cost	€ 150
Road scale factor	€ 1.2
Start working time	8:00 am

Table 5.1: Simulation Parameters Used for Time and Cost Calculation

Although customer-specific opening hours were not explicitly modeled, the driving time restriction implicitly defines a customer time window. Since it is assumed that drivers start working at 8:00 and can work a maximum of nine hours per day, the deliveries can only occur between 8:00 and 17:00. The deliveries that may take longer than nine hours to complete are automatically delivered on the next day, which effectively implies that the customer locations are considered to be closed after 17:00.

- **Distance calculation:** Distances were calculated using the Haversine formula (Kengpol & Chanchittakarn, 2025):

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{5.1}$$

Where:

- d is the great-circle distance between two points
- r is the Earth's radius (assumed as 6371 km)
- ϕ_1, ϕ_2 are the latitudes of the two points (in radians)
- $\Delta\phi$ is the difference in latitude
- $\Delta\lambda$ is the difference in longitude

The result was then multiplied by a road distance scale factor of 1.2 to approximate the real driving distance.

5.2 Output of the Model

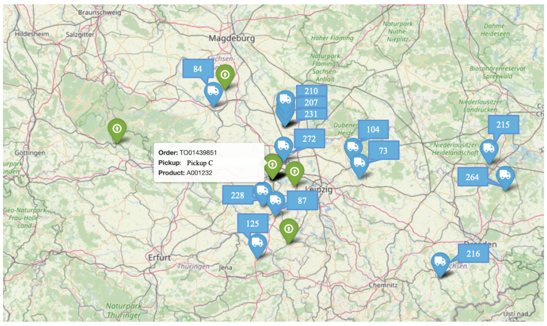
date	orderNumber	trailer_id	pickup	delivery	cleaning_station	cost	total_time	on_time	egal_violatior	legal_limit	Product_code	delivery_datetime
2025-01-28	TO01440117	76	Pickup A	Delivery E	Station 1	179.39	19.69	FALSE	TRUE	18	A001323	2025-01-30 09:41:25
2025-01-28	TO01440117	79	Pickup A	Delivery E	Station 1	185.65	19.76	FALSE	TRUE	18	A001323	2025-01-30 09:45:20
2025-01-28	TO01440117	132	Pickup A	Delivery E	Station 1	200.18	19.91	FALSE	TRUE	18	A001323	2025-01-30 09:54:25
2025-01-28	TO01440117	227	Pickup A	Delivery E	Station 1	226.91	20.19	FALSE	TRUE	18	A001323	2025-01-30 10:11:07
2025-01-28	TO01440117	276	Pickup A	Delivery E	Station 1	243.86	20.36	FALSE	TRUE	18	A001323	2025-01-30 10:21:43
2025-01-28	TO01435621	240	Pickup B	Delivery F	Station 2	183.44	13.11	TRUE	FALSE	18	A000063	2025-01-29 12:06:27
2025-01-28	TO01435621	280	Pickup B	Delivery F	Station 2	183.46	13.11	TRUE	FALSE	18	A000063	2025-01-29 12:06:28
2025-01-28	TO01435621	85	Pickup B	Delivery F	Station 2	185.15	13.13	TRUE	FALSE	18	A000063	2025-01-29 12:07:31
2025-01-28	TO01435621	247	Pickup B	Delivery F	Station 3	191.08	13.19	TRUE	FALSE	18	A000063	2025-01-29 12:11:13
2025-01-28	TO01435621	74	Pickup B	Delivery F	Station 3	191.08	13.19	TRUE	FALSE	18	A000063	2025-01-29 12:11:13
2025-01-28	TO01439851	272	Pickup C	Delivery G	Station 4	167.52	11.13	TRUE	FALSE	18	A001232	2025-01-29 10:07:31
2025-01-28	TO01439851	228	Pickup C	Delivery G	Station 5	174.59	11.2	TRUE	FALSE	18	A001232	2025-01-29 10:11:56
2025-01-28	TO01439851	87	Pickup C	Delivery G	Station 6	181.06	11.27	TRUE	FALSE	18	A001232	2025-01-29 10:15:59
2025-01-28	TO01439851	231	Pickup C	Delivery G	Station 7	195.55	11.42	TRUE	FALSE	18	A001232	2025-01-29 10:25:02
2025-01-28	TO01439851	207	Pickup C	Delivery G	Station 7	195.55	11.42	TRUE	FALSE	18	A001232	2025-01-29 10:25:02
2025-01-28	TO01439420	120	Pickup D	Delivery H	Station 8	153.48	8.96	TRUE	FALSE	18	A005409	2025-01-28 16:57:46
2025-01-28	TO01439420	260	Pickup D	Delivery H	Station 8	153.48	8.96	TRUE	FALSE	18	A005409	2025-01-28 16:57:46
2025-01-28	TO01439420	129	Pickup D	Delivery H	Station 8	153.48	8.96	TRUE	FALSE	18	A005409	2025-01-28 16:57:46
2025-01-28	TO01439420	235	Pickup D	Delivery H	Station 8	153.48	8.96	TRUE	FALSE	18	A005409	2025-01-28 16:57:46
2025-01-28	TO01439420	70	Pickup D	Delivery H	Station 8	153.48	8.96	TRUE	FALSE	18	A005409	2025-01-28 16:57:46

Figure 5.1: Example of the output of the model

On the chosen day, 71 orders were processed and Figure 5.1 shows a fragment of the output of the model, including trailer assignments, selected cleaning stations, estimated costs, total completion time per order, compliance with estimated delivery and legal driving restrictions. For each order, the model provides the top 5 trailer options, ranked by cost.

To verify how the model applies proximity and cleaning constraints in practice, a targeted example is shown for order *TO01439851*, with pickup at location C. As seen in Figure 5.2a, the closest trailers to the customer's location are *#272, #228, #87, and #231/207 (same location)*. And the output of the model shown in Figure 5.1 confirms that the selection of the trailers prioritizes spatial proximity to the pickup location.

Additionally, the model checks the last product carried by each trailer. In this case, none of the candidate trailers previously carried the same *ProductCode* as the current order. Therefore, a cleaning is required before loading the next order. Figure 5.2b shows the closest cleaning locations to the selected trailers, and the output shown in Figure 5.1 confirms that the model assigns each trailer to the cleaning location that leads to the least detour. This example demonstrates that the model correctly applies both proximity-based selection and cleaning logic, as defined in the heuristic. Therefore, it can be said that the results match the expected behavior as described in Section 4.6.



(a) Example of the output

(b) Trailers and Cleaning stations

Figure 5.2: Overview of trailer assignment example and nearby cleaning stations

5.3 Observations

It can be seen that the model is able to generate the best five trailer assignments for each order, in terms of cost. This approach allows planners to have flexible options for trailer selection. However, an important observation is that the model often proposed the same trailers for multiple orders, particularly when those orders shared similar pickup locations. This behavior is due to the design of the model, which evaluates each order independently, assuming full trailer availability at the moment of assignment. As a result, unless a trailer is explicitly selected and reserved by a planner, it remains a candidate for subsequent orders, even if it has already been proposed to another order. This is because the planners input is required to finalize and reserve a trailer for execution.

To facilitate a rigorous and traceable evaluation of the model, the preferences of the planners were simulated as if they would always choose the top-ranked trailer proposed by the model. Under this assumption, the trailers will be immediately reserved after assignment and will be marked as unavailable until the order is delivered. This logic in the simulation avoids overlapping trailers and guarantees that each trailer is only used for one order at a time, which accurately reflects the real-world limitations. This decision allows the model to be evaluated in a fair, consistent and repeatable way, specially when comparing it to benchmark strategies. The resulting setup, which includes the dynamic updates of trailer availability and assignment traceability is further detailed in Chapter 6.

5.4 Summary

This chapter presented the results of the cost-based heuristic introduced in Chapter 4. The model was tested on a single planning day and a fragment of the results was presented in order to show how the trailer assignments are done. The visualizations confirmed that the model correctly incorporated prioritization based on distance (costs) and cleaning requirements. In Chapter 6, the model is validated through an automated selection process, in which only the highest ranked trailer is assigned to each order.

Chapter 6: Evaluation

This chapter evaluates the performance of the proposed model using realistic multi-day planning data. In contrast to Chapter 5, which demonstrated the model's logic and output on a single day, this chapter simulates how the model would perform in operational conditions, assuming the planner always selects the top-ranked assignment. The research question addressed in this chapter is: *How well does the model perform when tested with realistic planning data?* To answer this question, this chapter is structured in the following way: Section 6.1 explains the evaluation setup, Section 6.2 introduces the simulation, Section 6.3 presents the implementation of the heuristic in the simulation, and the Last Recently Used (LRU) benchmark that the proposed model was compared against. Section 6.4 presents the metrics that were used to evaluate the proposed heuristic and the benchmark. Section 6.5 evaluates the performance of each method across five samples. Section 6.6 provides a sensitivity analysis, Section 6.7 presents a dashboard. And Section 6.8 gives a summary of this chapter.

6.1 Evaluation Setup and Data Sampling

To evaluate the performance of the proposed heuristic (presented in Chapter 4 and 5), five test samples were created using historical data. Each sample consists of 14 nonconsecutive days, for each weekday (Monday to Sunday), two random days were selected from the last six months. This sampling strategy ensures a balanced representation of typical weekly planning patterns while capturing variation in order volumes, delivery patterns, and trailer availability. Nonconsecutive days are used to avoid clustering effects from odd weeks (e.g. holidays, strikes, etc), and it also allows to cover a broader range of scheduling conditions.

The sampling procedure was automated in Python to select the required number of days. Each sample contained a set of customer orders, available trailers, and cleaning stations.

6.2 Simulation Framework

In order to objectively compare different trailer assignment methods, an adjustable simulation model was created. Using a consistent logic, this structure ensures that each strategy is evaluated under identical constraints, order sequences, and trailer conditions. In this simulation, each *loading* (laden) action was interpreted as a new order to be scheduled on that day. Using the associated *orderNumber*, the corresponding delivery information (lossen) was matched to reconstruct the full route of each order. This allowed the model to estimate the time needed to complete the order, and verify compliance with simplified driving time constraints, mentioned in Section 5.1. The information from the cleaning stations was also obtained from the historical data set. It was assumed that a trailer could be assigned to a given cleaning station if the company had used that station in the last six months. In this framework, both the proposed heuristic and a Least Recently Used (LRU) benchmark were tested. The LRU strategy selects the trailer that has been idle the longest, ignoring distance and cost, acting as a naive allocation policy aimed at maximizing trailer utilization. Figure 6.1 presents an overview of the simulation framework used to evaluate trailer assignment strategies.

For every day, the simulation framework makes the following basic actions:

1. Load all orders scheduled for that day (pickup and delivery), and sort them by delivery deadline.

2. Check trailer availability and working time limits.

3. Apply a specific decision-making policy (e.g., heuristic, LRU) to select a trailer.

4. Assign the trailer and update its location, working time, and availability.

5. Record all assignments and unassigned orders, and update outputs.

One of the main advantages of this approach is its adaptability, while the simulation logic is constant, other trailer assignment strategies can be "plugged in" as policies. Therefore, the models evaluated in this framework (LRU and heuristic), only differ in the decision making process that is applied to choose a trailer for a particular order. This approach allows for a fair comparison, since the variations of the outcome only depend on the assignment policy instead of the simulation structure.

Both the heuristic and LRU models were implemented in Python using the *pandas* library for data processing and *Folium* for map visualization. The input and output data were managed via Excel files.

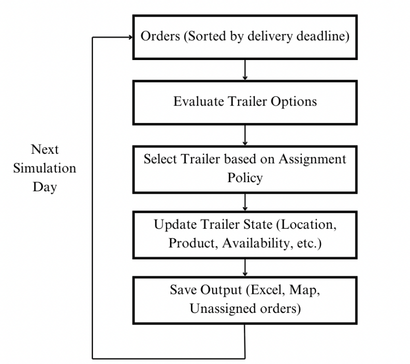


Figure 6.1: Simulation Framework

6.3 Implementation of the Heuristic Model

As previously mentioned, the initial purpose of the model is to function as a decision support tool that provides the planners with a ranked list of feasible trailer assignments to every order. However, it was necessary to simulate a deterministic behaviour to validate the model performance across multiple days. Therefore, during the evaluation phase, the model was configured to always select the top-ranked trailer for each order (which is the one with the lowest cost). Only one trailer was selected per order to ensure consistent trailer usage tracking.

The heuristic was integrated into the simulation framework as the assignment policy. For each order, it evaluates all available trailers and selects the one with the lowest estimated cost, taking into account travel distances, potential cleaning requirements, and feasibility constraints such as time limits and legal driving regulations.

Runtime and Practical Feasibility

The total simulation time for all five samples, was approximately 1034.29 seconds, (around 17.2 minutes) on a standard laptop (MacBook Air, Apple M1 chip, 8GB RAM). This corresponds to an average of about 14.77 seconds per day. Although this time is not optimal, the model demonstrates acceptable performance. Future improvements, such as algorithmic tuning or implementation in a compiled language, could reduce computation time and support near-real-time planning needs.

6.4 Evaluation Metrics

The following metrics were used to evaluate the LRU and heuristic models. These indicators were chosen because they reflect what is most important to the company (e.g., cost efficiency, delivery reliability, and legal compliance).

- Average cost per order
- Average time to complete the order
- Percentage of on-time deliveries
- Percentage of legal working hour violations
- Number of assigned vs. unassigned orders
- Average trailer working time per day
- Average trailer idle time

6.5 Performance Comparison

Figures 6.2, 6.3, 6.4 and 6.5 present visualizations to compare both models (LRU and heuristic) across the five samples. For more information on each sample, the reader is referred to Appendix A.

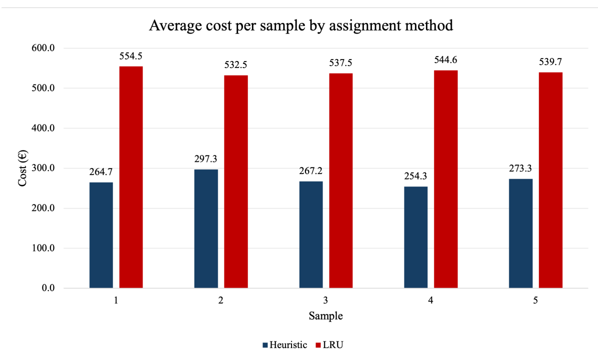


Figure 6.2: Average Cost

In Figure 6.2, it can be seen that the heuristic (cost-based method) performs significantly better than the LRU method in all samples, in the first sample, the heuristic costs are 47.7% lower than the LRU, in sample 2 by 55.8%, in sample 3 by 49.7%, sample 4 by 46.7%, and in sample 5 by 50.6%.

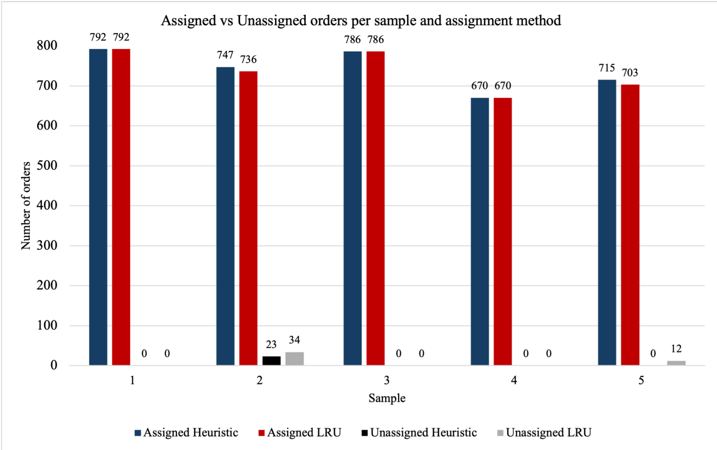


Figure 6.3: Assigned vs Unassigned Orders

Figure 6.3 presents the number of orders that were assigned and unassigned in each sample per assignment method. It can be seen that the number of orders assigned in sample 1, 3 and 4 is the same, however in sample 2 both methods were not able to assign certain orders, which represent 3% of the total orders for the heuristic, and 4.4% of the orders for the LRU. And in sample 5, the LRU method was not able to assign 1.67% of the orders.

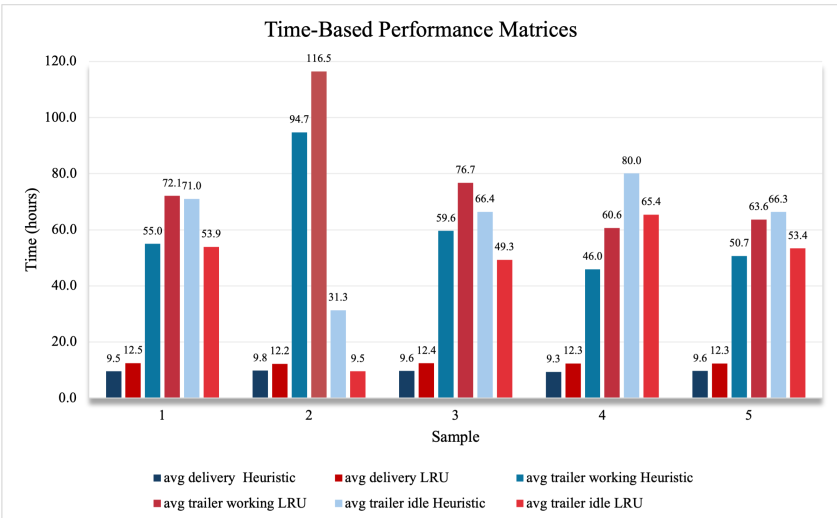


Figure 6.4: Time-based Performance

Figures 6.3 and 6.4 indicate that the heuristic outperforms the LRU in terms of order assignment and time efficiency. In Figure 6.4 it can be seen that on average, LRU takes 2.8 hours longer to deliver orders and requires drivers to work 16.7 hours more compared to the cost-based method. Additionally, the trailers in the cost-based heuristic spend more time idle, which suggests a more selective and cost-efficient assignment.

The cost-based approach is able to fulfill more orders, in a shorter amount of time, and with a better trailer utilization, which indicates a more efficient use of resources.

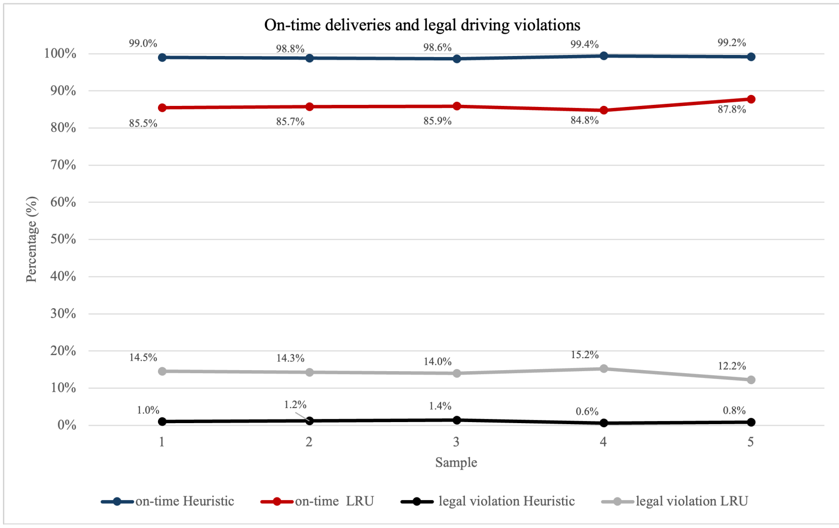


Figure 6.5: On-Time Deliveries and Legal Driving Time Violations

Figure 6.5 presents the percentage of orders that were delivered earlier or on their scheduled delivery date, these orders were classified as on-time deliveries. Additionally, an analysis was made regarding the percentage of orders that respected the legal driving time constraint of 9 hours per day. The results show that the cost-based heuristic consistently outperforms the LRU method in terms of service level and compliance. On average, the heuristic achieves 13.1.% more on-time deliveries than LRU. And only 1% of the heuristic assignments exceed the legal driving time limit, compared to 14% in the LRU model. This highlights the superior ability of the heuristic to generate feasible plans that align with legal and operational constraints.

These differences indicate that although the LRU method aims to decrease the idle time of the trailers, this leads to infeasible assignments, while the heuristic is able to comply better with the regulations and leads to better outcomes.

To combine the performance comparison, Table 6.1 summarizes the mean and standard deviation of each metric across the five sample runs, allowing to see the differences between the two methods through a statistical comparison.

Metric	**Heuristic (Mean $\pm$ SD)**	**LRU (Mean $\pm$ SD)**
Avg cost	271.35 ± 16.03	541.76 ± 8.34
Avg time to deliver order	9.57 ± 0.16	12.33 ± 0.11
Avg trailer working time	61.18 ± 19.41	77.91 ± 22.50
Avg trailer idle time	63.02 ± 18.59	46.29 ± 21.40
% on-time deliveries	$98.99\% \pm 0.31\%$	$85.93\% \pm 1.11\%$
% legal violations	$1.01\% \pm 0.31\%$	$14.048\% \pm 1.11\%$
# of assigned orders	742 ± 50.92	737.40 ± 52.61
# of unassigned orders	4.6 ± 10.28	9.20 ± 14.81

Table 6.1: Performance comparison of heuristic vs. LRU model

Analysis

Each metric reflects the average of all samples per assignment method (LRU and heuristic). The mean performance is compared, and the standard deviation is provided to show how consistently each model performs under different planning conditions. The results show that the models performs consistently even when demand patterns change. The results confirmed the patterns that were previously observed, they indicate that the heuristic model consistently outperforms the LRU method in every evaluation metric. On average, it achieves a 50% cost reduction, delivers orders 2.8 hours faster and has significantly less legal violations than the LRU model. This result has a direct impact on fleet compliance, driver well-being, and risk reduction in practice. Although the cost-based model has a higher idle time than the LRU, this reflects a more selective assignment method rather than under-utilization.

Additionally, the number of assigned and unassigned orders in both models is almost the same. This suggests that the results in the cost-based approach were achieved without compromising planning feasibility, but instead this logic led to higher quality assignments. Therefore, taking all of this into account, it can be said that the heuristic delivers stable, efficient and regulation-aware planning outcomes across variable weekly demand scenarios. This indicates that the proposed heuristic is a strong candidate for real-world implementation in dynamic, constraint-rich environments.

While statistical metrics provide strong evidence, these visualizations enhance transparency of model logic, and support qualitative feasibility checks.

6.6 Sensitivity Analysis

To see the role that cleaning plays in the performance of the model, a sensitivity analysis was conducted. This analysis was done with three scenarios: the first one is the normal output of the model, doing the cleaning only when it is required (if the previous product carried is not the same as the next product carried), the second is forcing every trailer to make a cleaning before loading the next product, and the third scenario is if the cleanings are never required.

Model	Cleaning condition	Avg cost	Avg delivery time	On-time delivery	Legal violation	Orders assigned
Heuristic	Normal	271.30	9.58	98.99%	1.01%	742
Heuristic	All cleaning	289.76	9.68	98.96%	1.04%	742
Heuristic	No cleaning	135.32	8.64	99.66%	0.34%	742
LRU	Normal	541.76	12.33	85.93%	14.05%	737
LRU	All cleaning	548.18	12.38	85.79%	14.19%	738
LRU	No cleaning	396.18	11.35	89.34%	10.63%	739

Table 6.2: Performance metrics for different models and cleaning conditions.

The model performs similarly in the *normal* and *all cleaning* scenarios, showing minor differences in cost, delivery time, on-time delivery and legal violation metrics. This suggests that under real-world conditions, a majority of the orders already require cleaning. Although Section 2.3 stated that approximately 70% of orders require cleaning, the stricter modeling assumption that the *productCode* must match exactly may exaggerate cleaning needs. In practice, planners may allow trailers to carry a product from the same family group after a related product, even if the *productCode* is not identical. This indicates that the model could slightly overestimate the impact of cleaning requirements compared to real operations.

However comparing the *normal* scenario to the *no cleaning* it can be said that cleaning plays a very important role, since it impacts significantly the average cost (reducing them by 50% in the heuristic, and by 26.8% in the LRU), and also the average time, by reducing it by 10% in the heuristic, and by 8% in the LRU. Therefore, it can be said that the LRU is less sensitive to the cleaning assumption but performs substantially worse overall.

Additionally, it can also be seen that the heuristic remains highly feasible and reliable under all scenarios, with 98.9% on-time performance and minimal legal violations.

6.7 Potential for Implementation

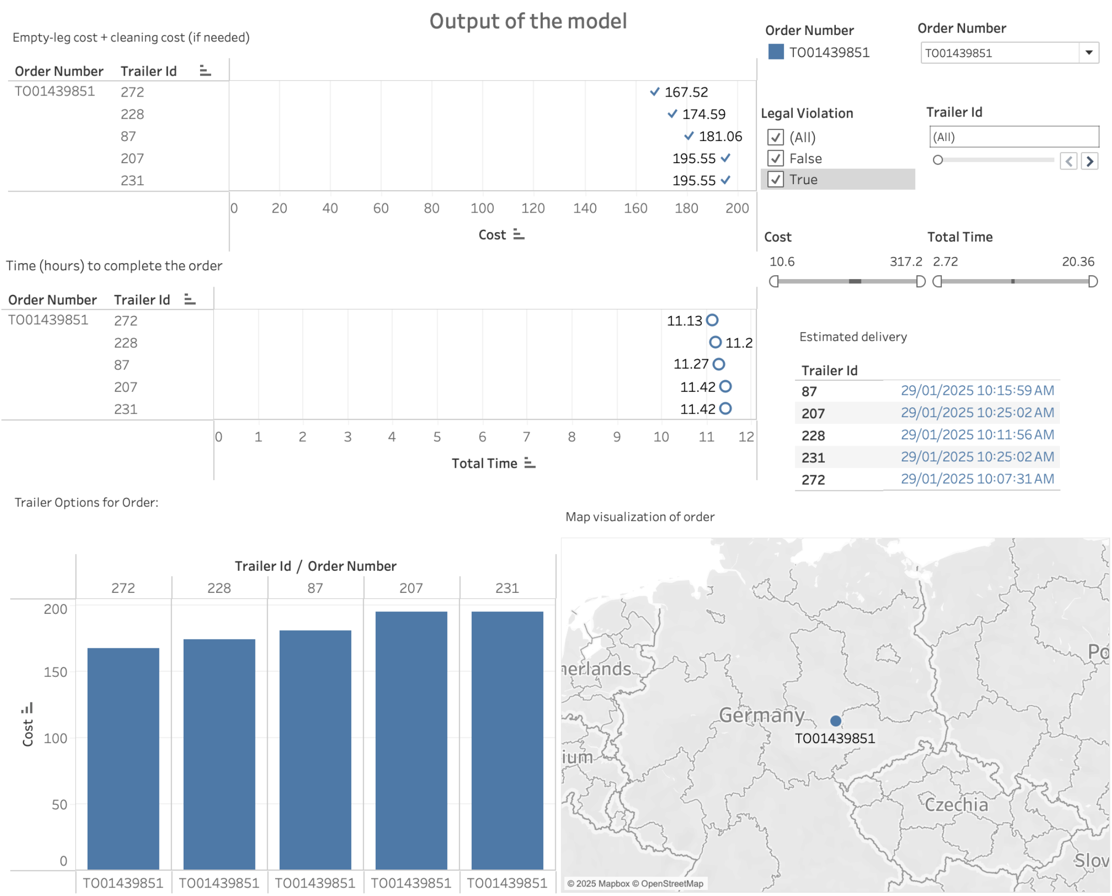


Figure 6.6: Dashboard visualization

To support the interpretation of the results of the model, and facilitate decision making, a dashboard was created using *Tableau*, as showed in Figure 6.6. This dashboard presents each order together with its best five trailer assignments, which allows planners to quickly compare the advantages and disadvantages of every assignment in terms of cost, estimated time to complete the order, estimated arrival time, and compliance with legal violations (marked as a checkmark if it complies with the legal constraints and flagged with a cross otherwise).

This dashboard serves as a prototype for the company to see how this model could be integrated into the daily planning workflow. Ideally, it would be connected to live operational data, automatically importing trailer availability, order details, and displaying real-time trailer recommendations. This integration could:

- Reduce manual planning effort
- Promote consistency and traceability
- Enchance transparency of planning logic
- Provide cost-effective assignments while respecting operational constraints.

Therefore, this dashboard shows the potential of combining a simple heuristic model with a user-friendly interface. By implementing this solution, the company could move towards a more efficient, transparent, and scalable planning.

6.8 Summary

The results presented in this chapter demonstrate that the proposed heuristic model performs effectively when tested with realistic planning data. It consistently outperformed the LRU benchmark across the five simulation samples, by significantly reducing costs, improving delivery speed, and minimizing legal driving hour violations, all without compromising feasibility.

The low variability in performance metrics indicates that the model proved to be strong across varying weekly scenarios. These findings validate the practical usefulness of the model and its potential to support real-world transportation planning decisions. A sensitivity analysis was performed to evaluate the impact of cleaning requirements. The results confirmed that this constraint has a significant influence on the cost and execution time, which highlights the importance of modeling the cleaning processes with precision in transport planning.

Finally, the dashboard serves as a prototype to visualize how the tool could be implemented into the company's planning workflow. By presenting assignment recommendations in a clear and interpretable format, it demonstrates how the model can enhance decision-making in practice.

Chapter 7: Conclusions and Recommendations

This chapter concludes the study by restating the research goal and answering the main research question: *How can the trailer assignment process at Nijhof-Wassink be enhanced to support planners in their decision-making and reduce the time spent on planning?* in Section 7.1, presenting the findings in Section 7.2, the contribution to research and practice in Section 7.3, the limitations of the model in Section 7.4, proposing future improvements in Section 7.5 and giving recommendations in Section 7.6. And lastly, Section 7.7 gives a final conclusion of the study.

7.1 Research Goal

The goal of this thesis was to support the planning of the Dry Bulk Logistics (DBL) department of Nijhof-Wassink, by developing a decision support tool that proposes trailer to order assignments. The tool supports planners in their decision making by offering consistent, transparent, and feasible suggestions based on cost, distance, cleaning requirements, and legal driving constraints. This approach helps reduce the time spent on planning by automating the evaluation of alternatives and highlighting the most valuable options, minimizing the need for manual checks.

7.2 Main Findings

The initial purpose of the tool was to propose several suggestions of trailer assignments for each order. However, the model was validated by simulating that the planner will always choose the highest-ranked option out of all the proposed options, which is the one with the lowest cost. Simulating with this behavior, the model proved to propose feasible trailer-to-order assignments in a reasonable amount of time. It demonstrated a strong performance across the five samples (each consisting of 14 random days) in which it was tested. The model also consistently outperformed the LRU benchmark, by reducing the average cost per assignment by 50%, decreasing the average delivery time by 22.3%, and reducing the working time per trailer by 16.7 hours on average. Additionally, 98.99% of the deliveries were on time, outperforming the LRU by 13.06%. Only 1.01% of the orders violated the legal driving times, compared to 14% of the LRU orders. This was achieved without compromising feasibility, since 99.38% of the orders were successfully fulfilled.

These results indicate that the proposed heuristic can deliver significant cost and time savings without sacrificing feasibility, making it a practical and efficient support tool for real-world trailer planning.

7.3 Contribution to Research and Practice

This study can be seen as a combination of transportation planning, heuristic-based automation, and operational decision support. Unlike the models proposed in the literature, which usually require complex optimization frameworks and may be harder to interpret (compared to the model present in this study). This research proposes a practical, cost-based decision support tool that mimics the reasoning of experienced planners to assign trailers to orders. Although previous studies have addressed trailer routing, scheduling, and assignment problems, only a few of them have explored the specific context of planner-supported trailer assignment under real-world conditions, including trailer cleaning requirements, availability constraints, and legal driving regulations. Therefore, the model developed in this thesis offers a solution that incorporates these constraints, is easy to interpret, and is useful for day-to-day use.

Additionally, this work demonstrates how manual trailer planning, based on experience, can evolve into a structured, data-driven process, improving and supporting human decision making. This not only contributes to existing research, but it also provides a practical basis for real-world implementation in the transportation logistics context.

7.4 Limitations

While the heuristic model shows a good performance, there are certain limitations that are important to acknowledge:

- **Parameters:** The model assumes fixed travel speeds, loading/unloading durations, and cleaning times. These values do not account for real-world fluctuations, such as traffic congestion, or variations in service length per customer location or product
- **No real-time re-optimization:** Once an order is assigned, the model does not dynamically reschedule or reshuffle assignments, even if better options appear later
- **No real-time input:** Traffic disruptions, road conditions, or sudden order changes are not considered
- **Simplified trailer availability:** A trailer becomes available the day after completing an assignment, regardless of how many hours it actually worked. So, when trailers are utilized for short-distance tasks only, this constraint may cause under-utilization
- **Cleaning station availability:** The nearest cleaning station is chosen, assuming unlimited capacity and no delays. In reality, cleaning stations may be occupied or have limited operating hours
- **No consideration for human factors:** Individual driver shifts are not considered, as well as their return to depots

- **Locally optimal, not globally optimal:** The heuristic selects the best trailer for each order individually, according to current availability. However, it does not evaluate all orders jointly to find the optimal trailer assignment. This local decision-making can lead to situations where a better global combination is missed, for example, assigning a trailer to an early order when it would be more suitable for a later, geographically closer order
- **No forward planning or order sequencing:** The model does not include logic to chain compatible orders or look ahead for future assignments. Incorporating sequencing or look-ahead strategies could improve the quality of planning over multiple days

These limitations show space for future improvement. In particular, integrating dynamic re-optimization and including more real-world operational constraints, as well as incorporating look-ahead mechanisms or order sequencing logic could further enhance the model's planning capabilities.

7.5 Future Improvements

To enhance the current model and move closer to real-world planning complexity, the following suggestions are proposed for future work:

① **Integration of Machine Learning Techniques:** to predict orders that are likely to miss delivery deadlines or violate legal driving limits. This would help planners anticipate and mitigate potential risks. Additionally, with machine learning, loading, unloading and cleaning times per facility can be better estimated based on historical data, covering the parameters limitation. And the implicit preferences from planners can be learned, such as particular trailer to order assignments or the use of specific cleaning stations, among others

② **Multi-order assignment per trailer:** the model can be extended to allow trailers to handle more than one order per day, when feasible. This can be done by carefully tracking the available time and legal limits

③ **Realistic travel times:** currently the distance calculations are done using the haversine formula, in the future, travel distances and times can be obtained from *GoogleMaps* to better account for road networks and congestion

④ **Use of advanced optimization methods:** To address the limitation of locally optimal assignments, metaheuristics could improve overall trailer assignment quality by considering broader sequencing and trade-offs across cost, time, and utilization, especially in larger-scale scenarios

⑤ **Forward planning:** To address the limitation of one-order-at-a-time decisions and return to depot, the model could be extended to sequence multiple compatible orders per trailer. By considering future assignments, cleaning dependencies, and return-to-depot constraints, this enhancement would allow trailers to follow feasible multi-order routes over time. Incorporating routing logic with start/end at the home base could significantly improve planning efficiency and trailer utilization.

These improvements could significantly improve the realism, adaptability, and usability of the model in operational environments, clearing the way for its integration into real-world decision support systems.

7.6 Recommendations for Implementation

To evolve the model from a conceptual prototype to a practical tool, the following recommendations are proposed. These recommendations aim to guarantee a smooth integration with the current planning practices, build trust among the planners, and promote its adaptability in the long-term.

- Begin by running the model in parallel with manual planning to compare suggestions with actual decisions and build confidence in its reliability.
- Introduce the model as a decision support tool that can help the planners instead of presenting it as an automation tool. And train the planners to understand and interpret the outputs of the model.
- Refine the dashboard prototype developed in this study (presented in Section 6.6), to support daily planning with real-time data and interactive features.
- Use the tool as a training simulator for new planners to expose them to real-world constraints and trade-offs in decision-making in a low-risk environment.
- Integration with existing system: incorporate the model within the system that planners currently use to allow seamless access to real-time data and planner interfaces.
- Feedback loop for continuous improvement: create a mechanism for planners to provide feedback on the suggestions of the model. This feedback can improve the logic, adjust cost parameters, or identify overlooked constraints.

By integrating the model within the planners workflow as a flexible support tool, and not as a replacement, organizations could achieve a better resource assignation, while maintaining the operational control and human expertise.

7.7 Final Conclusion

This thesis shows that an interpretable, cost-based heuristic can support the assignment of trailers in full-truckload logistics, while addressing real-world operational restrictions. The model offers feasible and cost-effective options while allowing the planners to be in control. The model presented in this thesis works as a bridge between human experience and automated assistance, leading the way towards a more intelligent and efficient planning system. Additionally, this thesis also shows that heuristic can generate realistic assignments that are easy to interpret even for users without a technical expertise.

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Appendix A: Output Summary for each Sample

n=1

Metric	Method 1 (Heuristic)	Method 2 (LRU)
Avg cost	264.67	554.469
min cost	0	10.62
max cost	844.03	1846.33
total cost	209620.35	439139.65
Avg time to deliver order	9.507	12.46
#on time delivery	784	677
#legal violation	8	115
#assigned orders	792	792
#unassigned orders	0	0
avg trailer working time	54.96	72.06
avg trailer idle time	71.03	53.93
#of trailers used	131	137

Table 1: Performance Comparison of Method 1 and Method 2 for $n = 1$.

n=2

Metric	Method 1 (Heuristic)	Method 2 (LRU)
Avg cost	297.27	532.479
min cost	0	10.62
max cost	1397.93	1802.85
total cost	222067.2	391904.97
Avg time to deliver order	9.76	12.185
# on time delivery	738	631
# legal violation	9	105
# assigned orders	747	736
# unassigned orders	23	34
avg trailer working time	94.72	116.469
avg trailer idle time	31.27	9.5306
# of trailers used	77	77

Table 2: Comparison of Method 1 (Heuristic) and Method 2 (LRU) for $n = 2$.

n=3

Metric	Method 1 (Heuristic)	Method 2 (LRU)
Avg cost	267.22	537.5
Min cost	0	10.62
Max cost	771.88	1828.02
Total cost	210041.36	422479.11
Avg time to deliver order	9.62	12.397
# On-time deliveries	775	675
# Legal violations	11	110
# Assigned orders	786	786
# Unassigned orders	0	0
Avg trailer working time	59.59	76.725
Avg trailer idle time	66.40	49.27
# of trailers used	123	127

Table 3: Performance comparison (n=3) between Heuristic and LRU model

n=4

Metric	Method 1 (Heuristic)	Method 2 (LRU)
Avg cost	254.3025075	544.644
Min cost	10.62	160.26
Max cost	652.53	1838.45
Total cost	170382.68	364912.06
Avg time to deliver order	9.33	12.3099
# On-time deliveries	666	568
# Legal violations	4	102
# Assigned orders	670	670
# Unassigned orders	0	0
Avg trailer working time	45.95	60.64
Avg trailer idle time	80.04	65.35
# of trailers used	127	136

Table 4: Performance comparison (n=4) between Heuristic and LRU model

n=5

Metric	Method 1 (Heuristic)	Method 2 (LRU)
Avg cost	273.26	539.699
Min cost	0	10.62
Max cost	1225.42	1763.18
Total cost	195379.34	379408.69
Avg time to deliver order	9.641	12.311
# On-time deliveries	709	617
# Legal violations	6	86
# Assigned orders	715	703
# Unassigned orders	20	12
Avg trailer working time	50.68	63.64
Avg trailer idle time	66.31	53.3599
# of trailers used	135	136

Table 5: Performance comparison (n=5) between Heuristic and LRU model

Appendix A: Python Code:Trailer Assignment Heuristic

```
import pandas as pd
import json
from datetime import datetime, timedelta
from datetime import time as dt_time
from collections import defaultdict
import folium
import os
import time
import folium
from folium.plugins import MarkerCluster

def infer_limit(days):
    if days >= 0 and days <= 4:
        return (days + 1) * 9.0
    else:
        return 45.0
# CONSTANTS
HISTORICAL_FILE = '/Users/katinaaparicio/Downloads/THESIS/
    ModelValidation.xlsx'
COST_PER_KM = 1.2
CLEANING_COST = 150
CLEANING_TIME = 1.0
SPEED_KMPH = 80
LOADING_TIME = 1.0
UNLOADING_TIME = 1.5
ROAD_SCALE = 1.2
DRIVING_LIMITS = {'A-A': 9.0, 'A-B': 18.0, 'A-C': 27.0, 'A-D': 36.0, 'A
    -E': 45.0}
PICKUP_START = 8.0
DAILY_LIMIT = 9.0

#data from excel
historical_all = pd.read_excel(HISTORICAL_FILE, sheet_name="
    historical_data")
historical_all['DATE'] = pd.to_datetime(historical_all['DATE']).dt.date
cleaning_stations = pd.read_excel(HISTORICAL_FILE, sheet_name='cleaning
    ')
cleaning_stations.columns = cleaning_stations.columns.str.strip().str.
    lower()

#Random Samples that were previously made

sample_file = "/Users/katinaaparicio/Downloads/THESIS/
    samples_evaluation.xlsx"
all_samples = []
start_time = time.time()
for i in range(1, 6):
    df = pd.read_excel(sample_file, sheet_name=f"Sample{i}")
    sample_dates = sorted(df['SampleDate'].dropna().unique())
    all_samples.append([pd.to_datetime(d).date() for d in sample_dates
        ])
```

```python
# Haversine distance
distance_cache = {} #to make code faster
def haversine(lat1, lon1, lat2, lon2):
    key=(lat1,lon1,lat2,lon2)
    if key in distance_cache:
        return distance_cache[key]
    from math import radians, sin, cos, sqrt, atan2
    R = 6371
    dlat = radians(lat2 - lat1)
    dlon = radians(lon2 - lon1)
    a = sin(dlat/2)**2 + cos(radians(lat1)) * cos(radians(lat2)) * sin(
        dlon/2)**2
    c = 2 * atan2(sqrt(a), sqrt(1-a))
    distance= R * c
    distance_cache[key]=distance
    return distance


def run_heuristic_model(simulation_days, sample_index,writer):
    assignments = []
    unassigned_orders = []

    simulation_start_date = min(simulation_days)
    pre_sim = historical_all[historical_all['DATE'] <
        simulation_start_date] #initial location of trailer
    last_unloads = pre_sim[pre_sim['ACTION'].str.lower() == 'lossen'].
        sort_values(by='DATE').groupby('TRAILER').tail(1)

    initial_trailer_status = pd.DataFrame({
    'trailer_id': last_unloads['TRAILER'].values,
    'last_unload_date': last_unloads['DATE'].values,
    'last_unload_location': last_unloads['addressName'].values,
    'last_product': last_unloads['productCode'].values,
    'start_latitude': last_unloads['latitude'].values,
    'start_longitude': last_unloads['longitude'].values,
    'sample': sample_index
})
    trailer_status = pd.DataFrame({
        'trailer_id': last_unloads['TRAILER'],
        'current_x': last_unloads['longitude'],
        'current_y': last_unloads['latitude'],
        'location_name': last_unloads['addressName'],
        'last_product': last_unloads['productCode'],
        'last_unload_date': last_unloads['DATE'],
        'status': 'available',
        'next_available_date': simulation_start_date,
        'working_time': 0.0
    })
    unloadings = historical_all[historical_all['ACTION'].str.lower() ==
        'lossen']
    for current_date in simulation_days:
        trailer_status['worked_today'] = 0.0
        trailer_status.loc[trailer_status['next_available_date'] <=
            current_date, 'status'] = 'available'
        loadings = historical_all[(historical_all['ACTION'].str.lower()
            == 'laden') & (historical_all['DATE'] == current_date)]
```

```
        orders_today = pd.merge(loadings, unloadings, on='orderNumber',
             suffixes=('_pickup', '_delivery'))

        if orders_today.empty:
            print(f"No orders to plan on {current_date}")
            continue

        orders_today['DATE_pickup'] = pd.to_datetime(orders_today['
            DATE_pickup'])
        orders_today['DATE_delivery'] = pd.to_datetime(orders_today['
            DATE_delivery'])
        orders_today['days_diff'] = (orders_today['DATE_delivery'] -
            orders_today['DATE_pickup']).dt.days
        orders_today['legal_limit'] = orders_today['days_diff'].apply(
            infer_limit)
        orders_today = orders_today.sort_values(by='DATE_delivery')
        for _, order in orders_today.iterrows():
            available_trailers = trailer_status[trailer_status['status'
                ] == 'available']
            if available_trailers.empty:
                unassigned_orders.append({'date': current_date, '
                    orderNumber': order['orderNumber'], 'reason': 'No
                    trailers'})
                continue

            best_trailer = None
            best_cost = float('inf')
            best_clean_station_name = ''
            best_total_time = 0.0
            #look for the best trailer
            for _, trailer in available_trailers.iterrows():
                x0, y0 = trailer['current_x'], trailer['current_y']
                cleaning_required = trailer['last_product'] != order['
                    productCode_pickup'] #if the previous product that
                    the trailer transported is not the same as the next
                    order, a cleaning is required
                if cleaning_required:
                    clean_options = []
                    for _, station in cleaning_stations.iterrows():
                        d1 = haversine(y0, x0, station['y'], station['x
                            ']) * ROAD_SCALE
                        d2 = haversine(station['y'], station['x'],
                            order['latitude_pickup'], order['
                            longitude_pickup']) * ROAD_SCALE
                        total_dist=d1+d2 #distance from trailers
                            location to cleaning station, and from
                            cleaning to pickup
                        clean_options.append({
                            'total_dist': total_dist,
                            'name': station['name'],
                            'cost': CLEANING_COST,
                            'lat': station['y'],
                            'lon': station['x']
                            })
                    clean_options.sort(key=lambda x: x['total_dist']) #
                        sort the cleaning stations by the shortest total
                        distance
```

```
                best_clean = clean_options[0] #pick the best cleaning station with shortest total distance
                cleaning_station_name = best_clean['name']
                cost = best_clean['total_dist'] * COST_PER_KM + CLEANING_COST #calculate the cost of arriving to cleaning station and the cost for cleaning the trailer
                time_to_pickup = best_clean['total_dist'] / SPEED_KMPH + CLEANING_TIME
            else:#if no cleaning is required calculate distance from trailer's location to pickup directly
                cleaning_station_name = ''
                dist = haversine(y0, x0, order['latitude_pickup'], order['longitude_pickup']) * ROAD_SCALE
                cost = dist * COST_PER_KM
                time_to_pickup = dist / SPEED_KMPH
            dist_p2d = haversine(order['latitude_pickup'], order['longitude_pickup'], order['latitude_delivery'], order['longitude_delivery']) * ROAD_SCALE
            time_p2d = dist_p2d / SPEED_KMPH
            total_time = time_to_pickup + LOADING_TIME + time_p2d + UNLOADING_TIME
            full_days = int(total_time // DAILY_LIMIT)
            leftover = total_time % DAILY_LIMIT
            if cost < best_cost:
                best_cost = cost
                best_trailer = trailer
                best_total_time = total_time
                best_clean_station_name = cleaning_station_name
                best_full_days = full_days
                best_leftover = leftover

        if best_trailer is None:
            unassigned_orders.append({'date': current_date, 'orderNumber': order['orderNumber'], 'reason': 'No feasible trailer'})
            continue

        pickup_datetime = datetime.combine(order['DATE_pickup'], dt_time(hour=int(PICKUP_START)))
        delivery_datetime = pickup_datetime + timedelta(days=best_full_days, hours=best_leftover)
        available_again = delivery_datetime.date() + timedelta(days=1)
        on_time = delivery_datetime.date() <= order['DATE_delivery'].date() #the order is on time if it arrives on the expected day or earlier
        # Update trailer status
        idx = trailer_status[trailer_status['trailer_id'] == best_trailer['trailer_id']].index[0]
        trailer_status.at[idx, 'status'] = 'occupied'
        trailer_status.at[idx, 'current_x'] = order['longitude_delivery']
        trailer_status.at[idx, 'current_y'] = order['latitude_delivery']
        trailer_status.at[idx, 'last_product'] = order['productCode_pickup']
```

```
            trailer_status.at[idx, 'next_available_date'] =
                available_again
            trailer_status.at[idx, 'working_time'] += best_total_time
            trailer_status.at[idx, 'location_name'] = order['
                addressName_delivery']

            assignments.append({
                'date': current_date,
                'orderNumber': order['orderNumber'],
                'trailer_id': best_trailer['trailer_id'],
                'pickup':order['addressName_pickup'],
                'delivery':order['addressName_delivery'],
                'working_time': round(best_total_time, 2),
                'on_time': on_time,
                'expected_deliveryday':order['DATE_delivery'].date(),
                'delivery_datetime': delivery_datetime,
                'legal_violation': round(best_total_time, 2) > order['
                    legal_limit'],
                'legal_limit': round(order['legal_limit'], 2),
                'cleaning_station': best_clean_station_name,
                'Heuristic_cost': round(best_cost, 2),
                'Product_code':order['productCode_pickup']
            })

    assignments_df = pd.DataFrame(assignments)
```

The code in this appendix was developed with the help of *ChatGPT*, which helped to implement certain coding components and improve the structure and readability of the code. Given the ongoing development of programming skills, this assistance was essential to translate conceptual ideas into a working simulation.