UNIVERSITY OF TWENTE.

CAPE

FARMTRANS

Master Thesis

Development of a Tool for Optimisation of Vehicle Routing Problem with Heterogeneous Vehicles

by

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Abstract

This thesis develops a decision-support tool for optimising vehicle routing at Farm Trans, addressing a complex Heterogeneous Fleet Vehicle Routing Problem with Pickup and Delivery and Time Windows (HF-VRPPDTW). The solution incorporates real-world constraints such as driver breaks, vehicle capacities, and electric vehicle charging. A metaheuristic based on Simulated Annealing is used to generate high-quality solutions efficiently. The tool evaluates fleet configurations and order volumes using key performance indicators like distance, utilisation, and cost. Results show significant improvements over existing planning methods and support strategic decisions around electric fleet adoption.

Management Summary

This Master's thesis presents the development of a decision-support tool designed to address the Vehicle Routing Problem (VRP) encountered by Farm Trans, a logistics provider specialising in food transport. The study focuses on managing a heterogeneous fleet of diesel and electric vehicles, with complex constraints such as pickup and delivery, time windows, mandatory driver rest periods, and limited charging infrastructure. Farm Trans faces operational inefficiencies and lacks a generalised approach to route optimisation, which is especially crucial as they explore the integration of electric trucks into their fleet.

Objective and Scope

The primary objective is to build a flexible, scalable optimisation tool that can:

- Minimise operational costs (fixed, variable, tolls, labour).
- Improve delivery efficiency and truck utilisation.
- Support transition scenarios from diesel to electric trucking.
- Handle diverse planning constraints relevant to the refrigerated goods supply chain.

To do so, the thesis formalises the problem as a Heterogeneous Fleet Vehicle Routing Problem with Pickup and Delivery and Time Windows (HF-VRPPDTW), an NP-hard combinatorial optimisation problem. Due to the complexity and scale, an exact method is not computationally feasible, and a metaheuristic approach using Simulated Annealing (SA) is implemented. This is paired with a constructive heuristic to generate the initial solution.

Solution Features

The proposed solution includes the following key components:

- A route optimisation algorithm accounting for truck capacities, charging, breaks, and time windows.
- Configurable fleet and order input to model different real-world scenarios.
- Integrated logic for charging electric trucks during mandatory driver breaks to reduce downtime.

- KPIS to evaluate both operational and financial performance, including travel time, idle time, load utilisation, cost breakdowns, and fleet composition.

Experimental Validation

A series of experiments were conducted using real and synthetic data to simulate a variety of operational scenarios. These included different order volumes (38, 80, 120) and various diesel/electric fleet configurations (e.g., 41 diesel and 0–41 electric trucks). The results consistently showed that:

- The proposed method outperforms the current manual planning approach of Farm Trans in terms of distance, cost, and fleet efficiency.
- The tool enables robust decision-making under varying demand conditions.
- Integration of electric trucks can be cost-effective in many scenarios, although time window feasibility and charging constraints remain limiting factors.

Business Value and Implementation Considerations

The solution enables Farm Trans to:

- Evaluate trade-offs between diesel and electric deployment.
- Improve long-term planning by testing future fleet strategies in a controlled, data-driven way.
- Reduce costs through smarter route planning and better use of available assets.

Key challenges to implementation include integrating the tool into existing IT infrastructure, managing change among planners and drivers, and improving data on real-world charging and rest locations.

Conclusion and Recommendations

The tool developed in this research demonstrates clear potential to enhance operational performance and support Farm Trans's transition to a more sustainable fleet. Further development should focus on dynamic routing, realistic break/charging policies, and live integration with transport management systems (TMS). With these improvements, the tool can serve as a critical asset for day-to-day operations and strategic logistics planning.

Preface

Dear reader,

You're about to read my MSc thesis, "Development of a Tool for Optimisation with Heterogeneous Vehicle Loading, Routing, and Fleet Sizing." This research was carried out at CAPE Groep in Enschede, in collaboration with Farm Trans in Zevenbergen, as the final project for my Master's in Industrial Engineering and Management, with a specialisation in Production and Logistics Management at the University of Twente.

My time at CAPE was a truly valuable experience — not only did I grow professionally, but I also really enjoyed being part of the team. I'd like to thank all my colleagues there for their interest in my work and for creating such a welcoming and supportive environment. In particular, I want to thank Maik Wesselink for his supervision and guidance throughout the project.

I'm also grateful to Michiel van Gerwen from Farm Trans for the insightful sessions and for providing the input and information I needed to carry out this research.

A big thank you to my first supervisor, Breno Alves Beirigo, for his consistent feedback and support during both the conceptual and technical parts of this project. I also appreciate the involvement of Eduardo Lalla, who acted as my second supervisor and assessed my work.

And finally, to my friends, girlfriend, and family — thank you so much for your support and encouragement throughout this research.

I hope you enjoy reading my MSc thesis!

Max Derwig
Enschede
May 12, 2025

Contents

Acronyms

API Application Programming Interface. 40, 41, 80

CH Constructive Heuristic. 49, 50, 53, 58, 68, 69, 74, 75

CVRP Capacitated Vehicle Routing Problem. 20, 23, 24

EU European Union. 2

EVRP Electric Vehicle Routing Problem. 20, 21, 25, 28

FTL Full Truckload. 13, 14, 17, 61

HF-VRP Heterogeneous Fleet Vehicle Routing Problem. 20, 21, 27, 31

HF-VRPPDTW Heterogeneous Fleet Vehicle Routing Problem with Pickup and Delivery and Time Windows. 40

HF-VRPTW Heterogeneous Fleet Vehicle Routing Problem with Time Windows. 20, 21, 27

KPI Key Performance Indicator. 19

KPIs Key Performance Indicators. 31

SA Simulated Annealing. 49, 50, 53, 58, 68, 69, 74, 75, 77–79

TMS Transport Management System. 14

VRP Vehicle Routing Problem. 19–21, 28, 40, 49

VRPPD Vehicle Routing Problem with Pickup and Delivery. 27

VRPPDTW Vehicle Routing Problem with Pickup and Delivery with Time Windows. 49

VRPTW Vehicle Routing Problem with Time Windows. 21, 25, 27, 31

Glossary

API a set of functions and procedures allowing the creation of applications that access the features or data of an operating system, application, or other service.. v, 40, 41, 80

Benelux Belgium, The Netherlands, and Luxembourg. 7, 14

Customer A location or entity that receives a delivery or service during a VRP solution. 20

Feasible solution A solution to a VRP that satisfies all constraints and requirements. 20

NP-hard A problem for which there is no guarantee that it can be solved optimally in reasonable time. 20, 31, 40, 49

Optimal-solution All routes which yield the lowest value in the objective function. 20

Route A sequence of locations visited by a vehicle during a VRP solution. 20

List of Figures

List of Tables

List of Algorithms

Chapter 1

Introduction

This introductory chapter comprehensively overviews this MSc thesis's context, objectives, and structure. Section 1.1 introduces the companies for which this research matters. Section 1.2 discusses the study's background and context, highlighting the problem's importance. Next, Section 1.3 identifies the problem faced by the company. The problem statement, outlining the specific challenges faced by Farm Trans and the problem statement, is presented in Section 1.4. The research objectives are introduced in Section 1.5, providing a clear roadmap for the specific goals of this study. We outline the main research question (RQ1) and the sub-research questions (RQ2 to RQ7) in Section 1.6, aligning them with the content of subsequent chapters. Finally, Section 1.7 outlines the organisation of this thesis, giving readers an overview of the structure and content they can expect in the following sections, including the literature review, problem formulation, and research methodology.

1.1 CAPE & Farm Trans

The following sections introduce the companies connected to this research. Section 1.1.1 introduces CAPE, a consultancy firm. Section 1.1.2 introduces Farm Trans as one of CAPE's clients.

1.1.1 CAPE

CAPE was founded in 2000 and is a software developer and system integrator consultancy firm headquartered in Enschede. They specialise in delivering model-driven solutions to help companies transform digitally. Their main areas of expertise are Transport & Logistics, Supply Chain, Agrifood, and Smart Construction.

CAPE creates value by tuning three essential pillars: Human, Technology and Methodology. The human pillar stands for collaboration to improve. Adapting new systems is essential for a successful project, and the people in the organisation are responsible for adjusting the latest software. CAPE strives to create user-friendly software to make the adaptation as smooth as possible. To do so, they use the process as a starting point and automate and optimise it. The philosophy behind this is that they can focus on the content while delegating repetitive tasks as much as possible.

The technology pillar represents the technology CAPE relies on to bring value to its clients. To do so, CAPE uses various technologies to develop robust solutions.

The tool they use most often is Mendix, a low-code platform used to create powerful applications that provide their customers with insight into their processes, orders, and operations.

1.1.2 Farm Trans

One of CAPE's clients is Farm Trans in Zevenbergen (NL). Founded in 1987, Farm Trans operates in the (food) logistics sector. Originally established to transport products for Farm Frites, Farm Trans now specialises in IT and global food transport. Although much of its work remains dedicated to Farm Frites, it also serves other clients.

Farm Trans distinguishes itself by providing supply chain-wide support and optimising clients' transportation processes through their Connected Services branch. This branch focuses on long-term partnerships, leveraging data and technology to streamline logistics. They offer warehousing solutions, including cross-docking and storage in freezers (-20 °C) and cold rooms (0-4 °C). Cross-docking enables the consolidation of orders from multiple locations at their facilities or partner sites in Germany, ensuring efficient shipment. Additionally, Farm Trans uses intelligent IT solutions to map the flow of goods and chart the most efficient transportation routes.

Farm Trans divides their transportation processes into two groups: Bulk and Fresh & Frozen. Bulk transport started in 1987 for Farm Frites, which had large quantities of potatoes. Nowadays, they transport other dry bulk products, such as onions and animal feed products. Farm Trans uses dump trailers for bulk transport.

Fresh & Frozen transportation is temperature-controlled and often done in reef trailers. These products require conditions from -30°C to 30°C during transport. Such products include frozen foods, fresh foods, flowers and plants.

1.2 Background and Context

Electrification is becoming increasingly important in numerous sectors around the world. This also applies to transportation. The European Union aims for climate neutrality by 2050 [2]. Heavy-duty vehicles are responsible for 6% of the total energy-related emissions in the European Union (EU) [3]. European Regulations state that the emissions from diesel trucks are to be reduced by 45% by 2030 [4]. To meet these goals, Farm Trans decided to start with the electrification of its fleet.

Farm Trans actively prepares for these regulations and currently has multiple electric trucks on order. For Farm Trans to become familiar with electric trucks, they plan to use them for short-range transportation. In the future, they will also use them for long-range transportation. However, electric trucks are different from diesel trucks in several ways. Some of these differences include range, charging time, and maximum load. These differences result in limitations (e.g., range) and additional costs (e.g., charging time), so Farm Trans would like to investigate the possibilities of using electric trucks.

Farm Trans has no automated method to support the decision-making process when scheduling transportation operations. The planners look at the orders that need to be planned and determine a cut-off point, after which they do not accept any new orders. From this, they plan all orders that are currently known. The planner plans manually, so no automated method is used. When a planner sees a possibility to group orders in the same truck, he does this manually; again, no automated method is available. The lack of an automated method provides room for improvement since using a tool can significantly improve efficiency and reduce costs.

Additional costs or savings are essential when using electric trucks to remain competitive. Furthermore, unforeseen costs could financially hurt Farm Trans if certain factors are not adequately considered before starting transport. By researching the costs and possibilities of using electric trucks, Farm Trans can make the right decisions regarding what truck to use for what route.

Electrification is a transition process, meaning that it will take multiple years or decades before Farm Trans can become fully electric. Therefore, there will be an extended period during which Farm Trans can choose between using electric trucks or diesel trucks. Using an automated method will make it easier for Farm Trans to adapt their planning accordingly to changes in the future (e.g., a fully electric fleet).

1.3 Problem Identification

The transportation sector is highly competitive. Therefore, it is necessary to gain an advantage over competitors [5, 6]. This results in a necessity to use resources as efficiently as possible. Including not just the load in each truck, but the routing of each truck can also contribute to an increase in efficiency.

Farm Trans currently has no method or tool that incorporates heterogeneous vehicle loading. Additionally, they have no experience with electric trucks and this new technology's possible costs and risks. Therefore, the core problem of Farm Trans is;

No automated method for heterogeneous vehicle routing, resulting in a loss of efficiency, competitiveness and possibly additional costs

The absence of an automated method to plan and route the new electric trucks in combination with the conventional diesel trucks results in a loss of efficiency. Especially since scheduling electric trucks is more complex due to longer charging durations compared to refuelling diesel trucks. This increase in scheduling complexity, in combination with the lack of an automated method, results in a loss of efficiency, which increases costs and weakens Farm Trans's competitive position.

By creating a method to efficiently and feasibly plan diesel and electric trucks, Farm Trans becomes more efficient and strengthens its competitive position.

1.4 Problem Statement

The main objective of this research is to create and implement a method so that Farm Trans can use their electric and diesel trucks as efficiently as possible. This solution focuses on the decision of where to use electric trucks and where to use diesel trucks. Furthermore, the method includes additional costs and considerations for the solution to be as efficient as possible. These routes consider several parameters, including truck parameters, route parameters and costs. Additionally, the solution becomes more efficient by using grouping. The specific problem is formulated as follows:

To design a method for the specific routing problem at Farm Trans, focusing on the decision between diesel and electric trucks.

1.5 Research Objectives

The research objectives of this thesis are as follows:

i To analyse the current situation at Farm Trans, in terms of parameters, fleet characteristics, order characteristics, and current scheduling approach.

ii To conduct a comprehensive literature review of existing routing problem instances and solution approaches (including grouping and routing), focusing on those applicable to Farm Trans's specific requirements, such as electric trucks.

iii To analyse and model the routing problem at Farm Trans, considering factors such as truck choice, capacity constraints, delivery time windows, weight restrictions and geographical considerations.

iv To develop an efficient algorithm tailored to solving Farm Trans's routing problem, aiming to minimise transportation costs and improve efficiency.

v To experiment with different orders, fleet configurations and to explore the possibilities of simultaneous charging and resting.

vi To provide practical recommendations and insights to Farm Trans based on the results obtained to optimise their planning method.

1.6 Research Questions

To guide this research, the following research questions are formulated:

1.6.1 Main Research Question

The main research question of this research is:

RQ1: How can Farm Trans solve their routing problem as efficiently and effectively as possible, whilst including electric and diesel trucks, considering capacity, range, weight, and delivery time windows?

1.6.2 Sub-Research Questions

Each chapter of this thesis corresponds to a sub-research question addressing specific aspects of the main research question. These sub-research questions are as follows:

1. **Chapter 2: Problem Context**
    - **RQ2:** What is the current planning method used at Farm Trans, and what are the specific parameters (e.g., costs, range, capacity) and practical challenges that need to be addressed when designing an improved planning method for its routing and decision problem?
2. **Chapter 3: Literature Study**

- **RQ2:**What are the key definitions and solution approaches relevant to the routing and decision challenges at Farm Trans?

3. **Chapter 4: Problem Description**
    - **RQ3:** How can Farm Trans's routing and decision problem be formally defined, including its parameters, constraints, and objective?
4. **Chapter 5: Solution Approach**
    - **RQ4:** What algorithmic approach is developed to solve Farm Trans's routing and decision problem efficiently and feasibly?
5. **Chapter 6: Experimental Setup & Chapter 7: Results and Discussion**
    - **RQ6:** What are the practical implications of the results obtained, and what recommendations can be made to Farm Trans for optimising their transportation and delivery processes?
6. **Chapter 8: Conclusion and Recommendations**
    - **RQ7:** What are the practical implications of the results obtained, and what recommendations can be made to Farm Trans for optimising their transportation and delivery processes?

1.7 Thesis Structure

This thesis is structured as follows:

- **Chapter 2: Problem Context** - This chapter provides an in-depth review of Farm Trans, incorporating current operations, challenges and the current planning and routing approach.
- **Chapter 3: Literature Study** - This chapter reviews the existing literature on routing and decision problems and relevant solution approaches and algorithms for Farm Trans.
- **Chapter 4: Problem Description** - In this chapter, we formally define the problem faced by Farm Trans, specifying its parameters, constraints, and objectives.
- **Chapter 5: Solution Approach** - This chapter presents the algorithm or methodology developed to address the problem, including mathematical formulations and implementation details.
- **Chapter 6: Experimental Setup** - Here, we discuss the experimental setup, data collection, and results from testing the proposed solution on Farm Trans's data.
- **Chapter 7: Results and Discussion** - This chapter analyses the results, discusses the implications, and provides practical recommendations for Farm Trans.
- **Chapter 8: Conclusion and Recommendations** - The final chapter summarises the key findings, contributions, and future research directions.

Chapter 2

Problem Context

In this chapter, we explore Farm Trans's operations. Farm Trans maintains an extensive customer base worldwide, especially in Europe, which requires complex supply chain management. We examine Farm Trans's logistics and transportation network in Section 2.1, where a fleet of trucks actively transports goods from a depot to various customer locations in Europe. In this section, we elaborate on truck & trailer data, customer & order data, and costs. Section 2.2 elaborates on their current planning approach, incorporating parameters, loading, cross-docking and planning. In Section 2.3, we address the challenges that Farm Trans faces. These challenges give rise to a distinct and intricate variant of the Vehicle Routing Problem (VRP), tailored specifically to Farm Trans.

2.1 Farm Trans: Background and Operations

As mentioned earlier, Farm Trans is active in the food logistics sector. They transport produce all over the world using both sea and road transport methods. This study focuses on a part of their transportation operations, the Fresh & Frozen sector. This sector transports temperature-controlled goods, such as fresh food, flowers, fish, meat, bread, etc., that require cooling during transport. They service various European customers, especially in the Benelux, France and Germany.

2.1.1 Truck & Trailer Data

Farm Trans provided their trucks' data in Table 2.1. They currently have 36 trucks of the type 4x2 (4 wheels, two axles) and five trucks of the type 6x2 (6 wheels, three axles). All these trucks are diesel-powered.

Farm Trans has five electric trucks on order: one Volvo truck and 4 Mercedes Actros E600, which will be delivered later. Farm Trans purchased these trucks to explore electrification possibilities in their fleet. Once electric trucks prove viable and sustainable, Farm Trans will consider buying additional electric trucks. Table 2.1 provides an overview of truck specifications; this includes quantity, range, costs and charging or fueling time.

Farm Trans uses these trucks to pull 173 trailers. There are two types of trailers: single-temperature and multi-temperature. The first trailer can only be cooled to one temperature, while the second divides into two zones with different temperatures.

Farm Trans always places the coolest temperature in the trailer first and the warmer temperature later. Since the back of the trailer is colder.

Name	Type	Amount	Fuel(L)/ Electric capacity(kWh)	Range (km)	Charging time/ Fuelling time
4x2	Diesel	36	800	2,800	15min
6x2	Diesel	5	800	2,800	15min
Volvo FH Aero	Electric	1	540	300	2 hours Full charge (DC 250kW)
Mercedes eActros 600	Electric	4	621	500	1 hour 20% to 80% (DC 500A)

Table 2.1: Farm Trans's Truck Data

2.1.2 Customer & Order Data

One order line contains the following information:

- Pickup location
- Delivery location
- Number of pallets
- Weight
- Pickup time window
- Delivery time window

The pickup location is often the cross-dock facility in Lommel, Belgium. However, this can happen in other locations throughout Europe as well; 35% of all orders are pickup orders with a different pickup location than the cross-dock in Lommel. Delivery locations are primarily in Germany, France, and Austria. Figure 2.1 shows the order frequency per country from 2022 until 2024. We see that 98% of the orders are delivered in Germany.

Each order line contains the number of pallets and the total weight of the load. Figure 2.2 shows the number of pallets per order in a histogram. Most orders have fewer pallets; therefore, grouping orders can efficiently increase truck capacity utilisation.

Finally, there are time windows and always a time window for pickup and delivery. All time windows are considered hard deadlines, and planners can not violate these deadlines. Additionally, rejecting orders is not possible.

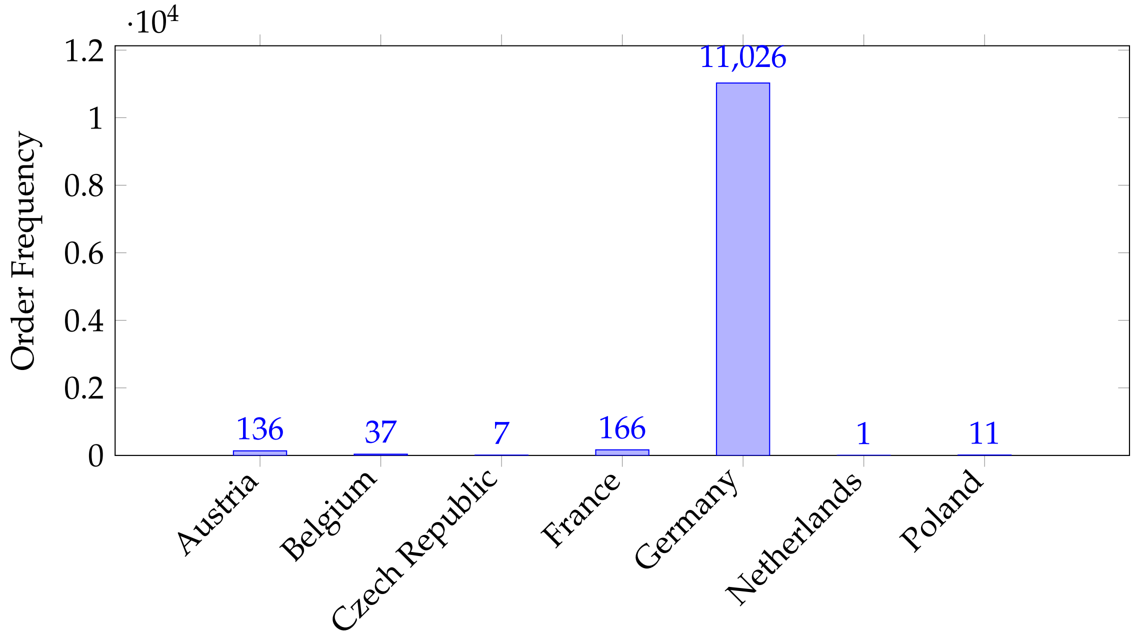


Figure 2.1: Order Frequency per Country

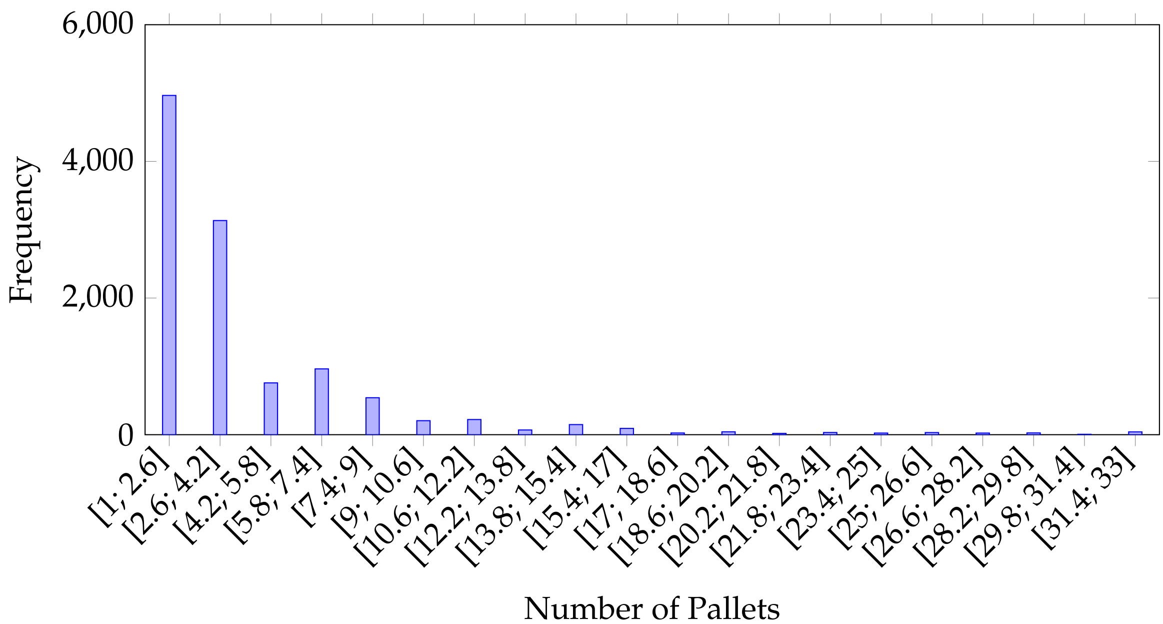


Figure 2.2: Histogram of Pallets per Order

2.1.3 Costs

This section consists of 3 subsections that elaborate on the costs: conventional truck costs, electric truck costs, and toll costs.

Conventional Truck Costs

A truck's costs consist of fixed and variable costs. Fixed costs are yearly, and variable costs are per kilometre. Farm Trans considers the following costs in their calculations:

- **Lease costs:** cost of leasing the truck for one year.
- **Depreciation:** estimated truck value reduction.
- **Eurovignette:** a certificate that trucks must drive in some countries.
- **Insurance:** insurance of the truck.
- **ICT:** on-board computer/dash-cam and telematics.
- **Tyres:** cost for tyres, calculated per kilometre
- **Repair & Maintenance (R&M):** cost for repairs and maintenance, calculated per kilometre.

Farm Trans uses a system with 13 yearly periods, thus four weeks per period. Specific costs are in Table 2.2. These are averages to understand the expenses; specific costs can differ per vehicle.

Cost Type	Price (€)		Period
	4x2	6x2	
Lease cost	€ 36,487.97	€ 18,477.73	per year
Depreciation	€ 416.69	€ 40.69	per year
Eurovignette	€ 1,250.00	€ 1,250.00	per year
Insurance	€ 3,377.47	€ 3,508.33	per year
ICT	€ 975.00	€ 975.00	per year
Tyres	€ 0.0142	€ 0.0208	per kilometre
R&M	€ 0.015	€ 0.015	per kilometre

Table 2.2: Farm Trans's Truck Costs

Of these costs, two are considered variable costs, namely, tyres and repair and maintenance. For these, Farm Trans uses the rates as shown in Table 2.3.

Additionally, we have fuel costs; Farm Trans states that their trucks drive 2,800 kilometres on 800 litres of diesel. 1 litre of diesel (excluding tax) costs € 1.487. Thus, a full tank costs 800*1.487=€1,189.60. Therefore, the cost per kilometre equals €1,189.60/2,800≈ €0.425 per kilometre. Table 2.3 shows all variable costs and the total cost per kilometre per truck type for diesel trucks.

Electric Truck Costs

Since Farm Trans purchases the electric trucks, there are no lease costs. However, since the trucks are not yet in Farm Trans's possession, it is difficult to know the costs for depreciation, euro vignette, insurance, tyres, and repair and maintenance.

It is possible to calculate the cost of electricity per kilometre. We know the Volvo FH Aero has an electric capacity of 540 kWh and a range of 300 km. Additionally,

Truck Type	Tyres (€/km)	Repair and Maintenance (€/km)	Diesel (€/km)	Total Costs (€/km)
4x2	0.0142	0.015	0.425	0.4542
6x2	0.0208	0.015	0.425	0.4608

Table 2.3: Farm Trans's Variable Costs per Diesel Truck Type

we use a price of € 0.32 per kWh. This results in a cost of € 0.58 per kilometre of electricity. The Mercedes eActros 600 has an electric capacity of 621 kWh and a range of 500 kilometres, resulting in a price of € 0.40 per kilometre on electricity. Based on a price of € 0.32 per kWh, we find costs as shown in Table 2.4.

Truck Type	Tyres (€/km)	Repair and Maintenance (€/km)	Electricity (€/km)	Total Costs (€/km)
Volvo FH Aero	Unknown	Unknown	0.58	Unknown
Mercedes eActros 600	Unknown	Unknown	0.40	Unknown

Table 2.4: Farm Trans's Variable Costs per Electric Truck Type

Toll Costs

In Europe, there are many different approaches to collecting tolls from trucks. In Denmark, Luxembourg, the Netherlands, and Sweden, the Eurovignette is used. The Eurovignette is a mandatory certificate for trucks weighing 12,000 kilograms or more. This certificate shows that a special tax has been paid. The price depends on the truck's emission class and the number of axles.

Other countries use a kilometre charge. Again, the height of this toll rate depends on the emission class and the truck's weight.

Since toll costs change regularly, the model should be able to adapt to these changes. For now, we consider the following toll costs per kilometre per country. France is an exception since it has different prices depending on the highway used.

Country	Toll type	Price (€/km)		
		4x2 and 6x2	Volvo	Mercedes
Austria	Kilometre charge	€ 0.46	€ 0.10	€ 0.10
Belgium	Kilometre charge	€ 0.29	€ 0.13	€ 0.13
France	Kilometre charge	Variable	Variable	Variable
Germany	Kilometre charge	€ 0.48	€ 0.10	€ 0.10
Great-Britain	HGV Levy Tax	£ 1,000.00 per year or £ 10.00 per day	£ 1,000.00 per year or £ 10.00 per day	£ 1,000.00 per year or £ 10.00 per day
Luxembourg	Eurovignette	€ 1,250.00 per year	€ 750.00 per year	€ 750.00 per year
Netherlands	Eurovignette	€ 1,250.00 per year	€ 750.00 per year	€ 750.00 per year

Table 2.5: Toll Cost per Kilometre per Country

2.2 Current Approach

Farm Trans faces a complex problem that involves optimising vehicle allocation, determining optimal routes, considering vehicle capacity constraints, adhering to delivery time windows, and minimising transportation costs. Solving this problem is paramount to enhancing the efficiency and competitiveness of Farm Trans's operations. To further specify the issue, this section describes the parameters and methods of Farm Trans's current approach.

2.2.1 Paramters

Farm Trans's problem involves essential parameters they use to schedule their fleet. We categorise these parameters as follows: truck parameters, route parameters, and costs.

- **Truck Parameters**

  1. **Type of Truck**
     The main decision in the solution is how to use electric and diesel trucks efficiently. This decision depends on other parameters listed below.
  2. **Weight/Capacity Restrictions**
     Each truck has different capacity restrictions in terms of weight or size.
  3. **Range of truck**
     Range is one of the most important parameters in the decision between electric and diesel trucks. Since electric trucks have shorter ranges than diesel trucks.
  4. **Fuelling & Charging**
     As mentioned earlier, charging takes time, so the solution method should consider these times. Farm Trans already includes refuelling time in their current solution approach.

- **Route Parameters**

  1. **Routing & Grouping**
     The problem instance includes a wide variety of possible routes. Each specific solution alters the parameters determining whether to use an electric or diesel truck.
  2. **Time-Windows & Deadlines**
     Farm Trans uses time windows with hard deadlines to ensure all customers get served on time.
  3. **Mandatory Resting Time**
     Drivers have to adhere to regulations concerning resting times. These influence the time windows and are therefore considered in the solution.
  4. **Combination between Resting and Charging**
     Since charging takes longer than fueling and no supervision is needed, it is

possible to combine resting with charging. The solution will explore these possibilities.

- **Costs**

  1. **Toll**
     Farm Trans explained that tolls in some countries depend on the type of truck. Therefore, the objective function includes the toll and aims to minimise total costs.
  2. **Variable Cost per Truck**
     The cost per kilometre is different for electric trucks and diesel trucks. This model incorporates the difference in the solution.

2.2.2 Loading

Farm Trans uses two types of pallets to load its goods: euro pallets and block pallets. The characteristics of these types are in Table 2.6. A euro pallet is smaller in width compared to a block pallet. Farm Trans uses load meters to measure capacity and loads. Load meters are a standardised benchmark in road transport. A loading meter is 1 meter of the loading space of a truck in length. Due to the width of a truck of approximately 2.40 m, one loading meter corresponds to approximately 2.4 m² (2.40 m width x 1 m length). This results in load meters per pallet type, as shown in Table 2.6. FTL stands for Full Truckload (FTL), and the column FTL shows the amount of that type of pallet needed to create a Full Truckload.

Type	Dimensions (m x m)	Surface (m^2)	Load meter	FTL
Euro Pallet	1.20 x 0.80	0.96	0.4	33
Block Pallet	1.20 x 1.00	1.00	0.5	26

Table 2.6: Farm Trans's Pallet Characteristics

Farm Trans has no data on the weight of each pallet. They do know the weight of the entire order. If they have to calculate the weight per pallet, they do it with an average weight of 750kg.

Each country has different regulations concerning a truck's maximum load. Since trucks must always adhere to these regulations, the country with the lowest maximum load through which the truck drives on a route becomes the bottleneck of that route.

2.2.3 Cross-Docking

As mentioned in Section 1.1.2, Farm Trans has cross-docking capabilities and enables the consolidation of orders from multiple locations at their facilities or partner sites in Germany, ensuring efficient shipment. However, this is outside the scope of this research. The focus is on efficient transportation when orders have been collected and are all present at the facility in Lommel or require pickup at other locations.

2.2.4 Current Planning

Farm Trans uses two separate planning approaches based on the destination of the order. They split between the Benelux and Germany. Planners schedule daily and for the next day; for Germany, they make the schedules for two days. For the Benelux, it works as in Figure 2.3:

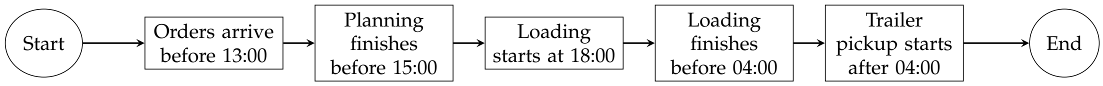


Figure 2.3: Timeline of Planning

It works the same for Germany but is scheduled one day further ahead. So, instead of making the schedule for tomorrow, they make it for the day after tomorrow. All the times remain the same, with only a one-day delay. According to this overview, planning can take up to 2 hours.
Farm Trans tries to incorporate grouping orders in their planning methodology. Grouping of orders means combining multiple orders in the same truck. However, this is currently done manually with no generic method. Therefore, this is an area where they believe a lot of improvement is possible.

2.2.5 Planning Method

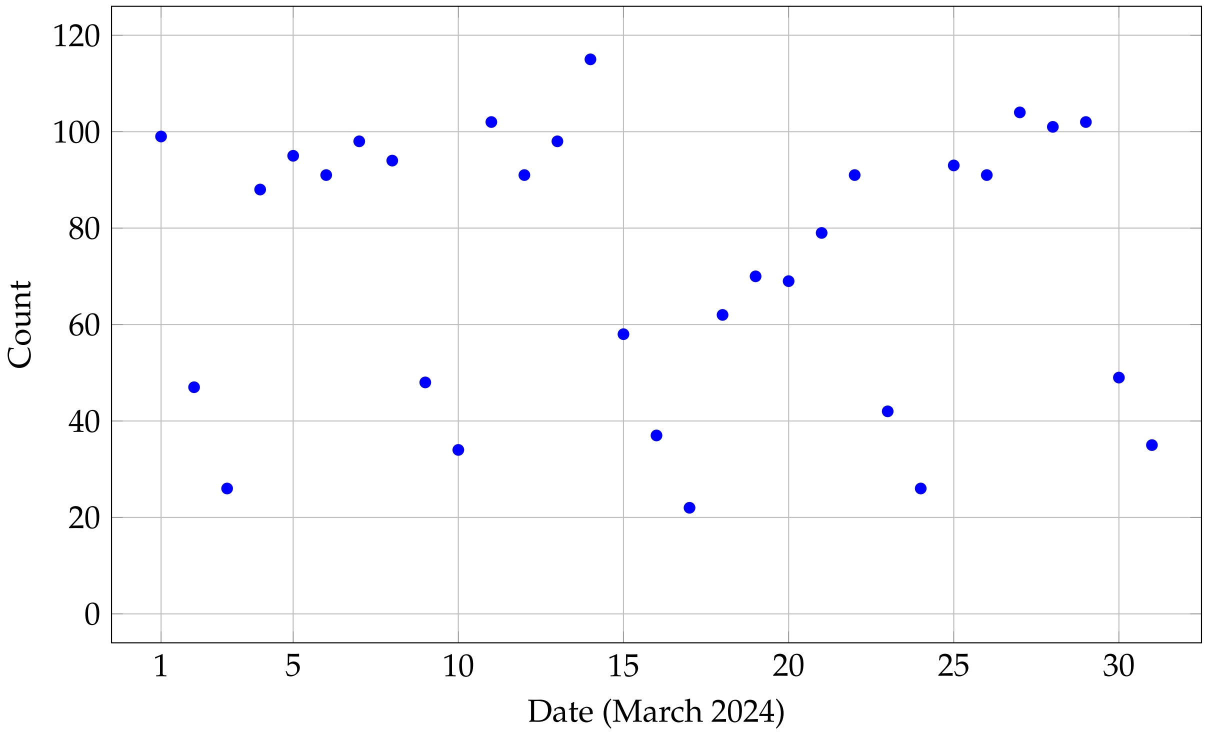
Farm Trans plans their logistic operations one to two days in advance. They separate the orders into three groups: Great Britain, FTL Benelux, and Germany. All groups receive their orders in the morning and schedule for the day after. They plan to pack the trucks that night so a driver can collect them the next day. They determine the load times of each trailer based on the delivery time windows and travel time.

The planner for FTL Benelux only receives Full Truckload (FTL) orders. The planner determines load times based on the delivery time windows. He then checks what trucks are available and creates a schedule. All this is done in Excel, from which he loads the schedule into their Transport Management System (TMS).

The planner for Germany receives all kinds of different order sizes. Once all the orders are in, he loads them into the TMS and manually combines them based on their delivery location. The system then creates a route and incorporates travel time. The first thing the planner checks is capacity. Do the orders he manually selected remain below the maximum weight and number of pallets? When this happens, the planner checks to see if all deliveries in the route meet their time windows. If this is not the case, he manually moves orders until the route becomes feasible. His final check is the payoff per kilometre; he looks at the payoff of the entire route and divides this by the total travel distance. When this value exceeds 3.5, it is profitable, and the planner schedules the route in the TMS. If this is not the case, he might add or remove some deliveries from the route to make it more profitable.

For Great Britain, the planning is slightly different. They have several trucks stationed in Great Britain. All the planners have to do is schedule a delivery to a port in the Netherlands or Belgium. The driver then loads the trailer but unhooks the truck. The driver in Great Britain then collects the trailer from the port and delivers it to the customer(s). Farm Trans has a facility in Great Britain that schedules the pickup.

Figure 2.4: Order Frequency in March 2024



2.3 Challenges in Transportation and Delivery

Farm Trans faces several significant challenges in its transportation and delivery operations, such as variability in demand, capacity constraints, time windows, rest times, grouping of orders, electric considerations, and costs.

2.3.1 High Variability in Demand

One of the primary challenges is the high variability in customer demand. Orders can vary greatly in quantity, size, and urgency, making it challenging to allocate vehicles efficiently and schedule deliveries optimally. Furthermore, many orders are last-minute, resulting in ad hoc planning that incorporates these last-minute orders.

Figure 2.4 shows the number of orders per day in March 2024. We observe a wide range of order frequencies, with a minimum of 20 and a maximum of 115. Upon closer examination, we noticed that the minimum occurs on weekends. This can be explained by the fact that fewer clients are open for pickup and delivery of orders.

2.3.2 Delivery Time Windows

All Farm Trans customers have strict delivery time windows, which Farm Trans must meet to ensure customer satisfaction and operational efficiency. Missing these time windows is not an option for Farm Trans.

Farm Trans has various delivery time windows, depending on the customer. They vary from a time interval of 1 hour to a time interval of 24 hours.

2.3.3 Mandatory Rest Time

Drivers must adhere to specified rest times per day and week. These regulations consist of three sections: maximum total driving time, maximum continuous driving time, and minimum rest time.

Maximum Total Driving Time

These rules apply whilst driving the truck. The driver is allowed to

- Drive a maximum of 10 hours per day twice a week (and a maximum of 9 hours per day on other working days in the same week);
- Drive a maximum of 56 hours per week (if you meet the conditions below);
- Drive a maximum of 90 hours per 2 weeks. This applies to weeks 1 and 2. But also to weeks 2 and 3, and so on.

Maximum Continuous Driving Time

A maximum applies not only to the total driving time but also to the uninterrupted driving time. Uninterrupted driving time is the total accumulated driving time between 2 interruptions (breaks). Or between a rest period and a break. These rules apply to the maximum continuous driving time:

- The maximum continuous driving time may not exceed 4.5 hours.
- After 4.5 hours of driving, the driver must take a break of 45 minutes. The driver may divide this 4.5-hour driving time into two parts. The first break will then last at least 15 minutes. In addition, the driver must take a break of at least 30 minutes within the 4.5 hours of driving time.
- A double-manned truck or bus does not have to stand still for 45 minutes every 4.5 hours. A stop is only required to change drivers (and driver card or registration sheet). The condition is that the driver taking a break does not assist the driver driving the vehicle. For example, with navigation.

Not only is driving work, but also other activities, such as loading and unloading. If you work more than 6 hours in a row (continuously), you should also take a break:

- Do you work continuously between 6 and 9 hours a day? Then, you must take a break of at least 30 minutes.
- Do you work continuously for more than 9 hours? Then, you must take a break of at least 45 minutes.

You may also take these breaks in 15-minute chunks.

Minimum Rest Time

As a truck driver, you must take daily and weekly rest. Daily rest is the period during which you are not allowed to work. You may also not be available to your employer. The daily rest is when you can freely dispose of your time and have no obligations to your employer. These rules apply to daily rest:

- Daily rest must be at least 11 hours in a row.
- Between 2 sufficient weekly rest periods, you may reduce the daily rest period three times to nine hours. This is called the reduced daily rest period. You do not have to make up for this reduction at another time.
- You may also take the daily rest in 2 parts. The 1st part must be at least 3 hours. The 2nd part must be at least 9 hours. The other way around (first 9 hours and then 3 hours) is not allowed. A daily rest in 2 parts counts as a regular daily rest period.
- The new daily rest period must end within 24 hours of the previous (daily or weekly rest). So, if you finish your weekly rest at 8 a.m. on Monday, your next rest must end before 8 a.m. on Tuesday. A 30-hour period applies to 2 drivers.
- Additional rules apply to international transport. Outside the Netherlands, a driver may take a reduced weekly rest period of 2 weeks. A shortened weekly rest lasts a minimum of 24 and a maximum of 45 hours. An extended regular weekly rest must compensate for this shortened rest. The number of hours the reduced weekly rest deviates from the standard 45-hour rest period. In addition, the driver must take a regular weekly rest at least twice in 4 weeks.

2.3.4 Grouping of Orders

Farm Trans currently groups orders manually when planning. The planner identifies orders near each other and attempts to combine them into a single truck. A generic method to group orders would be valuable for Farm Trans to maximise utilisation and create as many FTL's as possible.

2.3.5 Electric Considerations

The main reason for this research is the electrification of Farm Trans's transportation operations. Multiple electric trucks are on order, yet Farm Trans has no method to optimise their use in combination with its existing fleet. Electric trucks bring different considerations, such as range and charging time, which Farm Trans is unfamiliar with. Section 3.3.3 will elaborate on electric considerations and strategies.

2.3.6 Costs

The two main types of costs that Farm Trans considers when planning are the cost per kilometre and toll. Farm Trans uses a price per kilometre for each truck. The most significant costs considered here are fuel costs and depreciation. These variable costs per kilometre vary per truck type.

Additionally, some countries impose a toll, which Farm Trans must pay. These tolls can depend highly on the type of truck used. For instance, Germany has a toll of 0.35 cents per kilometre for a diesel truck. This toll is substantially less when transporting by an electric or hybrid truck; sometimes, the truck is exempt from paying the toll. Farm Trans considers these costs and tries to keep them to a minimum.

2.4 Summary

The current planning method at Farm Trans relies heavily on manual processes and basic route planning tools, which are increasingly inadequate in handling the operational complexity of its transportation and delivery network. Several key parameters and constraints must be considered when designing an improved planning method. These include vehicle range limitations (particularly for electric trucks), strict weight and loadmeter capacity constraints, diverse and interdependent cost components (such as fuel, tolls, labour, fixed vehicle costs, and per-kilometre expenses), and the operational objective of minimising idle time and improving vehicle utilisation.

Moreover, the fleet's heterogeneity—comprising diesel and electric trucks—introduces varying performance profiles, energy requirements, and route feasibility constraints. A critical operational factor further complicating planning is the legal requirement for mandatory rest times for drivers, which must be integrated into route scheduling to ensure regulatory compliance and driver welfare.

These factors—cost structures, sustainability goals, fleet heterogeneity, legal driving regulations, and operational constraints—create a complex and tightly interwoven planning environment. This makes Farm Trans's routing and decision problem a particularly challenging variant of the Vehicle Routing Problem (VRP), necessitating a tailored, data-driven optimisation approach that addresses both strategic and tactical objectives.

Chapter 3

Literature Study

This chapter comprehensively reviews the literature on the Vehicle Routing Problem (VRP) and its various variants. This literature study aims to set the stage for understanding and addressing the VRP variant encountered at Farm Trans, as discussed in subsequent sections.

In Section 3.1, we discuss the problem requirements. Next, in Section 3.2, we establish the foundational concepts and principles of the VRP, laying the groundwork for a deeper exploration of the problem. From there, Section 3.3 highlights certain VRP variants connected to this study. Next, Section 3.4 describes the specific VRP variant encountered at Farm Trans. Understanding this variant's unique constraints and objectives is essential, as this knowledge guides our approach to developing a customised solution. Section 3.5 elaborates on various Key Performance Indicator (KPI). We then move on to Section 3.6, where we examine existing approaches and methodologies used to solve VRP and its variants.

This literature study equips us with the necessary background knowledge and contextual understanding to develop a customised solution for Farm Trans, as discussed in subsequent chapters.

3.1 Problem Requirements

As mentioned in Chapter 2, Farm Trans faces a planning and routing problem. The focus of the problem is the electric trucks since Farm Trans does not yet know how to use electric trucks effectively. By creating a generic planning method for Farm Trans, they can use their electric and diesel trucks effectively. Furthermore, such a method can incorporate grouping orders to become even more efficient. Based on Chapter 2, there are requirements to which the solution method should adhere.

The solution method should result in a set of routes per truck. The overall objective is to minimise all costs while adhering to the time windows/deadlines the orders provide. These time windows are hard, meaning that they can not be violated. Furthermore, each truck has weight and load meter restrictions; these must also be adhered to.

Regarding costs, we have multiple considerations: toll, fuel/electricity, tyres, repair and maintenance, etc. The toll depends on the type of truck and the country in which it drives. Section 2.1.3 shows a cost per kilometre. Including tyres, repair & maintenance and fuel costs.

These requirements combined result in a problem instance called a Vehicle Routing Problem (VRP). The VRP is a well-known problem in logistics and transportation. It involves optimising the routes of a fleet of vehicles to deliver goods to a set of Customers [7]. A VRP is often a NP-hard problem, meaning there is no guarantee that an optimal solution can be found in a reasonable time [8]. Section 3.2 elaborates more on the Vehicle Routing Problem.

3.2 Fundamentals of the Vehicle Routing Problem

This section presents an overview of the basic concepts and principles of the Vehicle Routing Problem (VRP). We discuss the key elements, such as the problem formulation, objectives, constraints, and various VRP variants from the literature. This foundational knowledge is essential for understanding the context in which Farm Trans's specific VRP variant operates.

A key challenge in solving the VRP is finding a Feasible solution that minimises the total travel distance while adhering to various constraints [6]. The term Route refers to the sequence of locations visited by a vehicle during a VRP solution. As mentioned earlier, the VRP is often NP-hard. Therefore, finding an Optimal-solution is difficult in a reasonable time. Thus, finding a Feasible solution is the main objective. The final solution is the Feasible solution with the lowest cost.

There are many variants to be found in the literature of the VRP [9]. Figure 3.1 visualises some of the variations of the VRP found in the literature [9]. In the centre of Figure 3.1 we see the VRP, which is not a model but a collective name for all VRP variants. Adding parameters and constraints creates variants. The most standard form of the VRP is the Capacitated Vehicle Routing Problem (CVRP); this variant introduces capacity constraints to the vehicle.

The VRP variants in Figure 3.1 are not the only variants. Other variants relevant to this research are:

- Electric Vehicle Routing Problem (EVRP): deals with electric vehicles.
- Heterogeneous Fleet Vehicle Routing Problem (HF-VRP): deals with heterogeneous vehicles (e.g. each with their characteristics).
- Heterogeneous Fleet Vehicle Routing Problem with Time Windows (HF-VRPTW): deals with heterogeneous vehicles and time windows.

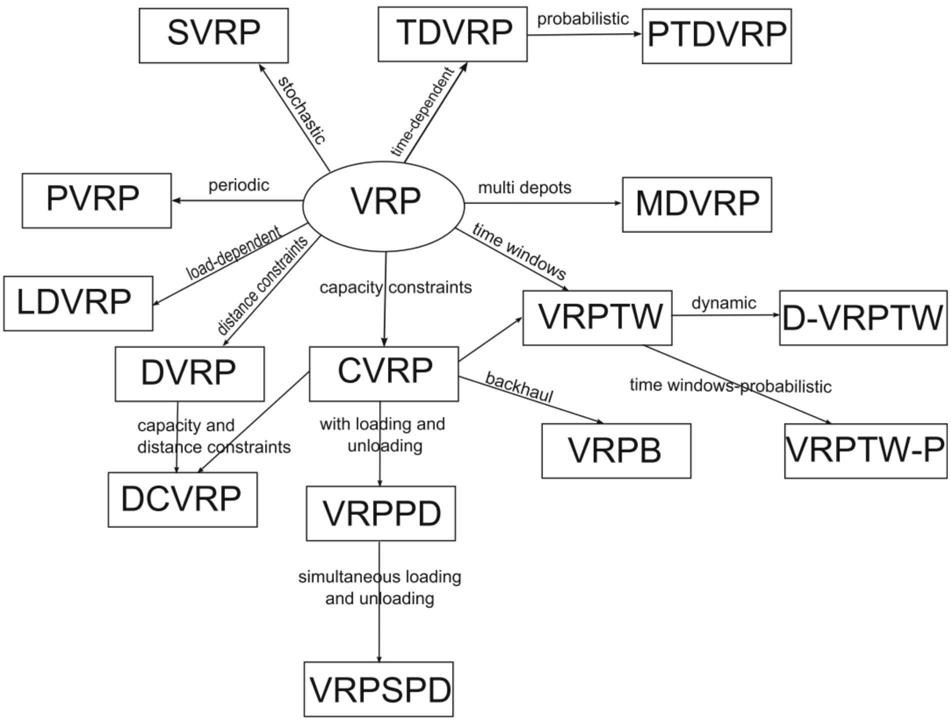


Figure 3.1: VRP Variants Hierarchy [10]

Figure 3.2 visualizes how the HF-VRPTW derives from the other variants of the VRP. We assume the VRP uses diesel trucks, combined with the EVRP results in the HF-VRP variant. When combining the HF-VRP with the VRPTW, the HF-VRPTW occurs. The VRP and its variants are fundamental problems in operations research and logistics.

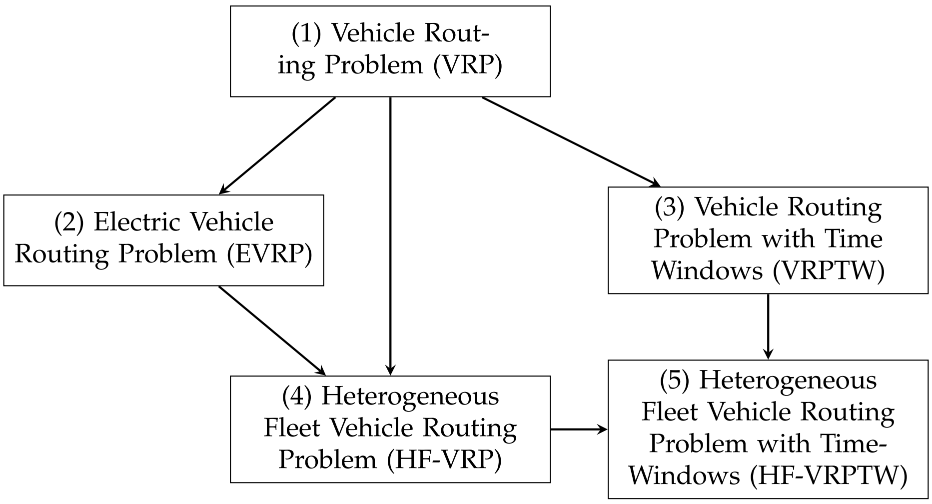


Figure 3.2: VRP and Variants

Figure 3.3 combines Figure 3.1 and Figure 3.2 into one complete overview of VRP variants relevant to this research. The colours indicate how different components get passed through to different variants. A full list of VRP variants is in Appendix A.

Figure 3.3: VRP and Variants Combined, showing the relations between variants

3.3 VRP Variants

This section focuses on the variants described in section 3.2. Section 3.3.1 provides the mathematical model of the CVRP. Next, Section 3.3.2 expands on this model by addressing time windows. Section 3.3.3 elaborates on using electric vehicles. Then Section 3.3.4 further explains the considerations when using pickup and delivery. Finally, Section 3.3.5 describes the additional constraints when using a heterogeneous fleet with time windows.

Most VRP models have some assumptions in common:

- All vehicles start at the central depot ($n = 0$) and finish their route at the central depot ($n = 0$ or $n = n + 1$).
- All VRP variants aim to minimise a function. This can either be a cost-dependent or distance-dependent function.
- All vehicles have a capacity restriction.
- Demand at a customer should be met by one vehicle (i.e. splitting orders is not allowed).

For understandability, most of the models in this research use the same notation:

Set of Customers, indexed by i and j	$\mathcal{C} = \{1, ..., n\}$
Set of Locations, where 0 and n+1 is the depot	$\mathcal{N} = \{0, ..., n+1\}$or $\mathcal{N} = \{0, ..., n\}$
Set of arcs between depot and all customers	$\mathcal{A}$
Set of vehicles in the fleet, indexed by r	$\mathcal{K} = \{1, ..., k\}$
Capacity of the vehicle	Q or Q_r
Cost of driving from i to j	c_{ij}
Distance between node i and j	d_{ij}
Demand of customer i	q_i
Set of charging stations	$\mathcal{F}$
Set of dummy nodes to allow multiple visits to a charging station	$\mathcal{F}'$
Set of customers and charging stations	$\mathcal{V}'$
Set of customers and depot node	$\mathcal{V}_0, \mathcal{V}_{N+1}$
Energy consumption rate of the vehicles per unit distance	h
Battery capacity of the vehicle	B
Time associated with driving from node i to j	t_{ij}
Time window associated with customer i	$[a_i, b_i]$

3.3.1 Standard Formulation

Model Description

One of the standard forms of the VRP is the Capacitated Vehicle Routing Problem (CVRP). This variant incorporates truck capacity constraints, meaning a truck can only transport a maximum amount of goods. Considering the vehicle capacity constraints is essential to achieve a feasible solution [10]. Otherwise, the solution might dictate that one vehicle should deliver all goods, while in the real world, the goods would not fit in that one vehicle.

In the CVRP, demands are known in advance, are deterministic, and should be delivered by one vehicle (i.e., splitting orders is not allowed). Vehicles are identical and originate from a single central depot. As mentioned earlier, the vehicles have capacity restrictions, and the objective is to minimise the total cost needed to serve all customers [11].

Within the CVRP, there are two alternatives: the two-index capacitated vehicle routing problem and the three-index capacitated vehicle routing problem [10]. The main difference is in the number of indices in the decision variable. The two-index formulation shows the use of the arc, whilst the three-index formulation also specifies which vehicle travels which arc. The three-index formulation is more flexible to incorporate additional constraints since it can address specific constraints to each vehicle [10, 12]. Since this research focuses on multiple vehicles, only the three-index formulation is considered.

Mathematical Model

As mentioned earlier, the main goal of the CVRP is to minimise costs. In this variant, the only costs are travel costs from one node to another. The model is based on the work of Kallehauge et al. [13] and uses the following variables:

$$x_{ijr} = \begin{cases} 1, & \text{if vehicle } r \text{ uses the arc between node } i \text{ and } j \\ 0, & \text{otherwise} \end{cases}$$

The model uses the following mathematical formulation:

$$\text{Minimize:} \quad \sum_{r \in K} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} c_{ij} x_{ijr} \tag{1.1}$$

Subject to:

$$\sum_{r \in K} \sum_{j \in \mathcal{N}} x_{ijr} = 1 \qquad \forall i \in C \tag{1.2}$$

$$\sum_{i \in C} q_i \sum_{j \in \mathcal{N}} x_{ijr} \leq Q \qquad \forall r \in K \tag{1.3}$$

$$\sum_{j \in \mathcal{N}} x_{0jr} = 1 \qquad \forall r \in K \tag{1.4}$$

$$\sum_{i \in \mathcal{N}} x_{ihr} - \sum_{j \in \mathcal{N}} x_{hjr} = 0 \qquad \forall h \in C, \forall r \in K \tag{1.5}$$

$$\sum_{i \in \mathcal{N}} x_{i,n+1,r} = 1 \qquad \forall r \in K \tag{1.6}$$

$$x_{ijr} \in \{0, 1\} \qquad \forall i, j \in \mathcal{N}, \forall r \in K \tag{1.7}$$

The objective function (1.1) minimizes travel cost. Constraint (1.2) ensures each customer is visited exactly once. Constraint (1.3) limits the load of a vehicle to its capacity.

Constraints (1.4), (1.5) and (1.6) are the flow constraints. Finally, constraint (1.7) is the binary constraint.

3.3.2 Time-Windows

The VRPTW adds a constraint to enforce time windows. A time window is the interval during which a vehicle must arrive at a customer [14]. These intervals can be hard or soft. When using hard time windows, violations are impossible, meaning that when a vehicle arrives too early, it must wait until the start of the window and a vehicle is not allowed to arrive late. Soft time windows allow violations. However, it incurs a penalty cost for arriving late. Therefore, these penalty costs are considered in the objective function and minimised [13].

To do so, the model incorporates one additional variable and two additional constraints. The variable s_{ir} denotes the time vehicle r starts to service customer i. The two additional constraints are:

$$x_{ijr}(s_{ir} + t_{ij} - s_{jr}) \leq 0 \qquad \forall i, j \in \mathcal{N}, \forall r \in K \tag{1.8}$$

$$a_i \leq s_{ir} \leq b_i \qquad \forall i \in \mathcal{N}, \forall r \in K \tag{1.9}$$

Constraint (1.8) creates the relationship between the current customer and its successor. Finally, constraint (1.9) enforces the time windows.

3.3.3 Electric Considerations

Model Description

With fuel accounting for 39% to 60% of operating costs in the transport industry, it is possible to consider alternative energy sources to remain competitive [15]. An alternative is electric trucks instead of diesel trucks [16]. However, electric trucks have a smaller range than diesel trucks and may require recharging during transport [17]. Charging takes longer than stopping for refuelling; this changes the model from the classic VRP to a distinctive variant, the EVRP.

The proposed model is based on the work of Kucukoglu et al. [18] and considers two charging policies, one for a partial charging policy and one for full charging. It therefore requires one additional variable y_i^r. This variable tracks the battery level of vehicle r when arriving at node i. Furthermore, four additional constraints are required:

$$\sum_{j \in \mathcal{C}'_{N+1}} \sum_{k \in K} x_{ij}^r \leq 1 \qquad \forall i \in \mathcal{F}' \tag{1.10}$$

$$y_j^r \leq y_i^r - (h \cdot d_{ij}) x_{ij}^r + B(1 - x_{ij}^r) \qquad \forall i \in \mathcal{C}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.11}$$

$$y_j^r \leq B - (h \cdot d_{ij}) x_{ij}^r \qquad \forall i \in \mathcal{F}' \cup \{0\}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.12}$$

$$y_0^r < B \qquad \forall r \in \mathcal{K} \tag{1.13}$$

Constraint (1.10) ensures that each dummy charging station can be visited at most once. Constraints (1.11) - (1.13) track the battery level and state when the full charging policy is used.

Additional Adaptations

This model has some additional adaptations. When considering partial charging, constraints (1.12) and (1.13) should be replaced by constraints (1.14) and (1.15). These constraints introduce a new decision variable Y_i representing the vehicle's battery level before leaving node i.

$$y_j^r \leq Y_i - (h \cdot d_{ij})x_{ij}^r + B(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}' \cup \{0\}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.14}$$
$$y_j^r \leq Y_i \leq B \qquad \forall i \in \mathcal{F}' \cup \{0\} \tag{1.15}$$

In case capacity needs to be considered in the EVRP, constraint (1.16) needs to be added to the model.

$$\sum_{i \in C} \sum_{j \in C'_{N+1}} q_i \cdot x_{ij}^r \leq Q \qquad \forall r \in \mathcal{K} \tag{1.16}$$

The proposed model can be extended further to incorporate time windows. This requires the following additional parameters, variables, and constraints:

Decision variable to track service start time at node i	p_i
Service time at node i	s_i
Recharging rate of the electric vehicles	g

Constraints:

$$p_i + (t_{ij} + s_i) \sum_{k \in \mathcal{K}} x_{ij}^r \leq p_j + b_0(1 - \sum_{k \in \mathcal{K}} x_{ij}^r) \qquad \forall i \in \mathcal{C}_0, \forall j \in \mathcal{C}'_{N+1} \tag{1.17}$$
$$p_i + t_{ij} \cdot x_{ij}^r + g(Q - y_i^r) \leq p_j + (b_0 + g \cdot Q)(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}', \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.18}$$
$$a_i \leq p_i \leq b_i \qquad \forall i \in \mathcal{C}'_{0,N+1} \tag{1.19}$$

When combining partial charging with time windows constraint (1.18) should be replaced with constraint (1.20).

$$p_i + t_{ij} \cdot x_{ij}^r + g(Y_i - y_i^r) \leq p_j + (b_0 + g \cdot Q)(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}', \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.20}$$

This model can be extended further to incorporate a heterogeneous fleet by replacing constraints (1.11)-(1.13), (1.14)-(1.15), (1.16), (1.17), and (1.18) with constraints (1.21)-(1.23), (1.24)-(1.25), (1.26), (1.27), and (1.28) respectively.

$$y_j^r \leq y_i^r - (h^r \cdot d_{ij})x_{ij}^r + Q^r(1 - x_{ij}^r) \qquad \forall i \in \mathcal{C}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.21}$$

$$y_j^r \leq Q^r - (h^r \cdot d_{ij})x_{ij}^r \qquad \forall i \in \mathcal{F}' \cup \{0\}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.22}$$

$$y_0^r \leq Q^r \qquad \forall r \in \mathcal{K} \tag{1.23}$$

$$y_j^r \leq Y_i - (h^r \cdot d_{ij})x_{ij}^r + Q^r(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}' \cup \{0\}, \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.24}$$

$$y_i^r \leq Y_i \leq Q^r \qquad \forall i \in \mathcal{F}' \cup \{0\} \tag{1.25}$$

$$\sum_{i \in \mathcal{C}} \sum_{j \in \mathcal{C}'_{N+1}} q_i x_{ij}^r \leq Q^r \qquad \forall r \in \mathcal{K} \tag{1.26}$$

$$p_i + t_{ij} \cdot x_{ij}^r + g^r(Q^r - y_i^r) \leq p_j + (l_0 + g^r Q^r)(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}', \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.27}$$

$$p_i + t_{ij} \cdot x_{ij}^r + g^r(Y_i - y_i^r) \leq p_j + (l_0 + g^r Q^r)(1 - x_{ij}^r) \qquad \forall i \in \mathcal{F}', \forall j \in \mathcal{C}'_{N+1}, \forall r \in \mathcal{K} \tag{1.28}$$

3.3.4 Vehicle Routing Problem with Pickup and Delivery

Most orders from Farm Trans originate in Lommel. However, some orders require pickup. Such a VRP is called a Vehicle Routing Problem with Pickup and Delivery (VRPPD). Desaulniers et al. [19] provide a model for the VRPPD, requiring additional constraints.

$$\sum_{k \in K} \sum_{j \in N_k \cup \{d(k)\}} x_{ijk} = 1 \qquad \forall i \in \mathcal{P} \tag{1.35}$$

$$\sum_{j \in N_k} x_{ijk} - \sum_{j \in N_k} x_{j,n+i,k} = 0 \qquad \forall k \in \mathcal{K}, \forall i \in \mathcal{P}_k \tag{1.36}$$

Constraints (1.35) and (1.36) ensure that each request (pickup and delivery) is served exactly once and by the same vehicle.

3.3.5 Heterogeneous Fleet with TW

The HF-VRPTW considers a heterogeneous fleet with time windows [20]. This model is, therefore, a combination of the VRPTW as described in Section 3.3.2 and the HF-VRP. This results in a model in which each vehicle has different characteristics and each customer has time windows. The vehicle-specific characteristics are capacity and fixed cost. Compared to other models, this model incorporates a fixed cost per vehicle, meaning that using a vehicle incurs initial costs. This model has no new constraints. As mentioned before, it combines the VRPTW and HVRP.

3.3.6 Combining Charging with Resting

As mentioned in Section 2.3.3, regulations exist for drivers to rest during transport. Since the range of an electric truck is shorter, more stops for charging are required compared to diesel trucks. Additionally, charging takes longer than fuelling. This poses the possibility of combining the charging of electric trucks with the mandatory resting times of drivers [21]. No models were found in the literature on this specific variant of the VRP.

3.3.7 Comparison between VRP Variants

Section 3.3 discusses various VRP variants. Each variant has different constraints which the model considers. Table 3.1 compares the different VRP variants and what elements each variant considers. Furthermore, additional papers are present in this table and categorised in standard models, electric truck models, pickup and delivery models, and break models. These categories provide insight into the most important parameter of the models in that category. All the models consider the capacity of trucks and the grouping of orders.

The "Objective Function" column lists the parameters each model aims to optimise. The following columns outline the constraints each model includes. For clarity, the table uses abbreviations to label constraints. In the "Fleet" category, var E indicates the use of electric trucks, var H refers to a heterogeneous fleet (where trucks differ in capabilities like capacity and range), and var E+D shows the use of both electric and diesel trucks. While var H and var E+D might seem similar, they represent different ideas: var H highlights varying truck capabilities, whereas var E+D indicates a mixed fleet without emphasising performance differences.

In the routing category, var P+D stands for pickup and delivery, and var TW means time windows are considered. In the truck category, var W represents the impact of weight on the range, and var B+R stands for the consideration that breaks and charging can be done simultaneously.

From table 3.1, we see that using the extended model of the EVRP variant incorporates the most considerations. The missing consideration is the combination of both diesel and electric trucks.

Table 3.1: Comparison between VRP Variants.

				Fleet			Routing		Truck		
Paper	Objective Function	Capacity	Grouping	E[1]	H[2]	E+D[3]	P+D[4]	TW[5]	B[6]	B+C[7]	Method
Standard Models											
Kallehauge et al. (2005) [13]	Travel cost	✓	✓	–	–	–	–	–	–	–	Column Generation
Molina et al. (2020) [14]	Travel cost	✓	✓	–	–	–	–	✓	–	–	Tabu Search
Riano et al. (2022) [20]	Travel cost, fixed cost	✓	✓	–	✓	–	–	✓	–	–	Simulated Annealing
Electric Truck Models											
Cortés-Murcia et al. (2019) [22]	Charging time	✓	✓	✓	✓	–		✓	–	–	Variable Neighbourhood Descent
Kucukoglu et al. (2019) [23]	Travel distance	✓	✓	✓	✓	–	–	✓	–	–	Simulated Annealing and Tabu Search
Kucukoglu et al. (2021) [18]	Travel distance	✓	✓	✓[8]	✓	–	–	✓[8]	–	–	Large Neighborhood Search
Lin et al. (2015) [16]	Charging cost, travel time cost, waiting time cost	✓	✓	✓	–	–	–	–	–	–	Exact method (small problem instance)
Pickup and Delivery Models											
Desaulniers et al. (2002) [19]	Travel cost	✓	✓	–	✓	–	✓	✓	–	–	Column Generation
Mahjoob et al. (2021) [24]	Fixed, travel, inventory, loading	✓	✓	–	✓	–	✓	–	–	–	Priori method
Yanik et al. (2013) [25]	Travel cost, fixed cost	✓	✓	–	✓	–	✓	✓	–	–	Genetic- and Savings Algorithm
Break Models											
Bernhardt et al. (2017) [26]	Fuel cost	✓	✓	–	–	–	–	✓	✓	–	Exact method
Kok et al. (2010) [27]	Vehicles used, Travel distance, Tuty time	✓	✓	–	–	–	–	✓	✓	–	Dynamic Programming
THIS PAPER	Variable, Fixed, Toll, Wage	✓	✓	✓	✓	✓	✓	✓	✓	✓	Simulated Annealing

[1] Considers Electric Trucks [2] Considers Heterogeneous Fleet [3] Considers both Electric and Diesel trucks [4] Considers Pickup and Deliveries
[5] Considers Time Windows [6] Considers Breaks [7] Considers combining Breaks with Charging [8] When using the extended model description.

3.4 Farm Trans's VRP Variant

Farm Trans faces a specific version of the VRP, a combination between the EVRP and the EVRP-WR, as mentioned in Section 3.3.7. This section elaborates on Farm Trans's specific VRP variant.

Capacity & Loading

Each truck has a maximum weight it can carry. Furthermore, weight restrictions per country state the weight a truck can take based on its type. An additional limitation is the space within the trailer; for this, Farm Trans uses load meters. Each trailer has a capacity of 13.2 load meters.

Farm Trans currently has no generic method for grouping orders. A VRP incorporates this in the solution to make routing as efficient as possible. However, if one truck takes multiple orders with different delivery locations, it is efficient to consider the unloading sequence when loading the trailer. This is to ensure that no unnecessary unloading is necessary for the customer. Since Farm Trans only uses pallets, it is unnecessary to consider a bin packaging problem; loading should occur in the reverse order of the route. So the delivered order is closest to the door without other orders being in the way.

Time-Windows

Orders need to be delivered within specified time windows. These time windows are hard and can not be missed. Furthermore, orders can not be rejected. All orders must be executed.

Fleet

The main decision in this VRP is the use of electric trucks. Therefore, Farm Trans must consider additional limitations associated with this use. An electric truck's range is shorter than a diesel truck's, and charging takes longer than refuelling. This must all be considered in the solution instance.

There are not as many charging stations as there are fuel stations. Therefore, the model should appoint the location where electric vehicles should recharge. Recharging an electric truck takes time; it would be beneficial if recharging occurred when the driver needs a break. There are regulations for how long a truck driver can drive a truck before needing a mandatory rest. Combining the break with recharging saves time and is financially beneficial.

Costs

The main goal of the model is to minimise costs in transportation operations. Therefore, the model considers several costs. First, the cost of fuel or electricity uses a price per kilometre. Furthermore, Farm Trans stated that there are two types of costs they calculate per kilometre: the cost of tyres and the cost of repair and maintenance, as shown in Section 2.3.6.

Additionally, there is the cost of tolls. Electric vehicles currently have a reduction in tolls compared to diesel trucks; this must be considered in the model since it can result in savings and more sustainable transportation.

3.5 Key Performance Indicators

To measure the solution's performance compared to the current solution method, KPIs are used. Radovic [28] created a list of KPIs often used in VRPs, shown in Appendix B. Not all the KPIs in this figure are relevant to this research, but some can provide insights when comparing solutions. Soysal and Çimen [29] propose the following KPIs; number of trucks used, total travel distance, total energy use, total driving time, total fuel cost, total wage cost and total routing cost.

The main objective of a VRP is to minimise costs by minimising the travelled distance. Therefore, total travel distance is an important KPI. Another KPI often used is the number of routes needed to deliver all orders.

Since this model uses a heterogeneous fleet, it is essential to have KPIs that indicate the solution's performance on this topic. The percentage of orders delivered using electric vehicles is a KPI that provides insight into this metric.

3.6 Existing Approaches to VRP and Variants

In this section, we explore the existing approaches and methodologies proposed to tackle various aspects of the Vehicle Routing Problem (VRP) and its numerous variants. We categorise these approaches into different subsections based on their nature and characteristics.

3.6.1 Exact Solution Methods

The exact solution methods are algorithms that guarantee an optimal solution to the VRP or its variants. Many mathematical programming solutions and approaches to solving the VRP have been proposed in recent years. Despite this effort, only the problems of around 100 customers can be optimally solved with a high computation time [30].

The VRPTW (Vehicle Routing Problem with Time Windows) and HF-VRP (Heterogeneous Vehicle Routing Problem) are both classified as NP-hard problems [31, 32]. As discussed in Section 2.3, Farm Trans's Fresh & Frozen department handles an average of 100 delivery orders per day. Since two key features of the Farm Trans routing problem—time windows and a heterogeneous fleet—are themselves NP-hard components, and given that solving instances of up to 100 orders requires significant computational effort for optimal solutions, we conclude that the Farm Trans routing problem is NP-hard. Therefore, this study does not include exact solution methods as possible approaches.

3.6.2 Heuristic Methods

Heuristic methods are problem-specific techniques that construct good, though not necessarily optimal, solutions to the Vehicle Routing Problem (VRP) in a computationally efficient manner. These methods are particularly useful when exact approaches become impractical due to problem complexity. Moreover, heuristics often serve as essential components or building blocks within broader metaheuristic frameworks. In this subsection, we explore classical heuristics such as the Nearest Neighbour algorithm, the (enhanced) Clarke-Wright Savings heuristic, and Solomon's insertion-based heuristics.

Nearest Neighbour

The nearest neighbour heuristic is a standard constructive heuristic used to create a feasible solution for any VRP problem. The logic behind the heuristic method is to start from the depot, select the nearest customer node to the depot, select the nearest customer node to the current customer, and so on. The depot is the start and end point of the route. The route is stopped when the vehicle's maximum capacity is reached.

Mazin et al. [33] propose a different approach using the K-Nearest Neighbour Algorithm.

Algorithm 1: K-Nearest Neighbour Algorithm

Begin;
Generate the *InitialSolution* by applying the nearest rule between nodes, i.e.
    Route 1: $1 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 10$;
    Route 2: $2 \rightarrow 3 \rightarrow 4 \rightarrow 8 \rightarrow 9$;
//d denotes the distance, q denotes demands, s is the concerned solution
Calculate the fitness of *InitialSolution* as follows:
    $d_s = d_{Route1} + d_{Route2} + ... + d_{RouteN}$,
    $q_s = q_{Route1} + q_{Route2} + ... + q_{RouteN}$,
    $d_{Route_i} = d_{0,1} + d_{1,2} + ... + d_{n-1,n}$,
    $q_{Route_i} = q_1 + q_2 + ... + q_n$,
//$Fitness_s$ is the fitness of the solution
$Fitness_s = d_s + q_s$;
Set best solution *(BestSol)* = *InitialSolution;*
Loop for 10,000 iterations, in each iteration:
    Generate new random solution *(NewSol)* with applying a nearest rule between nodes;
    Calculate the fitness of a *NewSol*;
    If *NewSol* is better than saved *BestSol*, then *BestSol* = *NewSol*;
End of loop;
Checking *BestSol* feasibility;
Write out the path of each route stored inside the *BestSol*;
End;

This algorithm creates multiple solutions over 10,000 iterations and every time a new solution is created a *Fitness* is calculated. This *Fitness* consists of the distance(d_s) and demand(q_s) of the solution. If the *Fitness* improves with a new solution, it becomes the *BestSolution*; if not, it is discarded.

Clarke-Wright Savings Heuristic

The Clarke and Wright Savings Heuristic [34] is a constructive heuristic that creates a feasible, near-optimal solution using the following formula:

$$s_{ij} = c_{i0} + c_{0j} - c_{ij} \tag{a}$$

With the following variables:

$$\begin{aligned} s_{ij} &= \text{Savings from joining customer } i \text{ and } j \text{ in the same route} \\ c_{ij} &= \text{Costs for travelling from node } i \text{ to node } j \end{aligned}$$

Suppose node $i = 0$ represents the depot, the following steps create a feasible near-optimal solution:

1. Start linking all solutions to the depot ($i = 0$).
2. Determine the savings for joining two customers and eliminating a trip back to the depot using Equation (a).
3. Sort savings non-incrementally.
4. Form a route by linking customers according to savings. Concerning:
   - Do not break any links formed earlier.
   - Stop when all customers are on the route.

Suppose the following costs from travelling from node i to node j, suppose A is the depot:

c_{ij}	0	1	2	3
0	-	8	9	13
1	8	-	4	11
2	9	4	-	5
3	13	11	5	-

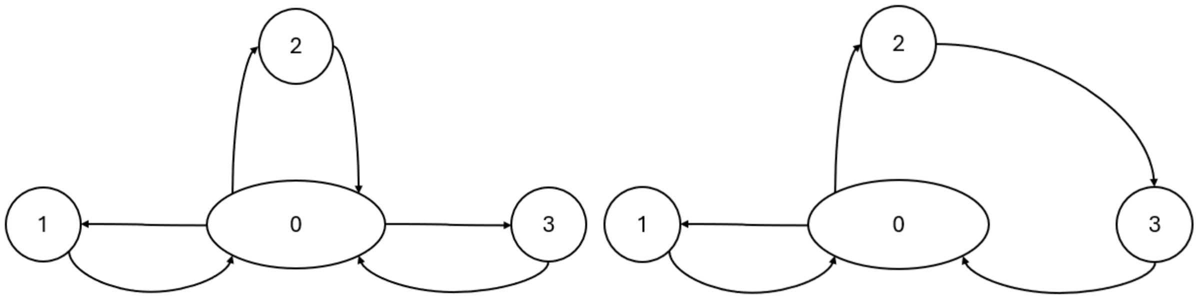
Table 3.2: Cost c_{ij} table for Clarke & Wright Heuristic

It is essential to note that since c_{ij} is symmetric, it is not necessary to calculate the savings for both s_{ij} and s_{ji} since these would result in the same savings.

Figure 3.4a visualises the initial state of the problem. All customer nodes are linked directly to the depot, resulting in three separate tours (Step 1). Next, calculate the savings for joining two customers by using Equation (a) (Step 2):

$$\begin{aligned} s_{12} &= c_{10} + c_{02} - c_{12} = 8 + 9 - 4 = 13 \\ s_{13} &= c_{10} + c_{03} - c_{13} = 8 + 13 - 11 = 10 \\ s_{23} &= c_{20} + c_{03} - c_{23} = 9 + 13 - 5 = 17 \end{aligned}$$

Next, the values of s_{ij} are sorted non-incrementally (Step 3), resulting in the connection between node $i = 2$ and $i = 3$ as shown in Figure 3.4b (Step 4). This connection does not break any previous connections since it is the first one. Not all customers are on the route yet, so the heuristic would continue calculating the new values s_{ij}.



(a) Initial State (b) Merged State

Figure 3.4: Clarke & Wright Savings Heuristic States

Enhanced Clarke & Wright's Method

The Clarke & Wright Method is very fast and simple to implement. However, some weaknesses exist.

Savings are the foundation of the heuristic, meaning that the approach iteratively accepts the best improvement. This results in good routes at the algorithm's beginning, but later, when fewer choices are available, the heuristic is left with customers located further away from each other, which might result in a circumferences route at the end of the heuristic. The solution considers a Route Shape Parameter (λ) to prevent circumferences routes.

Another improvement is to consider the spatial distribution of the customers by incorporating an additional term and parameter to the savings formula $\mu|c_{0i} + c_{j0}|$ where μ denotes the parameter to incorporate spatial distribution.

The final improvement considers customer demand when determining what routes to merge. The VRP considers not only the route but also the capacity of the vehicles. Therefore, it might be convenient to consider capacity constraints when merging two routes. The following addition considers this in the savings formula: $v\frac{d_i+d_j}{\bar{d}}$. Where v is a parameter to consider capacity in the savings formula, d_i is the demand of the customer i and $\bar{d}$ is the average demand calculated with $(\frac{1}{n})\sum_{i=1}^{n} d_i$.

Altinel and Öncan [35] propose an enhancement on the Clarke & Wright method to overcome these weaknesses. The savings formula changes to Equation (b):

$$s_{ij} = c_{i0} + c_{0j} - \lambda c_{ij} + \mu|c_{0i} + c_{j0}| + v\frac{d_i + d_j}{\bar{d}} \quad \text{(b)}$$

The proposed savings formula by Altinel and Öncan [35] combines multiple parameters and strives to obtain a better solution than the original Clarke & Wright method. However, the tuning of the parameters λ, μ and v is essential to obtain better solutions.

Solomon Nearest Neighbour Heuristic

The work of Clarke and Wright [34] is the foundation on which Solomon [36] built the Solomon Nearest Neighbour Heuristic. This heuristic incorporates the time windows denoted by $[e_i, l_i]$.

The heuristic uses additional variables where t_{ij} is the travel time between any two customers, and let d_{ij} be the distance between any two customers. s_i denotes the service time at each customer, and b_j is the service beginning at node j. v_{ij} stands for the urgency to deliver to customer j by calculating the remaining time until the vehicle's last possible service start. Additionally, the weights $\lambda_1, \lambda_2, \lambda_3$ are assigned to d_{ij}, T_{ij}, v_{ij} respectively. The following steps are taken in the Solomon heuristic:

1. Create a new metric (c_{ij}) to determine the closest customer.

2. Formulas;
   $b_j = max\{e_i, b_i + s_i + t_{ij}\}$
   $T_{ij} = b_j - (b_i + s_i)$
   $v_{ij} = l_j - (b_i + s_i + t_{ij})$
   $c_{ij} = \lambda_1 d_{ij} + \lambda_2 T_{ij} + \lambda_3 v_{ij}$
   $\lambda_1 + \lambda_2 + \lambda_3 = 1$

3. Select the customers constructively using the lowest c_{ij}.

The Solomon nearest neighbour heuristic constructs a feasible solution concerning the time windows. The weights $\lambda_1, \lambda_2, \lambda_3$ are used to give the three considerations additional importance. These considerations are distance (d_{ij}), difference between completion time at i and start of service at j (T_{ij}), and urgency to deliver to customer j (v_{ij}).

3.6.3 Metaheuristic Methods

Metaheuristic methods are high-level strategies designed to guide and improve heuristic-based search processes, enabling efficient approximations for complex VRP instances where exact solutions are computationally infeasible. Unlike simple heuristics, metaheuristics incorporate mechanisms for exploring a broader solution space and escaping local optima. The metaheuristic approaches discussed here—genetic algorithms, simulated annealing, and tabu search—are selected based on a comprehensive literature study and are informed by both their theoretical robustness and practical success in VRP applications.

Local Search

A local search is one of the most basic heuristics. It uses an initial solution from which we generate a neighbour solution [37]. This neighbour is then compared to the initial solution, and the new solution is accepted if it is better. If not, we maintain the original solution, and we compare another neighbour. Below is a description of a local search that uses the following two parameters. S is the set of feasible solutions. $N(x)$ is a set of neighbouring solutions of x.

1. Generate a feasible solution x (i.e. route in VRP)

2. Generate an unexamined neighbour y of x: $N(x) \bigcap S$

3. If $f(y) < f(x)$, set $x := y$. Go to Step 2

4. Stop, if all neighbours of x are examined without improvement: x is locally optimum solution

Suppose a route for a VRP can generate a neighbour by swapping two customers in the sequence. When the objective function yields a lower total cost, the neighbour is an improvement. When considering all neighbours of the current best solution and finding no improvement, the local search finishes.

Simulated Annealing

Simulated annealing (SA) is a metaheuristic capable of escaping a local optimum [38] and a well-known improvement heuristic. SA balances both exploration and exploitation.

Suppose a VRP is solved by minimising the objective function. Figure 3.5 visualises the value of the objective function. Solving starts at the black arrow, and the solution value decreases over time in the direction of the white arrow (exploitation). Usually, when reaching the lowest point of the parabola (local optimum), the algorithm stops. SA can escape this local optimum and continue with the algorithm (exploration). So, it is further to the right of the Local Optimum in Figure 3.5. It, therefore, accepts larger values (i.e. worse) than the current best to escape and hopefully descend again to a lower minimum than the local optimum (the global optimum).

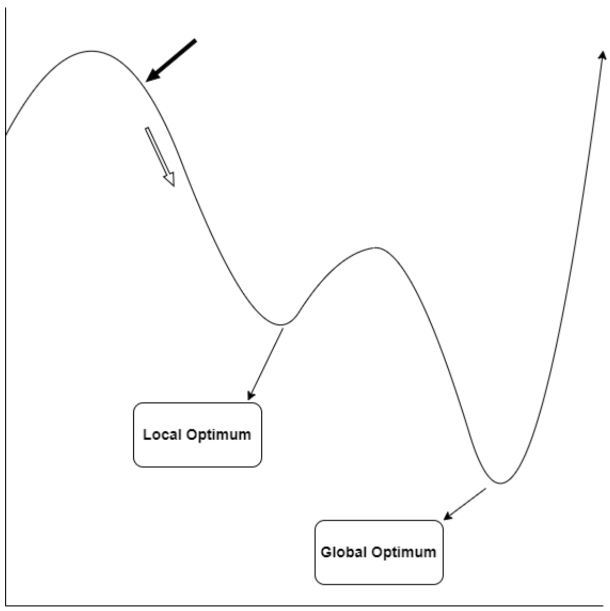


Figure 3.5: Local & Global Optimum Visualization

The SA algorithm escapes the local optimum by accepting solutions with a less optimal solution value. A constructive heuristic provides the initial solution (i_{start}), which SA needs as input. Additionally, the model initialises the variables $(c_k$ and $L_k)$. Accepting a worse solution is based on probability and the variable c_k. In the beginning, the value of c_k is large, thus almost every solution is accepted. After a fixed number of iterations called the Markov-Chain length, the temperature decreases by a factor of alpha. This shifts the focus from exploration to exploitation. Towards the end of the algorithm, SA focuses only on exploitation, not exploration. The algorithm stops when the temperature reaches a pre-determined value or when no improvement occurs for a pre-determined number of iterations.

The main advantage of SA is the possibility of exploration and exploitation. Compared to Local Search, SA is more likely to find a global optimum since Local Search only focuses on exploitation and ends up in a local optimum. SA is mighty when solving problems with large solution spaces.

Tabu Search

Tabu search is a robust global optimisation algorithm that uses a local search procedure to navigate a neighbourhood in search of better solution instances [1]. The algorithm stores visited solutions and uses these to avoid poor-scoring areas. Figure 3.7 visualizes the procedure.

Tabu search starts with an initial solution as input to the algorithm. From this solution, the method creates a candidate list containing neighbouring solutions. It selects the solution with the best objective value from this list. Then, the algorithm checks whether this solution appears on the Tabu list. If it does, the method removes it from the candidate list and checks the next candidate against the Tabu list. Once the algorithm finds a solution in the candidate list that doesn't appear on the Tabu list, it selects that solution as the new current solution and uses it to generate a fresh candidate list. The algorithm also updates the Tabu list with the newly banned solutions. This cycle continues until the stopping criterion is met.

The strength of Tabu search lies in its ability to eliminate undesirable neighbourhoods. As a result, it reduces the number of solutions the algorithm needs to consider before reaching an optimum.

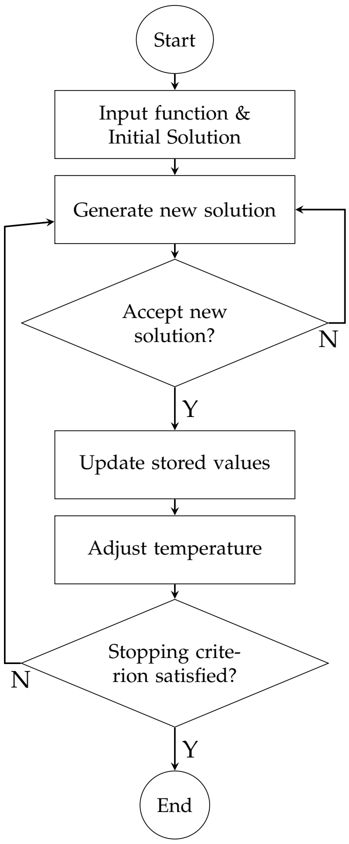


Figure 3.6: Simulated Annealing pseudo code

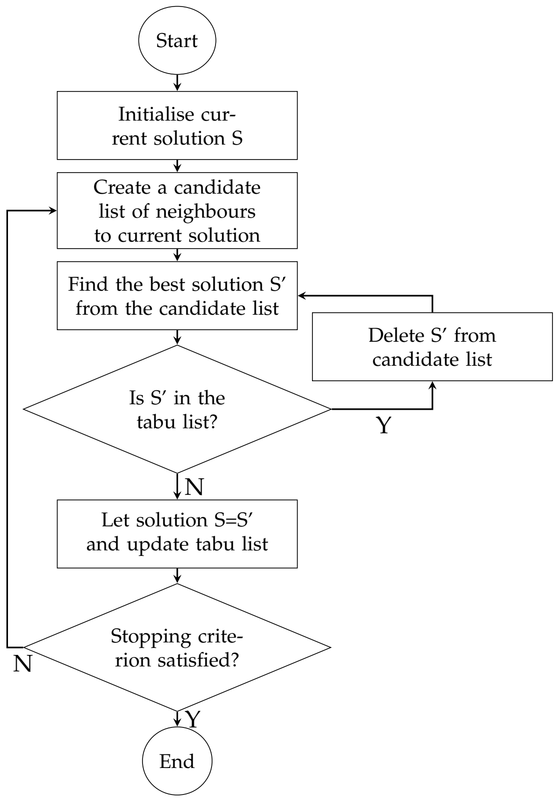


Figure 3.7: Tabu Search pseudo code [1]

3.6.4 Comparison between solution methods

Among the methods for solving the Vehicle Routing Problem (VRP), Enhanced Clarke & Wright's and Solomon's Nearest Neighbour are fast, constructive heuristics that provide quick but often suboptimal solutions. While useful for initial routing, they can struggle with complex constraints and typically get trapped in local optima.

In contrast, Simulated Annealing and Tabu Search are metaheuristic approaches that offer significantly better solution quality. Simulated Annealing explores the solution space probabilistically, occasionally accepting worse solutions to escape local minima. Tabu Search uses memory-based strategies to avoid revisiting recent solutions and systematically explores the neighbourhood for improvements.

While the heuristic methods are fast, Tabu Search and Simulated Annealing consistently yield higher-quality solutions, especially in larger or more constrained VRPs. Based on the literature review and Table 3.1, Tabu Search and Simulated Annealing are often used to solve VRP problem instances with similar specifications as the variant Farm Trans is facing.

3.7 Summary

This chapter has presented a comprehensive literature study on the Vehicle Routing Problem (VRP) and its many variants, with a particular focus on the specific routing and decision-making challenges faced by Farm Trans. We first introduced the foundational concepts of VRP and examined key variants such as the VRP with Time Windows (VRPTW) and the Heterogeneous VRP (HVRP), which are particularly relevant to Farm Trans's context.

We then reviewed a range of solution approaches, including classical heuristics (e.g., Clarke-Wright and Solomon's heuristic) and advanced metaheuristics (e.g., genetic algorithms, simulated annealing, and tabu search), highlighting their strengths, limitations, and applicability to large-scale, real-world routing problems. In addition, we identified the critical constraints and practical considerations—such as time windows, vehicle heterogeneity, range limitations, cost structures, and mandatory driver rest times—that define the complexity of Farm Trans's variant of the VRP.

In conclusion, the key definitions relevant to Farm Trans include those of VRPTW and HVRP, as they directly reflect the operational constraints and objectives of the company. The most suitable solution approaches are those that combine domain-specific heuristics with metaheuristic optimization techniques, as they offer the necessary flexibility and scalability to address the company's complex routing problem. This foundational understanding will directly inform the design of a tailored solution in the subsequent chapters.

Chapter 4

Problem Description

In this chapter, we provide a comprehensive and detailed exposition of the Vehicle Routing Problem (VRP) variant encountered by Farm Trans. The chapter is organised into five sections: "Formal Problem Definition" (Section 4.1), "Assumptions" (Section 4.2), "Definition" (Section 4.3), "Mathematical Formulation" (Section 4.4) and "Toy Instance" (Section 4.5). These sections collectively offer an in-depth understanding of the problem's scope, context, objectives, and complexities.

4.1 Formal Problem Definition

The problem is defined on an undirected graph $G = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ represents the set of nodes, and $\mathcal{A}$ denotes the set of arcs connecting them. The set of customers consists of pickup locations ($\mathcal{P}$) and delivery locations ($\mathcal{D}$). A central depot, denoted as 0, serves as the starting and ending point for all vehicle routes. Alongside customer nodes, the network includes charging stations ($\mathcal{CS}$) for electric vehicles, fuel stations ($\mathcal{FS}$) for conventional vehicles, and break locations ($\mathcal{BL}$) to accommodate mandatory rest periods.

The fleet comprises electric vehicles ($\mathcal{K}_e$) and conventional vehicles ($\mathcal{K}_d$), each with a maximum load capacity Q_r, battery and fuel capacities B_r and F_r, respectively, and specific consumption rates B_{con} and F_{con}. Vehicles incur various costs, including toll costs c_{ij}^{toll}, variable travel costs c_{ij}^{var}, fixed costs per vehicle c_r^{fixed}, and labor costs c_r^{labour}. The service time at each location s_i affects scheduling and overall efficiency.

Each vehicle must begin its route at the depot and return upon completing deliveries. The travel distance d_{ij} and travel time t_{ij} between nodes influence route planning and scheduling decisions. Battery and fuel levels, represented by y_i^r and f_i^r, are continuously updated as vehicles move between nodes. Vehicles must stop at charging stations or fuel stations to replenish energy levels when necessary. Customers have predefined service windows $[a_i, b_i]$ that must be respected, ensuring timely deliveries. The arrival time at each location T_i^r must adhere to these constraints.

The optimisation model seeks to minimise the total cost. Additionally, it aims to design efficient routing strategies that meet customer demands while complying with vehicle constraints. Balancing workload distribution across the fleet ensures operational efficiency and equitable service allocation. This formulation integrates routing and location-based decisions, providing a structured approach to minimising costs and optimising vehicle usage while maintaining reliable service levels.

4.2 Assumptions

This section outlines the foundational assumptions that underpin our problem formulation. These assumptions are crucial for delineating the problem's boundaries and simplifications, facilitating a clear understanding of the problem's context. Key assumptions include:

- **Single Depot**: Farm Trans operates from a single central depot in Lommel, Belgium, as the starting and ending point for all vehicles.
- **Heterogeneous Fleet**: We assume a fleet of heterogeneous vehicles with different performance characteristics.
- **Static Demand**: We consider a scenario with static customer demand, where customer orders do not change during the day.
- **Time Windows**: Customers have specified time windows during which deliveries must be made (i.e. time windows are hard deadlines).
- **Distances**: Distances between all locations are calculated using an Application Programming Interface (API). Resulting in a distance matrix; a matrix with travel distances between all locations.
- **Travel Times**: Travel times between locations are calculated using the distance matrix and an average 70 km/h speed.
- **No Split Deliveries**: We do not allow the splitting of customer deliveries across multiple vehicles.
- **Recharging**: Charging duration depends on the truck's electric capacity. The model uses different charging rates depending on the specific charger. A business relation of CAPE provides this data. Furthermore, we assume that we always charge the battery all the way; partial charging is not considered.
- **Dividing Breaks**: Breaks can not be divided into multiple breaks.
- **Daily Working Time**: We assume a maximum daily working time of 13 hours and a maximum daily driving time of 9 hours.

These assumptions provide a foundation for defining and modelling the VRP variant.

4.3 Definition

We define Farm Trans's VRP as a Heterogeneous Fleet Vehicle Routing Problem with Pickup and Delivery and Time Windows (HF-VRPPDTW). The VRP consists of a heterogeneous fleet incorporating electric and diesel trucks. Furthermore, all orders consist of corresponding pickup and delivery orders with hard time window constraints. The problem can be defined as NP-hard.

4.3.1 Problem Objectives

The primary objective of the VRP variant faced by Farm Trans includes minimising total transportation costs. These costs are separated into four distinct costs:

- **Variable Cost**:
  Consists of a price per kilometre, which differs per truck. Therefore, this minimises travel distance.
- **Toll Cost**:
  Consists of a rate per country per truck type. Again, it minimises travel distance and assigns trucks with lower toll rates to more expensive countries.
- **Labour Cost**:
  Consists of a standard hourly wage and minimises total travel time.
- **Fixed Cost**:
  Consists of a fixed cost per truck, only incurred when the truck is being used. Minimises the number of trucks used in a solution.

4.3.2 Problem Parameters

The problem is characterised by several parameters, which collectively define the problem and its complexity.

- **Customer Locations**: The locations of customer pickup and delivery points within the operational area.
- **Customer Demand**: The quantity of goods each customer requires for delivery.
- **Vehicle Capacities**: The maximum load capacity of each vehicle. In terms of weight and load meters.
- **Time Windows**: The time windows during which deliveries must be made to each customer.
- **Vehicle Range**: Each truck has a range it can travel on a full tank/battery.
- **Depot Location**: The location of the central depot from which all vehicles start and end their routes.
- **Distance Matrix**: A matrix detailing the distances between all pairs of nodes, calculated using an API.
- **Travel Times Matrix**: A matrix detailing the travel times between all pairs of nodes. Based on the Distance Matrix with a set average speed.
- **Charging Station Locations**: A list of charging stations the trucks can use to charge during transport.
- **Fuel Station Locations**: A list of fuel stations the trucks can use to refuel during transport.

- **Break Locations**: A list of break locations the trucks can use for breaks during transport.
- **Breaks**: The solution should incorporate breaks for the driver. Furthermore, this can be combined with charging.

4.4 Mathematical Formulation

The solution's foundation lies in developing a rigorous mathematical formulation for the VRP variant. In this section, we outline the objective function, decision variables, and constraints that constitute the optimisation problem. We provide a clear mathematical representation that captures the problem's essence and prepares it for algorithmic solutions. This model is based on the models from Kallehauge [13], Kucukoglu [18] and Desaulniers [19]. It has been tested in Python for correctness.

4.4.1 Notation

Set of Customers, indexed by i and j	$\mathcal{C} = \{1, ..., n\}$
Set of Pickup nodes	$\mathcal{P} = \{1, ..., n\}$
Set of Delivery nodes	$\mathcal{D} = \{n+1, ..., 2n\}$
Set of all nodes, where 0 is the depot	$\mathcal{N} = \mathcal{P} \cup \mathcal{D} \cup \mathcal{CS} \cup \mathcal{FS} \cup \mathcal{BL} \cup \{0\}$
Set of Charging Stations	$\mathcal{CS} = \{n*2+1, ..., n*2+4\}$
Set of Fuel Stations	$\mathcal{FS} = \{n*2+5, ..., n*2+8\}$
Set of Break Locations	$\mathcal{BL} = \{n*2+9, ..., n*2+12\}$
Set of Vehicles in Fleet, indexed by r	$\mathcal{K} = \{1, ..., k\}$
Set of Electric Vehicles	$\mathcal{K}_e = \{1\}$
Set of Conventional Vehicles	$\mathcal{K}_d = \{2\}$
Capacity of the vehicle	Q_r
Toll Cost of driving from i to j	c_{ij}^{toll}
Fixed Cost for using vehicle r	c_r^{fixed}
Variable Cost of driving from i to j	c_{ij}^{var}
Cost of labour for vehicle r	c_r^{labour}
Distance between node i and j	d_{ij}
Demand at node i	ℓ_i
Battery capacity of vehicle r	B_r
Fuel capacity of vehicle r	F_r
Battery consumption per unit distance	B_{con}
Fuel consumption per unit distance	F_{con}
Service time at node i	s_i
Earliest time at node i	a_i
Latest time at node i	b_i

Variables:

$$
\begin{aligned}
x_{ij}^r &= \begin{cases} 1, & \text{if vehicle } r \text{ uses the arc between node } i \text{ and } j \\ 0, & \text{otherwise} \end{cases} \\
L_i^r &= \text{Load carried by vehicle } r \text{ upon arrival at node } i \\
y_i^r &= \text{Battery level of vehicle } r \text{ upon arrival at node } i \\
f_i^r &= \text{Fuel level of vehicle } r \text{ upon arrival at node } i \\
T_i^r &= \text{Arrival time of vehicle } r \text{ at node } i \\
u_i^r &= \text{Continuous variable representing the position of node } i \text{ in the tour of vehicle } r
\end{aligned}
$$

4.4.2 Mathematical Formulation

$$
\begin{aligned}
\text{Minimize:} \quad & \sum_{r\in\mathcal{K}} \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} c_{ij}^{\text{toll}} \cdot x_{ij}^r && \text{(Toll Costs)} \\
& + \sum_{r\in\mathcal{K}} c_r^{\text{fixed}} \cdot \left(\sum_{j\in\mathcal{N}} x_{0j}^r \right) && \text{(Fixed Vehicle Costs)} \\
& + \sum_{r\in\mathcal{K}} \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} c_{ij}^{\text{var}} \cdot d_{ij} \cdot x_{ij}^r && \text{(Variable Travel Costs)} \\
& + \sum_{r\in\mathcal{K}} c_r^{\text{labour}} \cdot (p_{\text{end}(r)} - p_0) && \text{(Labour Costs)}
\end{aligned}
$$

$$\sum_{j\in\mathcal{N}, j\neq i} \sum_{r\in\mathcal{K}} x_{ij}^r = 1 \qquad \forall i \in \mathcal{P} \cup \mathcal{D} \tag{4.1}$$

$$\sum_{j\in\mathcal{N}, j\neq i} \sum_{r\in\mathcal{K}_e} x_{ij}^r \geq 0 \qquad \forall i \in \mathcal{F} \tag{4.2}$$

$$\sum_{j\in\mathcal{N}, j\neq 0} x_{0j}^r \leq 1 \qquad \forall r \in \mathcal{K} \tag{4.3}$$

$$\sum_{j\in\mathcal{N}, j\neq i} x_{ij}^r = \sum_{j\in\mathcal{N}, j\neq i} x_{ji}^r \qquad \forall i \in \mathcal{N}, i \neq 0, \forall r \in \mathcal{K} \tag{4.4}$$

$$y_j^r \leq y_i^r - B_{\text{con}} \cdot d_{ij} \cdot x_{ij}^r + B_{\text{cap}} \cdot (1 - x_{ij}^r) \qquad \forall i \in \mathcal{P} \cup \mathcal{D} \cup \mathcal{BL} \cup \mathcal{FS}, \forall j \in \mathcal{N}, i \neq j, \forall r \in \mathcal{K}_e \tag{4.5}$$

$$y_j^r \leq B_{\text{cap}} - B_{\text{con}} \cdot d_{ij} \cdot x_{ij}^r \qquad \forall i \in \{0\} \cup \mathcal{CS}, \forall j \in \mathcal{N}, i \neq j, \forall r \in \mathcal{K}_e \tag{4.6}$$

$$x_{ii}^r = 0 \qquad \forall i \in \mathcal{N}, \forall r \in \mathcal{K} \tag{4.7}$$

$$\sum_{j\in\mathcal{N}, j\neq i} \sum_{r\in\mathcal{K}} x_{ij}^r = 1 \qquad \forall i \in \mathcal{P} \cup \mathcal{D} \tag{4.8}$$

$$y_0^r \leq B_{\text{cap}} \qquad \forall r \in \mathcal{K}_e \tag{4.9}$$

$$u_i^r - u_j^r + |\mathcal{N}| \cdot x_{ij}^r \leq |\mathcal{N}| - 1 \qquad \forall i, j \in \mathcal{N}, i \neq j, i \neq 0, j \neq 0, \forall r \in \mathcal{K} \tag{4.10}$$

$$\sum_{j\in\mathcal{N}, j\neq i} \sum_{r\in\mathcal{K}} x_{ij}^r = 1 \qquad \forall i \in \mathcal{P} \cup \mathcal{D} \tag{4.11}$$

$$\sum_{j \in \mathcal{N}, j \neq i} \sum_{r \in \mathcal{K}_d} x_{ij}^r \geq 0 \qquad \forall i \in \mathcal{FS} \tag{4.12}$$

$$f_j^r \leq f_i^r - F_{\text{con}} \cdot d_{ij} \cdot x_{ij}^r + F_{\text{cap}} \cdot (1 - x_{ij}^r) \qquad \forall i \in \mathcal{P} \cup \mathcal{D} \cup \mathcal{BL} \cup \mathcal{CS}, \forall j \in \mathcal{N}, i \neq j, \forall r \in \mathcal{K}_d \tag{4.13}$$

$$f_j^r \leq F_{\text{cap}} - F_{\text{con}} \cdot d_{ij} \cdot x_{ij}^r \qquad \forall i \in \{0\} \cup \mathcal{FS}, \forall j \in \mathcal{N}, i \neq j, \forall r \in \mathcal{K}_d \tag{4.14}$$

$$f_0^r \leq F_{\text{cap}} \qquad \forall r \in \mathcal{K}_d \tag{4.15}$$

$$\sum_{j \in \mathcal{N}, j \neq i} x_{ij}^r = \sum_{j \in \mathcal{N}, j \neq i+n} x_{ji+n}^r \qquad \forall i \in \mathcal{P}, \forall r \in \mathcal{K} \tag{4.16}$$

$$T_j^r \geq T_i^r + s_i + t_{ij} - 1000 \cdot (1 - x_{ij}^r) \qquad \forall i, j \in \mathcal{N}, i \neq j, i \neq 0, j \neq 0, \forall r \in \mathcal{K} \tag{4.17}$$

$$T_i^r \geq a_i \qquad \forall i \in \mathcal{P} \cup \mathcal{D}, \forall r \in \mathcal{K} \tag{4.18a}$$

$$T_i^r \leq b_i \qquad \forall i \in \mathcal{P} \cup \mathcal{D}, \forall r \in \mathcal{K} \tag{4.18b}$$

$$T_{i+n}^r \geq T_i^r + s_i \qquad \forall i \in \mathcal{P}, \forall r \in \mathcal{K} \tag{4.19}$$

$$L_j^r \geq L_i^r + \ell_i - 1000 \cdot (1 - x_{ij}^r) \qquad \forall i, j \in \mathcal{N}, i \neq j, \forall r \in \mathcal{K} \tag{4.20}$$

$$L_i^r \leq Q_r \qquad \forall i \in \mathcal{N}, \forall r \in \mathcal{K} \tag{4.21a}$$

$$L_i^r \geq 0 \qquad \forall i \in \mathcal{N}, \forall r \in \mathcal{K} \tag{4.21b}$$

$$L_0^r = 0 \qquad \forall r \in \mathcal{K} \tag{4.22}$$

The objective function minimises the total cost. It consists of four components: toll cost, fixed cost, variable cost, and labour cost. Constraint (4.1) ensures each customer is visited exactly once. Constraint (4.2) enables multiple visits to charging stations. Constraint (4.3) ensures that each vehicle departs from the depot at most once. Constraint (4.4) guarantees flow conservation by ensuring that incoming arcs equal outgoing arcs for each node. Constraint (4.5) maintains battery levels at customer nodes, break locations, and fuel stations for electric vehicles. Constraint (4.6) ensures that battery levels for electric vehicles are properly initialised at the depot and charging stations. Constraint (4.7) prevents direct loops, ensuring a vehicle does not revisit the same node. Constraint (4.8) ensures that all customer nodes are visited by exactly one vehicle. Constraint (4.9) sets the initial battery level of electric vehicles to be within capacity. Constraint (4.10) prevents subtours by enforcing logical node sequencing. Constraint (4.11) ensures unique customer visits, preventing redundant assignments. Constraint (4.12) allows multiple visits to fuel stations by conventional vehicles. Constraint (4.13) ensures proper fuel consumption tracking for customer nodes, break locations, and charging stations. Constraint (4.14) sets fuel levels appropriately at the depot and fuel stations. Constraint (4.15) ensures the initial fuel level is within capacity. Constraint (4.16) enforces flow balance between pickup and delivery nodes. Constraint (4.17) maintains correct sequencing of travel times, excluding the depot. Constraints (4.18a) and (4.18b) enforce lower and upper bounds on time windows for customer nodes. Constraint (4.19) ensures that pickups occur before corresponding deliveries. Constraint (4.20) updates vehicle load based on pickup and delivery requirements. Constraints (4.21a) and (4.21b) enforce a non-negative load condition without exceeding vehicle capacity. Constraint (4.22) initialises the vehicle load to zero at the depot.

4.5 Example

The following small-sized instance shows the problem considerations and a solution, helping to create a better understanding of the problem at hand. Suppose we have two trucks, one diesel truck and one electric truck. These trucks have different characteristics, as shown in Table 4.1. We assume distance = time in this example instance.

Truck-ID	Type	Range	Refuel or Recharge Time
DT	Diesel	14	1
ET	Electric	9	2

Table 4.1: Toy Instance Truck Data

These trucks need to deliver three orders; these orders have a coordinate, weight and time window as shown in Table 4.2. Orders A and B originate from the central depot (Lommel, Belgium) and must be delivered to two distinct customer locations. Order C is different; this order requires pickup at location C1 and delivery at location C2.

ID	X-coordinate	Y-coordinate	Weight	Time Window	Country
A	2	8	2	[0, 5]	Netherlands
B	7	9	2	[8, 10]	Netherlands
C1	3	2	2	[0, 4]	Germany
C2	9	3	2	[2, 12]	Germany

Table 4.2: Toy Instance Order Information

Additionally, there is a charging station (CS) where the electric vehicle can recharge if necessary. The depot and charging station coordinates are shown in Table 4.3.

Location	X-coordinate	Y-coordinate
Depot	5	5
Charging Station	6	2

Table 4.3: Toy Instance Depot and Charging Station Coordinates

The Euclidean distance between all points is shown in Table 4.4.

	Depot	**CS**	**A**	**B**	**C1**	**C2**
Depot	0	3.16	4.24	4.47	3.61	4.47
CS	3.16	0	7.21	7.07	3.00	3.16
A	4.24	7.21	0	5.10	6.08	8.60
B	4.47	7.07	5.10	0	8.06	6.32
C1	3.61	3.00	6.08	8.06	0	6.08
C2	4.47	3.16	8.60	6.32	6.08	0

Table 4.4: Toy Instance Distance Matrix

Together, the locations of the depot, charging station and orders are visualised in Figure 4.1. Additionally, the time windows of the orders are shown in this figure.

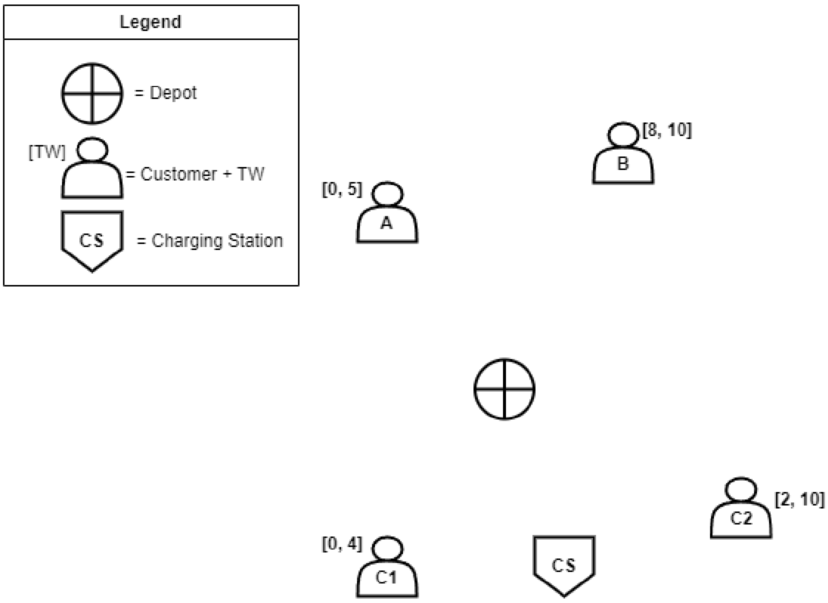


Figure 4.1: Map of Locations
(including time windows)

When solving this problem instance, we find the following routes.

$$DT : [Depot - A - B - Depot]$$
$$ET : [Depot - C1 - CS - C2 - Depot]$$

Figure 4.2 visualizes the routes and the arrival times at all locations. Both trucks handle two orders; each has a capacity of 4, and all orders weigh 2. Thus, the capacity is not exceeded.

DT travels a total distance of 13.81, which is within this truck's maximum range. The truck arrives at A at 4.24 and at B at 9.34. Both are within the time window for that order, meaning that truck DT's route is feasible.

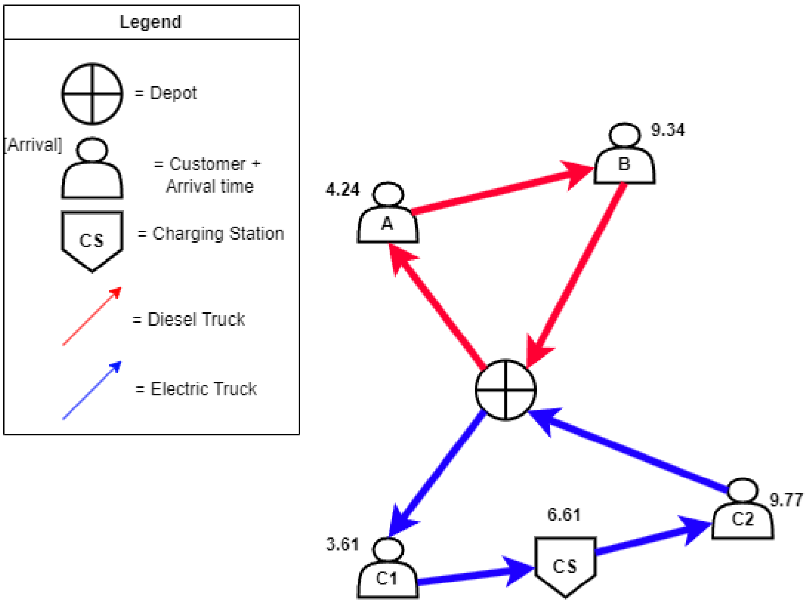


Figure 4.2: Map of Locations with Routes
(including arrival times)

ET travels a total distance of 14.24, larger than the maximum range. However, the truck recharges between the two customers. The distance from the depot to the CS is 6.61, and from there back to the depot, it is 7.63. Both are within this truck's maximum range. Additionally, charging takes two units. Thus, the truck arrives at C at 3.61 and at D at 11.77. Both are within the time window for that order, thus making this route feasible.

It is important to note that one truck could not deliver all these orders on time due to time window constraints. Therefore, this problem instance uses two trucks. Furthermore, using an electric truck benefits the transportation company since it is cheaper to drive an electric truck than a diesel truck due to toll prices as seen in Section 2.1.3. In this case, sending electric trucks to Germany is beneficial due to the significant benefit to the toll prices. Additionally, other routing was impossible due to the location of the charging station.

4.6 Summary

This chapter has comprehensively described the VRP variant faced by Farm Trans. We began by explaining the assumptions that define the problem's scope and context. We then provided a precise definition of the problem, specifying its objectives and parameters. Finally, we illustrated the practical implications of the problem through an example. This chapter sets the stage for the subsequent exploration of solution methodologies and experimental evaluations, providing a solid foundation for addressing Farm Trans's logistics challenges.

Chapter 5

Solution Approach

This chapter delves into the methodology and strategies employed to tackle Farm Trans's Vehicle Routing Problem (VRP) variant. Our approach is structured into several key subsections, each addressing a specific solution development and implementation aspect.

5.1 Algorithm Selection

Selecting an appropriate algorithm is crucial for solving complex optimisation problems like the VRP. As discussed in Chapter 4, this problem is NP-hard, making exact solution approaches impractical. Furthermore, Desaulniers et al. [19] present a wide range of VRPPDTW problem instances and note that all multi-vehicle cases require heuristic methods to solve. Only small instances, with approximately 10 nodes, could be solved optimally using exact methods. Based on Table 3.1, we define two candidate solution methods for this problem: Simulated Annealing and Tabu Search. Based on the comparison in section 3.3.7 and the arguments in Section 3.6.3, Simulated Annealing (SA) was chosen as the solution method due to its widespread use and its ability to balance diversification and intensification.

Based on Konstantakopoulos [39], Simulated Annealing is widely used due to its ease of implementation and the ability to improve solutions fast. As explained in Section 3.6.3, diversification allows the algorithm to escape local optima by accepting worse solutions, while intensification focuses on refining the current solution. Additionally, Farm Trans has a strict one-hour time limit for running the algorithm, which is the window between receiving orders and finalising their schedules. The combination of the characteristics of SA and the time constraints supports the use of SA, as it effectively requires time to diversify and intensify the solution space.

5.2 Metaheuristic Design

The algorithm has two components: a Constructive Heuristic (CH) and Simulated Annealing (SA). CH provides SA with a feasible, initial solution. SA then improves this solution.

5.2.1 Constructive Heuristic

The CH provides the SA with an initial feasible solution. We build a solution step by step. Figure 5.1 visualises the steps to create an initial solution. Algorithm 2 provides the pseudo code for the CH.

The algorithm starts by verifying whether a pickup-delivery order combination is feasible (Step 1). It checks whether the truck can travel from the pickup location to the delivery location within the given time window constraints. If the order is not feasible, it is excluded from the solution and not added to the list of planable pickup orders (Step 2). We then sort the remaining planable orders by their earliest pickup time window.

Next, the algorithm iterates over the available trucks, selecting the first truck (Step 3) and the first order from the planable orders list (Step 4). It then checks whether the truck has enough capacity to accommodate the selected pickup order (Step 5). If the truck lacks capacity, the algorithm determines the next pickup order (Step 4). If the order fits, an intermediate route is created from the truck's current position to the pickup location, incorporating necessary stops for charging, fueling, and breaks (Step 6).

Once we have established a route, the algorithm checks whether the truck arrives at the pickup location within the required time window (Step 7). If the truck arrives late, the algorithm selects the next pickup order (Step 4). If it arrives on time, the truck picks up the order, schedules it (Step 8), and removes it from the planable orders list (Step 9).

The algorithm then retrieves the corresponding delivery order (Step 10) and creates an intermediate route from the pickup location to the delivery destination (Step 11). It verifies whether the truck arrives within the delivery order's time window (Step 12). If the truck arrives too late, the algorithm restores the corresponding pickup order to the planable orders list (Step 13) and selects the next pickup order (Step 4). We schedule the delivery order if the truck arrives on time (Step 14).

The algorithm then checks whether all planable orders have been tried for the current truck (Step 15). It selects the next pickup order if there are still remaining orders (Step 4). If all orders have been tried for this truck, the algorithm checks whether another truck is available (Step 16). If a new truck is available, the algorithm selects it and repeats the process (Step 3). If no trucks remain, the algorithm terminates.

Finally, it could be the case that a solution can not include all orders. Therefore, the CH returns a list called *unplannedOrders*, which includes unscheduled orders due to capacity constraints, time-windows or a lack of trucks.

Intermediate Route

The function Intermediate Route creates a route between any two starting points and incorporates fuel stops, charging stops and breaks. This function is used often in the CH but also in the SA when we have an altered solution and require a new route between two new points. Since this study incorporates electric and diesel trucks, the intermediate route function consists of two parts, depending on the truck used.

If a diesel truck is used, we must schedule fuel stops and breaks sequentially, meaning we schedule the fuel stops and then insert the breaks when necessary.

For electric trucks, we only need to schedule breaks since we always recharge the truck when taking a break. Additionally, it can be the case that only charging during breaks is insufficient and additional charging is required. These are all scheduled simultaneously, meaning after an event is scheduled (e.g. break, handling, charging), we check what time we have left until all other events must take place, and we schedule the earliest one.

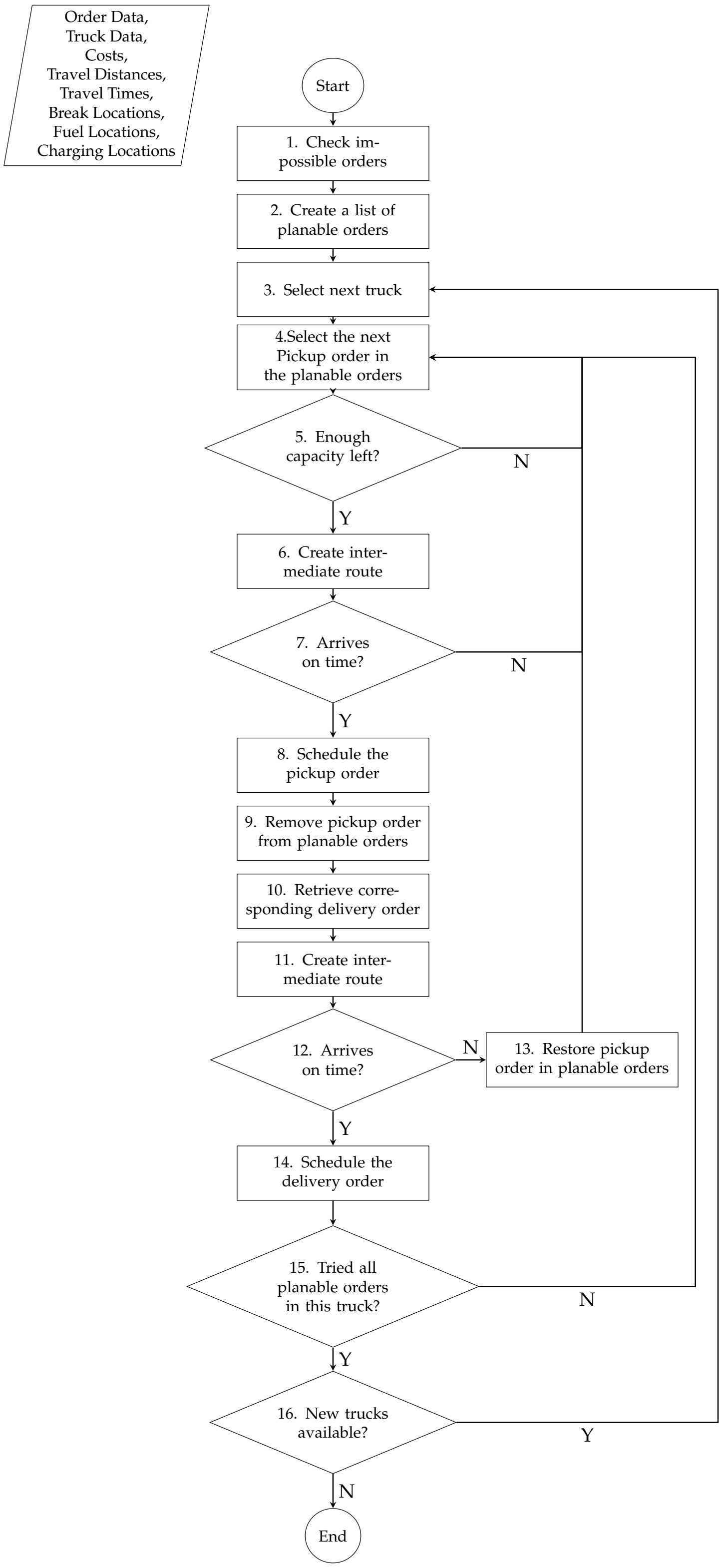


Figure 5.1: Flowchart of the Constructive Heuristic

Algorithm 2: Constructive Heuristic

```
Input: Trucks, Orders, Depot, Distance Matrix, Travel Times Matrix
Output: Feasible Solution, Unplanned Orders
Function checkPickupDeliveryTWs()
Function createRouteBreaks(truck, order, breaks)
Function removeOrder(truck, order)
Function createIntermediateRoute(currentPosition, order)
Function scheduleReturnToDepot(truck, breaks, Depot)
Function ConstructiveHeuristic()
    for truck ∈ Trucks do
        Save truck state
    impossibleOrders ← checkPickupDeliveryTWs()
    plannableOrders ← sorted orders by earliest start time, exclude impossibleOrders
    for truck ∈ Trucks do
        if plannableOrders = ∅ then
            break
        for order ∈ plannableOrders do
            if order is pickup then
                if truck has capacity for order then
                    breaks, travelTime ←
                      createIntermediateRoute(truck.currentPosition, order)
                    pickupArrivalTime ← truck.lastTime + travelTime
                    if pickupArrivalTime > order.endTime then
                        continue
                    createRouteBreaks(truck, order, breaks)
                    Remove order from plannableOrders
                    deliveryOrder ← corresponding delivery order
                    if deliveryOrder exists then
                        breaks, deliveryTravelTime ←
                          createIntermediateRoute(truck.currentPosition, deliveryOrder)
                        deliveryArrivalTime ← truck.lastTime + deliveryTravelTime
                        if deliveryArrivalTime < deliveryOrder.endTime then
                            createRouteBreaks(truck, deliveryOrder, breaks)
                            continue
                        else
                            RemoveOrdertruck, order
                            Add order back to plannableOrders
                            continue
                else
                    continue
    for truck ∈ Trucks do
        if truck used then
            breaks, travelTime ← createIntermediateRoute(truck.lastPosition, Depot)
            scheduleReturnToDepot(truck, breaks, Depot)
    unplannedOrders ← Orders not in any truck's route
    return unplannedOrders
```

5.2.2 Simulated Annealing

The SA algorithm uses the initial solution from the CH and tries to improve this solution. Therefore, operators alter the solution to create new solutions. SA uses diversification and intensification to move through the solution space and compare solutions. First, we explain the algorithm and then the operators used.

Figure 5.2 is based on figure 3.6, it visualizes the SA algorithm. In this case, the initial function and solution is the CH. Operators generate the new solution. Furthermore, the created algorithm includes a Markov chain, meaning that the temperature is only adjusted when reaching the Markov chain length. An additional stopping criterion next to the temperature is the running time; Farm Trans have a strict 1-hour limit to run the algorithm. The algorithm stops and returns the best solution if it exceeds the 1-hour time limit. Algorithm 3 provides pseudo code for the SA algorithm.

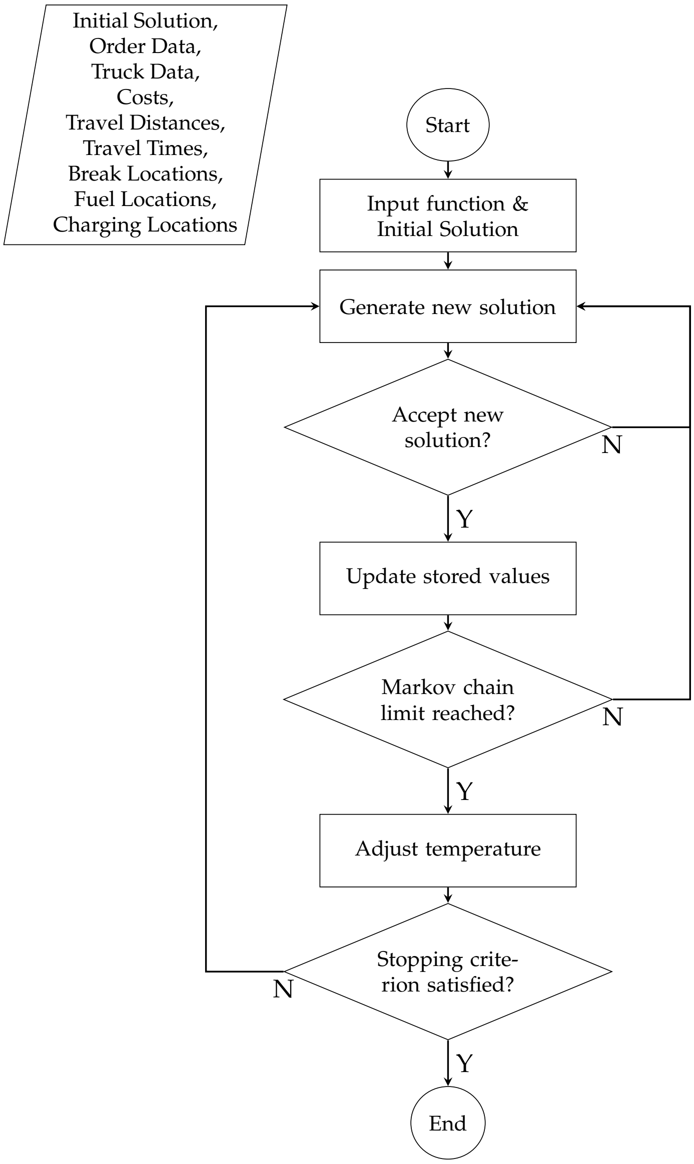


Figure 5.2: Flowchart of Simulated Annealing

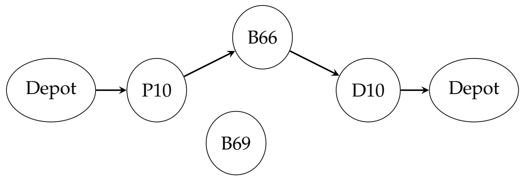
Algorithm 3: Simulated Annealing for VRP

```
Input: Initial VRP solution, InitialTemperature, Temp_end, MarkovChainLength, CoolingRate,
       Operators, maxRunningTime
Output: Optimised VRP solution
Function saveSolution(name)
Function loadSolution(name)
Function checkFeasibility()
Function checkFeasibleRoutes()
Function ObjectiveFunction(Labour_Cost)
Function applyOperator()
Function visualizeResults()
Function SimulatedAnnealing()
    startTime ← current time
    currentTime ← current time
    saveSolution("CH_sol")
    saveSolution("Best_sol")
    saveSolution("Current_sol")
    currentCost ← ObjectiveFunction(Labour_Cost)
    initCost ← currentCost
    bestCost ← currentCost
    //Initialize parameters
    Temp ← InitialTemperature
    M ← MarkovChainLength
    while Temp > Temp_end and currentTime − startTime < maxRunningTime do
        while M > 1 do
            //Apply a random operator
            applyOperator()
            //Check feasibility
            feasible ← checkFeasibility()
            if not feasible then
                loadSolution("Current_sol")
            if feasible then
                violations ← checkFeasibleRoutes()
                if violations then
                    loadSolution("Current_sol")
            //Evaluate solution
            newCost ← ObjectiveFunction(Labour_Cost)
            delta ← newCost − currentCost
            randomVar ← random value in [0,1]
            expValue ← −delta/Temp
            expProb ← e^expValue
            if δ < 0 or randomVar < expProb then
                saveSolution("Current_sol")
                currentCost ← newCost
                if currentCost < bestCost then
                    saveSolution("Best_sol")
                    bestCost ← currentCost
            else
                loadSolution("Current_sol")
            M ← M − 1
            currentTime ← current time
        //Cooling step
        Temp ← Temp × CoolingRate
        M ← MarkovChainLength
    //Finalizing results
    loadSolution("Best_sol")
```

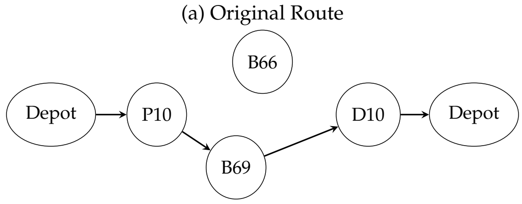
Simulated Annealing uses operators to change the solution and look for other solutions. This algorithm uses ten operators, which are divided into four categories: break operators, one truck operators, two truck operators, and insert unscheduled order.

Break Operators

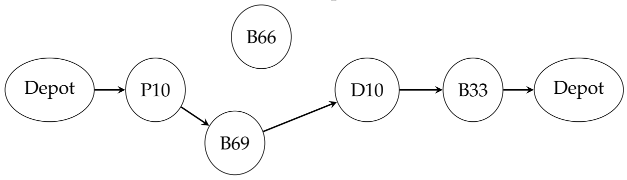
Move Break: The move break operator randomly selects a truck and then randomly selects either a break, fuel stop or charging stop in the route of that truck. Next, the five closest locations around the selected location are selected, and one is randomly chosen. This new location replaces the old selected location, creating a new route. Figure 5.3 visualizes the move break operator. The break previously taken at location B66 moves to location B69. After the repair, this results in an additional break at break location B33.



(a) Original Route



(b) Route operator



(c) Route after operator and repair

Figure 5.3: Visualisation of the move break operator

Move Long Break: An alternative to the move break operator is the move long break operator. The start is the same. However, it only selects a break which is longer than 11 hours. Thus, a break resets the daily working limit. This break is then removed from the route and randomly inserted. This insert is not entirely random since it must be before the original place where it was. Next, we repair the new solution using a separate function. Thus, all charging stops, fuel stops and breaks after the inserted break are removed and rebuilt using the intermediate route function. Figure 5.4 visualises the move long break operator. We moved the long break B66 to location B70. The repair adds break, B38.

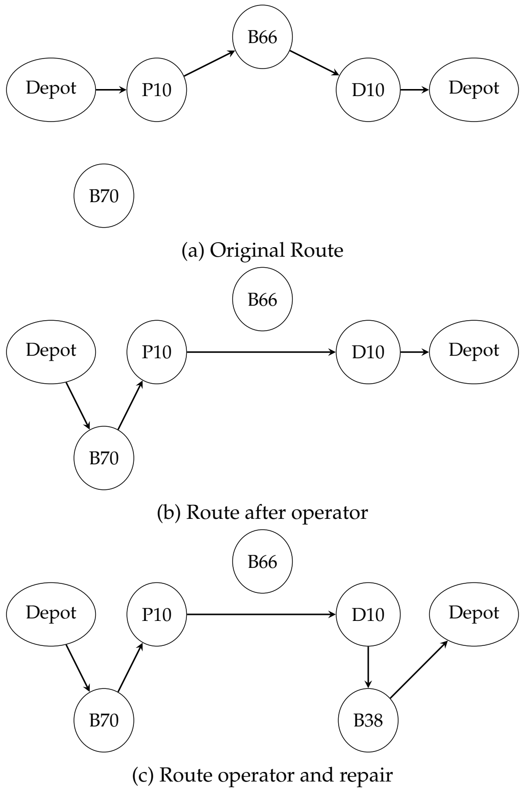


Figure 5.4: Visualisation of the move long break operator

One Truck Operators

Random Insertion in Route: The random insertion operator randomly selects a truck and randomly selects an order in the route of that truck. This order is removed from the route and then inserted randomly. However, the insert considers that a delivery order should be after the corresponding pickup order and a pickup order before the corresponding delivery order. Next, the route is repaired for breaks, fueling, and charging. Figure 5.5 visualizes this operator. Delivery order D10 is randomly selected and moved forward in the route between P10 and P12. The repair results in an additional break at B133.

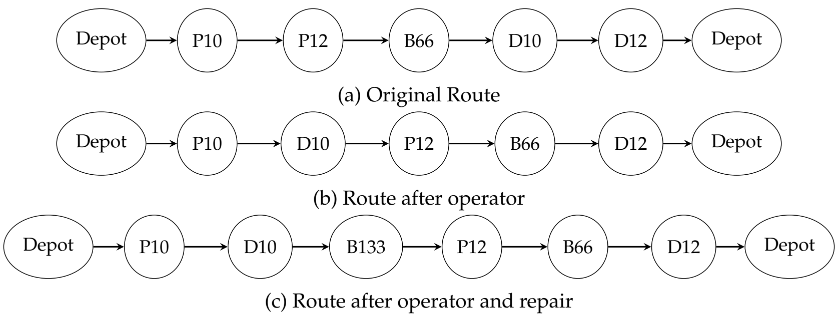


Figure 5.5: Visualisation of the random insertion in the route operator

Random Swap in Route: The random swap in route operator randomly selects a truck and randomly selects two orders in the route of that truck. We swap these two orders from their positions in the route. Next, the route is repaired for breaks, fueling and charging. Figure 5.6 visualizes this operator, P10 and P12 are swapped from their position. In this instance, the repair does not result in changes in breaks, fuelling or charging.

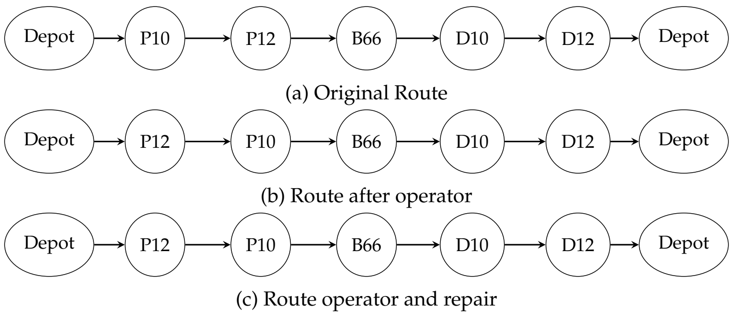


Figure 5.6: Visualisation of the random swap in the route operator

Two Truck Operators

Random Insertion between Trucks: The random insertion between trucks operator randomly selects two trucks and randomly selects a pickup order and the corresponding delivery order in the route of one of those trucks [40]. These orders are then removed from the original truck and randomly inserted into the route of the other truck. The insert only accounts for the fact that the delivery order should be after the pickup order. Next, the route is repaired for breaks, fueling, and charging. Figure 5.7 visualizes this operator. P10 and D10 are selected from another truck and randomly inserted into the route of this truck. And finally, the new route is repaired. *Random Swap between*

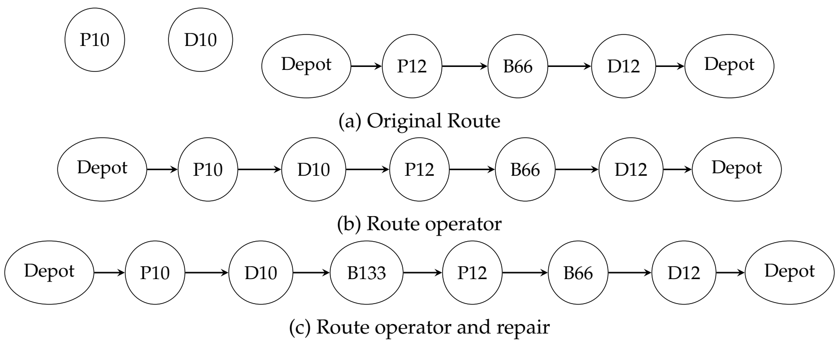


Figure 5.7: Visualisation of the random insertion between the truck operator

Trucks: The random swap between trucks operator randomly selects two trucks and randomly selects two pickup orders and two corresponding delivery orders in each truck's route [40][41]. The two pickup and delivery orders are swapped from their positions in different trucks. Next, both routes are repaired for breaks, fueling, and charging. Figure 5.8 visualizes the swap. P10 and D10 are selected from another truck and swapped with P12 and D12. And finally, the new route is repaired. *Move Route to unused Truck:* The moving route to an unused truck randomly selects two trucks. One truck is in use, and one truck is not in use. Then, the route from the used truck is moved to the unused truck and repaired for breaks, fueling, and charging.

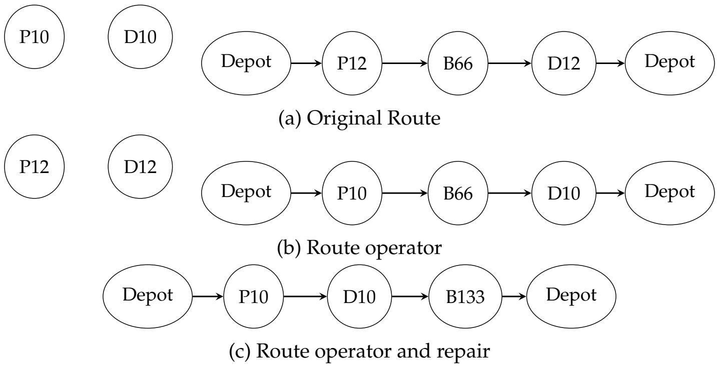


Figure 5.8: Visualisation of the random swap between the truck operator

Swap Routes between Trucks: The swap route between trucks operator selects two random used trucks and swaps the routes between both trucks. Next, both routes are repaired for breaks, fueling, and charging.

Insert Unscheduled Order

This category contains a single operator: the insert unscheduled operator. It selects an empty truck and attempts to assign it an unscheduled order. Unscheduled orders can result from the Constructive Heuristic (CH) being unable to fit all orders, due to trucks being full or time window constraints caused by existing routes. As Simulated Annealing (SA) optimises the solution, it may free up a truck, creating an opportunity to insert one or more of these previously unscheduled orders.

This operator functions similarly to the CH. It begins by selecting the unscheduled order with the earliest pickup deadline and attempts to schedule it. If successful, it continues adding additional orders one by one, as long as they fit within the truck's capacity and time window constraints. The process stops when no further orders can be added feasibly.

5.3 Summary

This chapter outlines the methodology designed to solve Farm Trans's complex VRP variant. Given the problem's NP-hard nature, exact methods were deemed impractical. Instead, a metaheuristic approach using Simulated Annealing (SA) was selected due to its proven ability to balance solution quality and computational efficiency. The solution method consists of two key components: a Constructive Heuristic (CH), which generates an initial feasible solution, and SA, which iteratively improves it by exploring the solution space. Operators for route swapping and inserting unscheduled orders are also introduced to refine the solutions dynamically. This chapter establishes the mathematical and algorithmic basis for the experimental work that follows.

Chapter 6

Experimental Setup

This chapter outlines our experimental setup for assessing the proposed solution to resolve Farm Trans's VRP variant (detailed in Chapter 5).

We define diverse experimental scenarios in Section 6.1. We cover crucial elements, including data collection and preprocessing in Section 6.2. Next, we provide an overview of software tools and the computational environment in Section 6.3. We conduct extensive parameter tuning in Section 6.4. And finally, introduce performance metrics in Section 6.5.

This chapter establishes the foundation for evaluating the effectiveness of our solution in tackling the real-world challenges posed by Farm Trans's VRP variant, including data management, scenario design, computational resources, parameter optimisation, performance measurement and experimental procedures.

6.1 Experimental Scenarios

To comprehensively assess the proposed solution, we define a set of experimental scenarios that represent different operational conditions and challenges faced by Farm Trans. The main objective of this research is to provide Farm Trans with a systematic approach to scheduling diesel and electric trucks. The experiments will focus on these decisions since they want to explore the possibilities of electrifying their fleet.

We use three distinct order datasets to validate and analyse the performance of the proposed method. The first order dataset has been selected together with Farm Trans to get a good representation of an average scheduling problem instance; we call this order dataset $Orders_{38}$, since it contains 38 orders. In the second order dataset, we increase the number of orders to 80; the order characteristics are similar to the $Orders_{38}$ dataset regarding time windows, locations and weight. We call this dataset $Orders_{80}$. Finally, we again increased the number of orders to 120 for the final order dataset ($Orders_{120}$), with the same characteristics.

Furthermore, we test on fleet configurations and derive five scenarios to experiment on. Farm Trans has 41 diesel trucks, so we keep the number of trucks steady at 41 for all experiments. We, therefore, vary the number of electric trucks per experiment. Experiment $D_{41}E_0$ has 41 diesel and zero electric trucks. We then increase the number of electric trucks per experiment until we have the same amount of electric and diesel trucks (e.g. Experiment $D_{41}E_{41}$).

When we combine the order data experiments with the fleet configuration, we get the experiments as shown in table 6.1. D denotes the number of available diesel trucks, E denotes the number of available electric trucks, and O denotes the number of orders that need to be scheduled.

ExperimentID	Electric Trucks	Orders
$D_{41}E_0O_{38}$	0	38
$D_{41}E_5O_{38}$	5	38
$D_{41}E_{15}O_{38}$	15	38
$D_{41}E_{30}O_{38}$	30	38
$D_{41}E_{41}O_{38}$	41	38
$D_{41}E_0O_{80}$	0	80
$D_{41}E_5O_{80}$	5	80
$D_{41}E_{15}O_{80}$	15	80
$D_{41}E_{30}O_{80}$	30	80
$D_{41}E_{41}O_{80}$	41	80
$D_{41}E_0O_{120}$	0	120
$D_{41}E_5O_{120}$	5	120
$D_{41}E_{15}O_{120}$	15	120
$D_{41}E_{30}O_{120}$	30	120
$D_{41}E_{41}O_{120}$	41	120

Table 6.1: Fleet Configuration for Experimentation (D=Diesel, E=Electric)

Additionally, with technological advancements in electric driving, it is safe to assume that the range of electric trucks will increase in the future. We, therefore, derived an additional set of experiments to test the influence of additional range on the solution. These experiments are shown in Table 6.2; we maintain a fleet of 41 diesel and 41 electric trucks and use the order data set with 38 orders (O_{38}). Experiments $E_{1,000}$ and $E_{1,500}$ have an electric truck range of 1,000 km and 1,500 km, respectively. We will compare experiments $E_{1,000}$ and $E_{1,500}$ to experiment $D_{41}E_{41}$ since in experiment $D_{41}E_{41}$, the original range of 500 kilometers for electric trucks is considered whilst having the same fleet configuration.

ExperimentID	Range Electric Trucks (km)
$E_{1,000}$	1,000
$E_{1,500}$	1,500

Table 6.2: Range Configuration for Experimentation

The first set of experiments will compare different fleet and order configurations and provide insights into whether electrifying the fleet is profitable and favourable for performance. The second set of experiments provides insight into the possibilities of future scenarios where the range of electric trucks is increased. We increase the range by doubling and tripling the original range (500 km). The most crucial metric in these experiments is the E/D ratio, which is the number of routes executed by electric trucks under different circumstances. We execute each experiment 3 times to account for randomness and ensure statistical validity.

6.2 Data Collection and Preprocessing

Data is a critical component of our experimental setup. This section details the data sources related to Farm Trans's VRP operations. We explain the data collection process, including how we gathered information on customer locations, vehicle capacities, time windows, and other relevant parameters. Additionally, we describe any data preprocessing steps undertaken to clean and prepare the dataset for experimentation.

6.2.1 Order Data

Order data is one of the primary data inputs for the solution. It consists of a table with order lines. Appendix D visualises this table. One row contains all the information for one pickup delivery pair.

One orderline contains the OrderID specific to that order, the customerID, the amount of pallets and pallettype. And finally the weight, loadmeters and temperature of the order. Table D.2 is the continuation of Table D.1 and provides information regarding pickup and delivery. The address, the latitude and the longitude of both pickup and delivery locations. Furthermore, it contains the time windows for pickup and delivery. Finally, it contains the required time to load and unload the order.

To validate the model, Farm Trans provided order data for 2024. From this, we created a dataset containing all pickups that occur on 1 day and all corresponding deliveries. We used only orders in which all data were present. Furthermore, orders executed in the United Kingdom were excluded from this dataset since Farm Trans has a separate scheduling department in the United Kingdom.

This dataset contains 38 orders; all pickups must be done on 1-3-2024. Delivery time windows vary between 1-3-2024 and 2-3-2024. The orders vary in size; there are FTL orders and orders of one pallet. Twenty-nine orders require pickup in Belgium, 11 of those at the depot. Eight orders require pickup in the Netherlands, and one is in France. Deliveries are evenly spread over the following four countries: the Netherlands, Belgium, Germany and France.

6.2.2 Truck Data

We based the truck data on the data provided in Section 2.1.1, and it is shown in Table 6.3. The license plate poses as a truck ID; the type indicates if the truck is electric or diesel. The range represents the range a truck can drive on a full charge or tank. Recharge/refuel shows how long it takes for a truck to be refuelled or recharged. For refuelling, a time of 15 minutes is scheduled, independent of the amount of fuel. Recharge has no set time since it depends on the charger and the kWh. The price per kilometre is based on the explanation in Section 2.1.3. Capacity (Weight) and Capacity (Load meters) provide the capacity of each truck. Finally, Capacity (Fuel/Electric) shows the maximum capacity for litres of diesel or kWh.

License-Plate	Type	Range	Recharge/ Refuel	Price/km	Capacity (Weight)	Capacity (Load-meters)	Capacity (Fuel/ Electric)
LP2	Diesel	2800	00:15	0.425	25000	13.2	800
LP1	Electric	300	-	0.58	25000	13.2	540

Table 6.3: Example Instance of Truck Data

6.2.3 Locations

To create feasible routes, we use charging locations, fuel locations, and break locations in addition to order locations and the depot.

Fuel locations and break locations are identical. Thus, each break location is a fuel location and vice versa. These locations are fictional and created in a grid across Europe. The grid has an intermediate distance of 50 km per location. An assumption is that each location in the grid is a break location. Thus, the break locations are the same as the fuel locations.

We use the charging locations from the dataset provided by a CAPE partner. The dataset included 286 charging locations across Europe and contained the power each location can provide to charge the truck. This power calculates a specific charging time based on the selected charging location.

6.2.4 Financial

As described in Section 4.3.1, the model uses an objective function consisting of 4 cost types: toll, hourly wage, price per kilometre and fixed cost. The model includes toll costs in a separate table, which shows the toll price per kilometre per country based on the truck type (e.g. diesel or electric).

For the hourly wage, we use an estimate provided by Farm Trans of € 40,-. Additionally, we use a price per kilometre per truck based on the calculation in Section 2.1.3. This cost differs per truck based on the data provided by Farm Trans. Finally, we incur fixed costs when using a truck for a route. The fixed cost is € 1,000.

6.2.5 Travel Distance & Travel Time

We use a Google API to determine travel distances. Farm Trans calculates travel times with an average speed of 70 km/h; we maintained this assumption when creating travel times based on the distances from the Google API.

6.3 Software and Computational Environment

The experiments were performed on a Lenovo ThinkPad P1 Gen 2 laptop equipped with an Intel Core i7-9750h processor (6 cores, 2.6 GHz), 16 GB of RAM, and an NVIDIA Quadro T1000 GPU (4 GB VRAM). The operating system used was Windows 11 Home, and the simulations were implemented in Python 3.9.19. Python uses a variety of packages to run the experiments; they are listed in Appendix C.

6.4 Parameter Tuning

Before conducting the experiments, several trial runs were undertaken to tune the algorithm parameters to ensure convergence and speed and to obtain high-quality solutions in a reasonable computation time. These parameters were initial temperature (T_{init}), end temperature (T_{end}), cooling rate (c) and Markov Chain Length (ML). Since this algorithm is designed for Farm Trans, we use a dataset from Farm Trans to tune the algorithm's parameters.

The initial temperature influences the algorithm's exploration before descending steepest. Additionally, it influences the algorithm's running time. The end temperature determines when the algorithm ends and thus influences the running time. The cooling rate balances the amount of exploration and exploitation and the running time. Finally, the Markov Chain Length is the number of iterations before the temperature decreases.

The algorithm's performance is measured using the objective function and the running time. The main objective is to minimise the objective function. Furthermore, the algorithm has a maximum running time of 1 hour.

We use the Python package Optuna to run multiple trials with different settings. It requires parameter intervals and tries to find the best settings based on past results. The following settings were the initial intervals provided to Optuna.

- Initial Temperature = [300, 400, 500, 600]
- End Temperature = [0.025, 0.05, 0.075, 0.1]
- Cooling Rate = [0.95, 0.96, 0.97, 0.98]
- Markov Chain Length = [100, 200, 300]

Based on these settings, Optuna conducted 20 trials, and for each setting, ran the algorithm 5 times to achieve an average and account for randomness. We visualise the results in Table E.1, Appendix E. Furthermore, Optuna returned the best-performing settings, as shown in Table 6.4. These settings return the lowest average objective value.

Based on Figure 6.1, we see sufficient exploration at the beginning of the algorithm and, later on, more exploitation. However, the run time is 1 hour, which means the algorithm terminated before reaching the final temperature due to the 1-hour time constraint. Additionally, we notice in Figure 6.1 that the objective improves very little in the last 40,000 iterations. The additional run time does not contribute to the eventual gain in objective value.

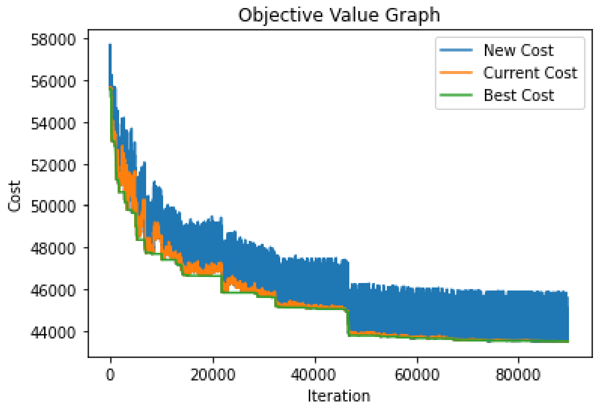


Figure 6.1: Objective Value Graph for best-performing settings

Parameter	Desription	Value
T_{init}	Initial Temperature	500
T_{end}	End-Temperature	0.05
c	Cooling Rate	0.98
ML	Markov Chain Length	300

Table 6.4: Parameter Settings After First Tuning

Based on these observations, the algorithm terminates earlier to prevent unnecessary run time against low gains. This can be achieved by increasing the End Temperature.

We also see in Figure 6.1 that the most significant improvements in objective value are achieved in the first half of the algorithm. Improvements in later stages are much less significant in value. We, therefore, determine an additional set of experiments. In these experiments, we only vary the End temperature whilst maintaining all other parameters at the values of Table 6.4. Table F.1 in Appendix F visualizes the results.

From Table F.1, we see that End Temperatures 0.05, 0.1 and 0.5 run for 60 minutes. This is too long, as mentioned earlier. Furthermore, we see a running time of 21 minutes for an End Temperature of 50 with an objective value of 46,217.90. The run time is shorter but yields an additional 1,725.34 on the objective value compared to the End Temperature of 0.1. This reduction in running time does not outweigh the increase in objective value. We, therefore, look at the End Temperature of 5, which yields an objective value of 44,905.21 and requires a running time of 41.11. Additionally, we see in Figure 6.2 that there is sufficient exploration and later sufficient exploitation.

Based on the experiments and the objective function graphs, we determine that the settings in Table 6.5 are the best-performing parameter settings and will be used for validation and experimentation.

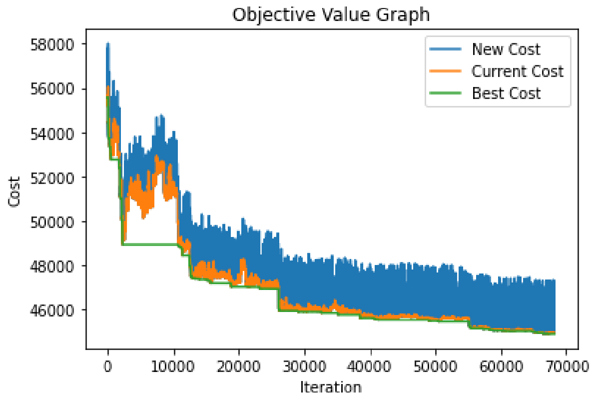


Figure 6.2: Objective Value Graph for Experiment 24

Parameter	Desription	Value
T_{init}	Initial Temperature	500
T_{end}	End-Temperature	5
c	Cooling Rate	0.98
ML	Markov Chain Length	300

Table 6.5: Parameter Settings After Second Tuning

6.5 Performance Metrics

To evaluate the effectiveness of the proposed solution, we define a set of performance metrics that measure various aspects of solution quality, efficiency, and robustness.

Table 6.6 shows the key performance indicators (KPIs) used to evaluate the effectiveness and efficiency of the HF-VRPPDTW solution, providing a comprehensive overview of both operational and cost-related aspects. Total Travel Distance and Total Time measure the overall distance and duration travelled by all trucks, indicating routing efficiency. Total Idle Time reflects periods where trucks are not in motion, helping to identify underutilization. Resource usage is assessed through Average Weight Utilisation and Average Load Meter Utilisation, showing how well vehicle capacities are leveraged. The Total Number of Trucks Used gives insight into fleet deployment. Environmental and energy efficiency are monitored via the electric/diesel ratio, along with the electric and diesel ratios, which quantify how much of the available electric and diesel fleets are utilised. Financial efficiency is evaluated using Total Toll Cost, Total Labour Cost, Total Fixed Cost, and Total Kilometre Cost, representing various expense categories. Finally, total cost aggregates all expenses to provide a holistic economic view, and unscheduled orders highlight service gaps by counting how many orders were not assigned to the solution.

Metric	Explanation
Total Travel Distance	Total Travel Distance of all trucks
Total Time	Total time of all trucks
Total Idle Time	Total Idle Time of all trucks
Average Weight Utilization	Average Weight Utilization Over All Trucks
Average Load Meter Utilisation	Average load meter utilisation over all trucks
Total Number of Trucks Used	Total number of trucks used
Electric/Diesel Ratio	Ratio of used electric over diesel trucks
Electric Ratio	Ratio of used electric trucks over total electric trucks
Diesel Ratio	Ratio of used diesel trucks over total diesel trucks
Total Toll Cost	Total toll cost of all trucks
Total Labour Cost	Total labour cost of all trucks
Total Fixed Cost	Total fixed cost of all trucks
Total Kilometre Cost	Total kilometre cost of all trucks
Total Cost	Total cost of all trucks
Unscheduled Orders	The amount of unscheduled orders in a solution

Table 6.6: Performance Metrics to Compare Experiments

6.6 Summary

Chapter 6 describes the experimental design for evaluating the proposed solution. We defined a variety of experimental scenarios, each representing different combinations of electric and diesel truck fleets and varying numbers of orders. Data preprocessing steps are explained for order data, truck data, location coordinates, and cost structures. The software tools, computing environment, and parameter tuning process for SA are also discussed in detail. Finally, the chapter defines a comprehensive set of Key Performance Indicators (KPI's) to assess operational efficiency, cost-effectiveness, and fleet utilisation. This chapter builds a robust foundation for validating the solution under realistic operational constraints.

Chapter 7

Results and Discussions

This chapter presents the results of the experiments to assess the proposed solution for addressing the Vehicle Routing Problem (VRP) variant encountered at Farm Trans. In Section 7.1, we validate the solution's performance compared to the current performance of Farm Trans's planning method. In Section 7.2, we analyse the experiments as described in Section 6.1.

7.1 Comparison with Previous Approaches

To validate the new method, we looked at Farm Trans's historical order data. We compared Farm Trans's solution to the algorithm's proposed solution over a dataset of orders to determine the improvements. However, such a comparison is difficult. Farm Trans has no generic method to schedule fuel stops, charging stops, or breaks. Therefore, a direct comparison could be deceiving since the algorithm's proposed solution incorporates these additional stops, resulting in a higher driving distance. Additionally, Farm Trans currently has no electric trucks. We, therefore, compare three methods:

- The method of Farm Trans
- The proposed method
- The proposed method without stops

We compare these solutions on several KPI's: Total Driving Distance, number of trucks used, weight utilisation, and loadmeter utilisation. It is impossible to use other KPI's since farm trans does not have data on arrival and departure times. We use the same dataset as Farm Trans and discard the use of electric trucks. Table 7.1 visualises these metrics of the proposed solutions.
First, let us compare the method of Farm Trans to the proposed method without stops. The proposed method yields a lower total driving distance, about 1300 kilometres less, which is an improvement of 10.82%. Additionally, we see higher utilisation for both weight and load meters. Based on these observations, we determine that the proposed solution beats the solution of Farm Trans.

Additionally, we added the proposed solution with stops. This solution still yields a lower total driving distance (5.6%) and higher utilizations than Farm Trans's solution. Additionally, it does account for fuel stops and breaks, thus creating a complete solution while still beating Farm Trans's solution.

Solution Method	**Total Driving Distance (km)**	**Number of Trucks**	**Weight Utilization**	**Loadmeter Utilization**
Farm Trans's method	12,209.20	21	0.24	0.29
Proposed solution without stops	10,888.89	21	0.28	0.30
Proposed solution with stops	11,531.60	21	0.28	0.31

Table 7.1: Performance Metrics per Method

Overall, we can determine that the proposed method to solve Farm Trans's VRP outperforms their current method. It yields a complete solution incorporating breaks and fuel stops while reducing the total driving distance against a higher average utilisation.

7.2 Experimental Analysis

Based on the experiments as described in Section 6.1 we retrieved the average results in Table 7.2, Table 7.4, Table 7.5 and Table 7.6. Table 7.2 shows the amount of unscheduled orders after the Constructive Heuristic (CH) and Simulated Annealing (SA). Table 7.4 shows the performance metrics of the initial solutions. The table consists of three parts, each part corresponds with one order dataset ($Order_{38}$, $Order_{80}$, $Order_{120}$). Within each part we find five experiments with different fleet configurations ($D_{41}E_0$, $D_{41}E_5$, $D_{41}E_{15}$, $D_{41}E_{30}$, $D_{41}E_{41}$). Table 7.5 has the same structure as table 7.4 and shows the average performance metrics after improvement using Simulated Annealing (SA). Table 7.6 consists of three experiments with increasing ranges (E_{500}, $E_{1,000}$, $E_{1,500}$). First, we will discuss the fleet configuration experiments and then the range experiments.

7.2.1 Fleet Configuration & Order Dataset Experiments

The main objective of the first set of experiments was to provide Farm Trans with insight into the possibilities of electrifying its fleet. The first set of experiments increases the number of available electric trucks to solve the VRP instance in which we vary the order dataset, as shown in Table 6.1.

Fleet

Figure 7.1 visualises the used trucks to solve the VRP instances with different order datasets. We grouped the experiments in the table into three clusters, each for one order dataset. Within each cluster, we see five experiments for the different fleet configurations. We begin with the O_{38} cluster.

The experiments use around 21 trucks to solve the VRP problem for O_{38}. Furthermore, in Table 7.2 we see zero unscheduled orders after the CH no matter the fleet configuration, thus all orders are being delivered. Experiment $D_{41}E_0O_{38}$ shows no electric trucks since there were none available. From experiment $D_{41}E_5O_{38}$ until experiment $D_{41}E_{41}O_{38}$, we see an increase in the use of electric trucks. When we look at the E/D Ratio in Table 7.5, we see an increase from 0% in experiment $D_{41}E_0$ to 85.08%

in experiment $D_{41}E_{41}O_{38}$. In experiments $D_{41}E_5O_{38}$ and $D_{41}E_{15}O_{38}$, we also see that 100% of the available electric trucks were used.

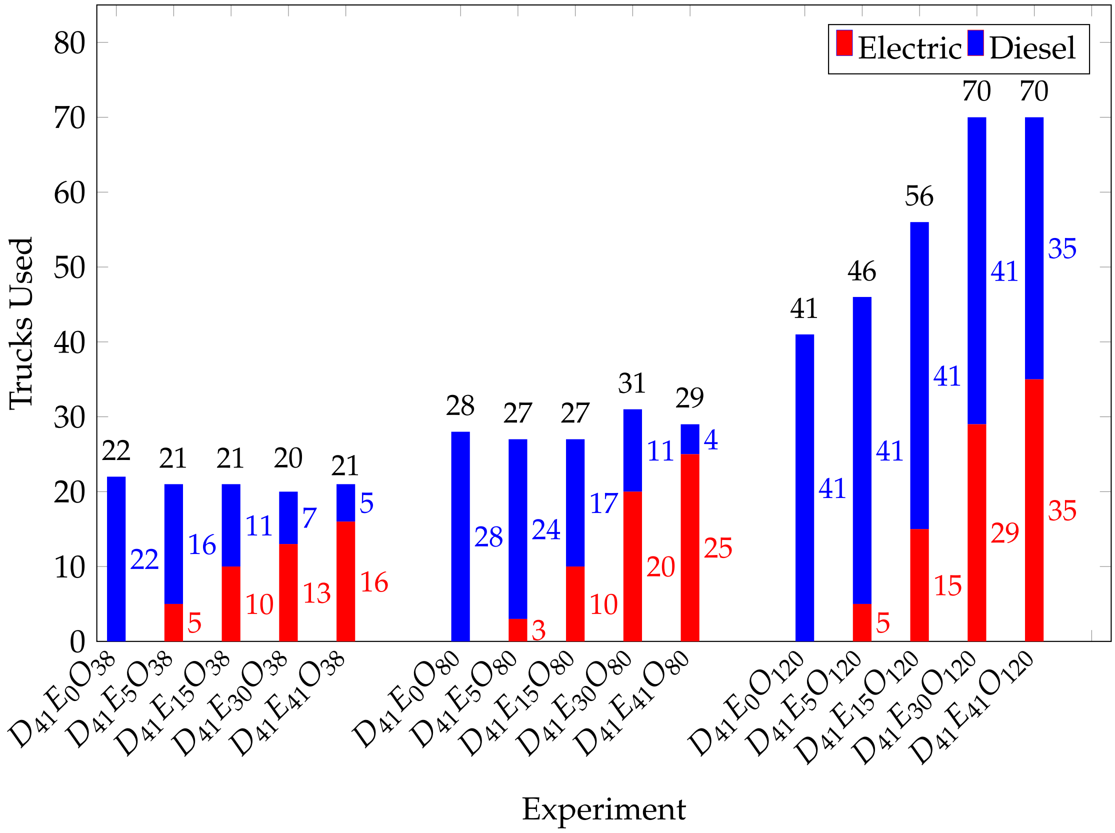


Figure 7.1: Configuration of Electric and Diesel Trucks used per Experiment

However, not all the electric trucks are always used. For instance, in $D_{41}E_{41}O_{38}$ we still use five diesel trucks while there are still 25 electric trucks available. Charging stations can explain this. Fuel stations are much more frequent than charging stations, so an electric truck cannot reach a specific location without getting an empty battery. Therefore, this route must always be executed by a diesel truck.

The same reasoning applies to the experiments with the order dataset O_{80}. We see an increase in the use of electric trucks and some routes remain to de executed by diesel trucks. In Table 7.2 we see that some orders are not planned after the CH. However, we see that all orders are planned after SA. This means that the proposed solution was able to bundle orders from different trucks and thus create empty trucks. These trucks could then be used to schedule the unscheduled orders, resulting in all orders being delivered.

The final cluster with order dataset O_{120} is different. We notice that the total number of trucks used increases between experiments, whilst this was not the case for the previous two clusters. This can be explained by the unscheduled orders. In $D_{41}E_0O_{120}$ we use all the trucks available (41 diesel trucks). But after SA 46 orders remain unscheduled. This also happens with $D_{41}E_5O_{120}$ and $D_{41}E_{15}O_{120}$, all the trucks are used, but 39 and 30 orders remain unscheduled, respectively. In experiments $D_{41}E_{30}O_{120}$ and $D_{41}E_{41}O_{120}$ we see a different pattern. Not all the trucks are used, but 10 orders remain unscheduled in both experiments. Upon closer examination, these 10 orders were infeasible. The pickup and delivery time windows were too close to each other, so no truck could meet the delivery time window.

ExperimentID	Unscheduled Orders Initial Solution	Unscheduled Orders Final Solution
$D_{41}E_{0}O_{38}$	0	0
$D_{41}E_{5}O_{38}$	0	0
$D_{41}E_{15}O_{38}$	0	0
$D_{41}E_{30}O_{38}$	0	0
$D_{41}E_{41}O_{38}$	0	0
$D_{41}E_{0}O_{80}$	31	0
$D_{41}E_{5}O_{80}$	26	0
$D_{41}E_{15}O_{80}$	16	0
$D_{41}E_{30}O_{80}$	1	0
$D_{41}E_{41}O_{80}$	0	0
$D_{41}E_{0}O_{120}$	71	46
$D_{41}E_{5}O_{120}$	62	39
$D_{41}E_{15}O_{120}$	54	30
$D_{41}E_{30}O_{120}$	36	10
$D_{41}E_{41}O_{120}$	25	10

Table 7.2: Unscheduled Orders per Experiment

Overall we see that the proposed method prefers electric trucks over diesel trucks when possible. It is important to note that the increase in the use of electric trucks is based on the costs. In these instances, electric trucks are favourable due to their lower costs. Diesel trucks are only used for routes where electric trucks can not adhere to the time windows or no charging locations are on the route, so an electric truck can not reach the destination. Furthermore, we see that the proposed method has the ability to schedule orders that remained unscheduled in the initial solution.

Costs

The primary objective of the model is cost minimisation; therefore, the use of electric trucks over diesel trucks must be justified by financial benefits. Analysing the experiments with order dataset O_{38} in Figure 7.2, we observe that the significant reduction in total costs across scenarios is mainly due to lower toll costs. Since tolls are cheaper for electric trucks, increasing their availability directly contributes to lower overall costs.

For example, comparing scenarios $D_{41}E_0O_{38}$ and $D_{41}E_{15}O_{38}$, increasing the number of electric trucks from 0 to 15 more than halves the toll costs—from approximately €3,100 to €1,500.

Additionally, total kilometre costs decrease, as the algorithm identifies more efficient routes, reducing total driving distance. Labour costs remain relatively stable across experiments, while fixed costs drop to a minimum of €20,000 due to fewer trucks being utilised.

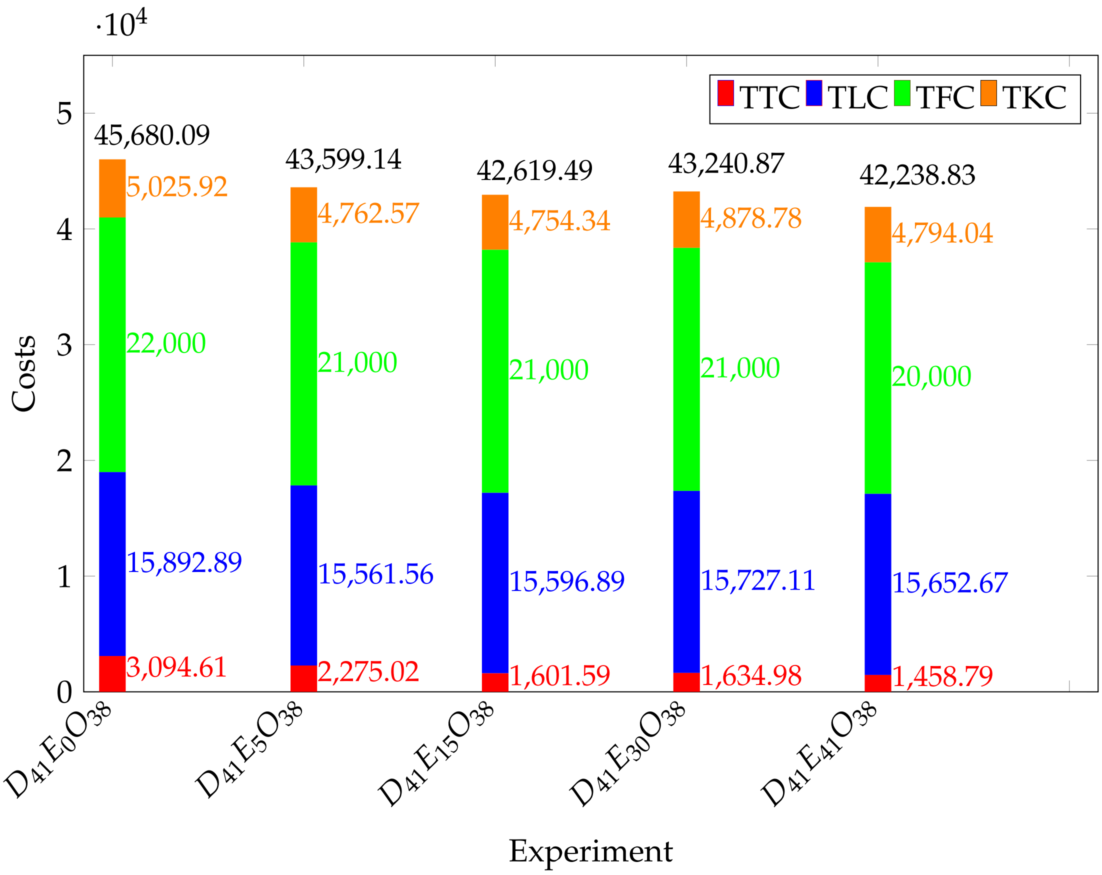


Figure 7.2: Stacked Bar Chart of Cost Breakdown per Experiment for O_{38}

The same reasoning does not apply to the experiments with the order dataset O_{80}. In Figure 7.3 we see a decrease in total toll cost, due to more use of electric trucks, similar to the previous order dataset (O_{38}). However, experiment $D_{41}E_{30}O_{80}$ shows an unexpected increase in total costs. For this experiment, we see an increase in total labour, fixed, and kilometre costs. It is curious to see that experiment $D_{41}E_{30}O_{120}$ later yields a lower total cost and decreases further in all four cost components. Due to this observation, we must conclude that the increased costs of $D_{41}E_{30}O_{80}$ are a random spike.

Except for experiment $D_{41}E_{30}O_{80}$, the total costs decrease throughout the experiments, which is in line with the conclusion of the previous set of experiments.

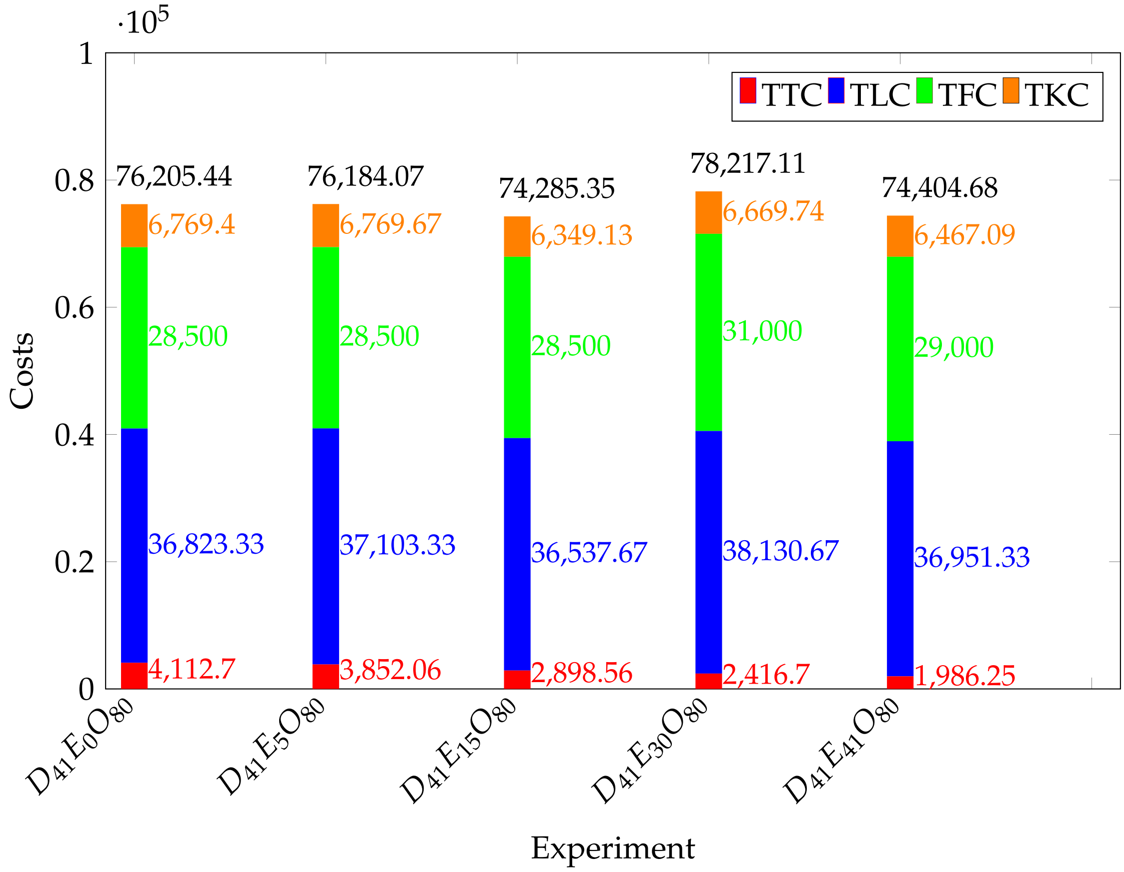


Figure 7.3: Stacked Bar Chart of Cost Breakdown per Experiment for O_{80}

The experiments with order dataset O_{120} differ from the previous two experiment sets. This is due to the unscheduled orders at the start of the algorithm, as shown in Table 7.2. All the costs increase throughout the experiments since the increased availability of trucks enables the algorithm to schedule more orders. This increase in orders results in an increase in all costs, as shown in Figure 7.4. Again we notice very small differences between experiments $D_{41}E_{30}O_{120}$ and $D_{41}E_{41}O_{120}$. This is due to the infeasibility of some orders due to time window constraints, as explained earlier in this section.

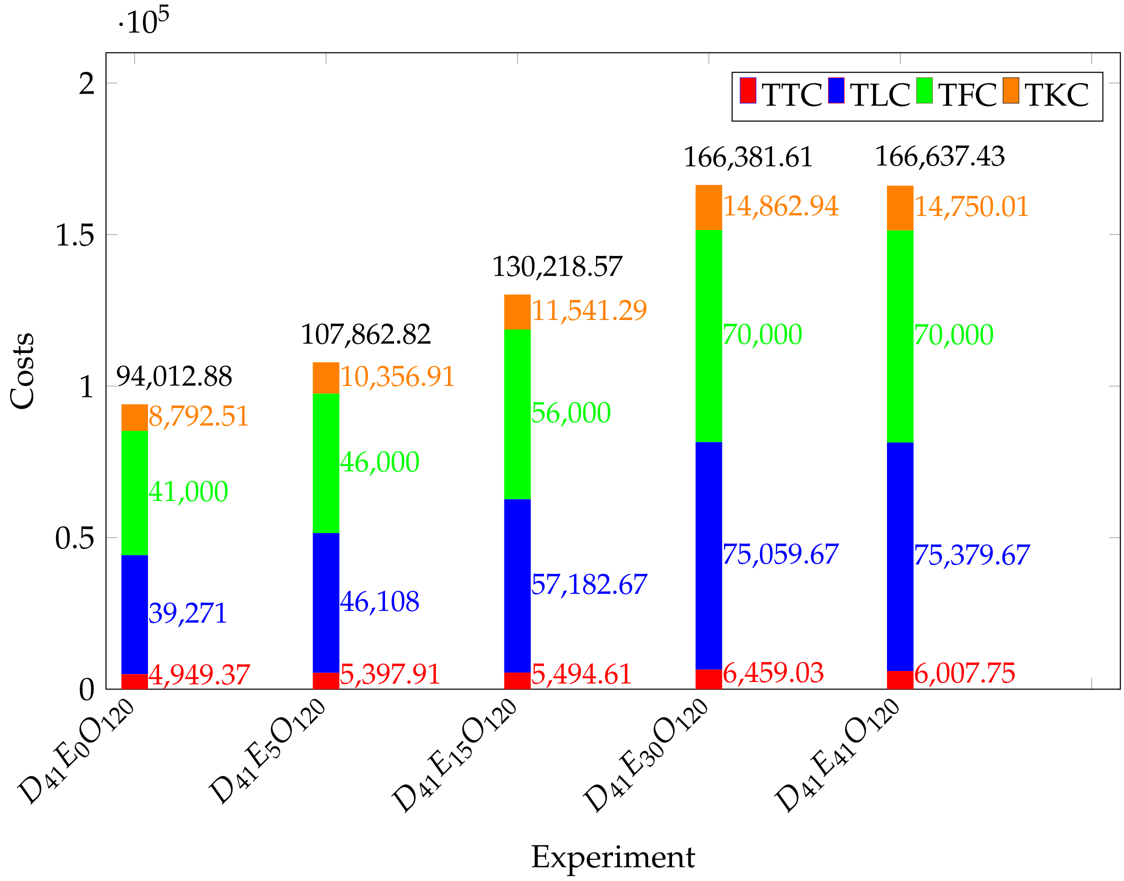


Figure 7.4: Stacked Bar Chart of Cost Breakdown per Experiment for O_{120}

7.2.2 Range Experiments

The second set of experiments increases the range of electric trucks. Experiment E_{500} is the current situation with a range of 500km; experiments $E_{1,000}$ and $E_{1,500}$ have increased ranges of 1,000km and 1,500km, respectively. The output is shown in Table 7.6. In this experiment, we only consider the order dataset O_{38}.

Throughout experiments E_{500}, $E_{1,000}$ and $E_{1,500}$, the E/D ratio remains the same at about 85%. By increasing the range of electric trucks, we also increase the charging time since more electric power needs to be stored to drive longer distances. This makes it impossible for electric trucks to reach some delivery locations within the time window. Therefore, diesel trucks have the advantage of having a longer range and shorter refuel times.

Upon closer examination of the proposed solutions, we noticed that electric trucks cannot reach the delivery location within a specific time window due to the additional charging time required. Thus, the model decides to use diesel trucks to deliver these orders.

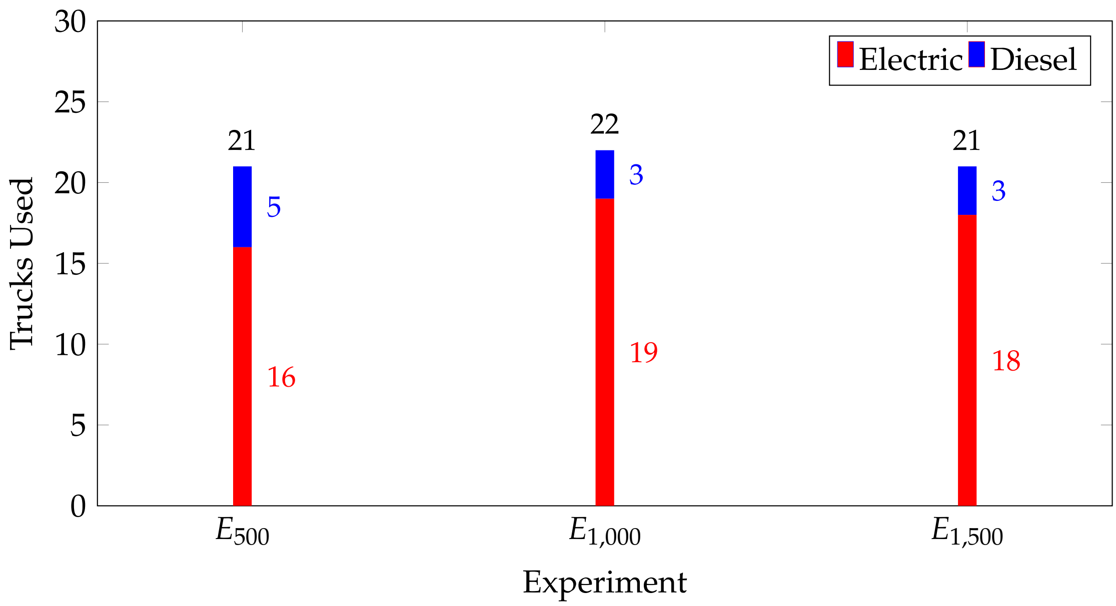


Figure 7.5: Stacked Bar Chart of Trucks used per Experiment with Increased Range

7.2.3 Comparison Between Initial Solution and Final Solution

To measure the performance of the proposed method, we compare the performance metrics of the initial solution after the Constructive Heuristic (CH) and the final solution after Simulated Annealing (SA). We look at the unscheduled orders, truck usage and costs when comparing the initial solution with the final solution.

Unscheduled Orders

One of the most important metrics is the number of unscheduled orders. In Table 7.2 we see that for the experiments with order dataset O_{38}, we have no unscheduled orders in the initial solution and thus no unscheduled orders in the final solution. The experiments with the order dataset O_{80} show unscheduled orders in the initial solution, but after optimisation using SA, we have no unscheduled orders remaining. Thus, the SA freed up enough space for all the orders in all the different fleet configurations. Finally, we have the experiments with order dataset O_{120}, again we start with unscheduled orders in the initial solution, but after further optimisation using SA we still have unscheduled orders. As mentioned before the experiments $D_{41}E_0O_{120}$, $D_{41}E_5O_{120}$, and $D_{41}E_{15}O_{120}$ have too few trucks to meet the demand of all orders. Thus, after optimisation, some orders remain unscheduled. Experiments $D_{41}E_{30}O_{120}$ and $D_{41}E_{41}O_{120}$ should have enough trucks to meet all demand, since some trucks remain unused (Figure 7.1). However, upon closer examination, we see that the remaining unscheduled orders are infeasible due to time window constraints.

The proposed method can insert unscheduled orders. However, this depends on first creating an empty truck where the unscheduled order can be placed.

Truck Usage

The CH does not distinguish between electric and diesel trucks. It is therefore unnecessary to evaluate the distribution of electric and diesel trucks between the initial and final solutions. We can, however, analyse the total number of trucks used between the initial solution and the final solution to determine the performance of the proposed method.

For the experiments with the order datasets O_{38} and O_{80}, we see a steady decrease in total trucks used. However, for the experiments with O_{120}, we see that the total number of trucks used increases in some instances. This is due to the unscheduled orders at the beginning of SA. In Table 7.2 we see that there are a lot of unscheduled orders at the start of SA. The algorithm allocates orders to different trucks and constructs better routes to incorporate more orders, resulting in an increased number of trucks used.

ExperimentID	Used Trucks in Initial Solution	Used Trucks in Final Solution	Difference
$D_{41}E_0O_{38}$	25	22	-3
$D_{41}E_5O_{38}$	26	21	-5
$D_{41}E_{15}O_{38}$	27	21	-6
$D_{41}E_{30}O_{38}$	27	20	-7
$D_{41}E_{41}O_{38}$	27	21	-6
$D_{41}E_0O_{80}$	41	28	-13
$D_{41}E_5O_{80}$	46	27	-19
$D_{41}E_{15}O_{80}$	56	27	-29
$D_{41}E_{30}O_{80}$	71	30	-41
$D_{41}E_{41}O_{80}$	71	28	-43
$D_{41}E_0O_{120}$	36	41	5
$D_{41}E_5O_{120}$	41	46	5
$D_{41}E_{15}O_{120}$	48	56	8
$D_{41}E_{30}O_{120}$	65	70	5
$D_{41}E_{41}O_{120}$	76	70	-6

Table 7.3: Number of trucks used in initial and final solutions for each experiment.

Overall, we see that the proposed method reduces the number of trucks used when all orders are scheduled. If not all orders are scheduled, the proposed method can increase the number of trucks used to meet as much demand as possible.

Costs

Since the main objective of the proposed method is to minimise total costs, we examine the difference in costs between the initial and final solutions. When we compare the cost structures in Table 7.4 with Table 7.5, we see that the total costs almost always reduce between the initial and final solutions. Only experiment $D_{41}E_{15}O_{120}$ and $D_{41}E_{30}O_{120}$ see an increase in total cost. This can be explained by the increased number of scheduled orders in the final solution compared to the initial solution, which, in turn, brings additional costs.

The separate cost components (e.g., toll, labour, fixed, and kilometre) vary between the initial and final solutions. Sometimes increasing and sometimes decreasing. This is due to balancing the total costs. The algorithm only looks at total costs and accepts increases in a component of the objective value as long as the total objective value decreases.

Table 7.4: Performance Metrics Output of Initial Solution per Experiment

Exp. ID	TDD[1]	TT[2]	TIT[3]	AWU[4]	ALU[5]	TTU[6]	E/D[7]	E[8]	D[9]	TTC[10]	TLC[11]	TFC[12]	TKC[13]	TC[14]	UO[15]
Orders$_{38}$															
$D_{41}E_0O_{38}$	13,820.12	20d 22h 32m	5d 7h 47m	0.65	0.72	26	0	NA	63.41	3,614.10	20,101.33	26,000	5,873.55	55,588.98	0
$D_{41}E_5O_{38}$	13,912.46	20d 22h 12m	5d 6h 7m	0.64	0.72	26	19.23	100	51.22	3,383.67	20,088.00	26,000	5,860.53	55,332.20	0
$D_{41}E_{15}O_{38}$	14,616.42	21d 6h 47m	5d 2h 47.5m	0.68	0.75	27	55.56	100	29.27	2,686.47	20,431.33	27,000	6,008.89	56,126.69	0
$D_{41}E_{30}O_{38}$	15,022.84	22d 0h 42m	5d 3h 52m	0.69	0.73	28	100	93.33	0	1,599.09	21,148.00	28,000	6,009.14	56,756.22	0
$D_{41}E_{41}O_{38}$	15,022.84	22d 0h 42m	5d 3h 52m	0.69	0.73	28	100	68.29	0	1,599.09	21,148.00	28,000	6,009.14	56,756.22	0
Orders$_{80}$															
$D_{41}E_0O_{80}$	14,226.18	52d 20h 54m	36d 19h 14m	0.22	0.24	41	0	NA	100	3,703.20	50,756.00	41,000	6,046.13	101,505.33	31
$D_{41}E_5O_{80}$	15,791.20	59d 2h 19m	41d 1h 49m	0.20	0.23	46	10.87	100	100	3,495.79	56,732.67	46,000	6,650.44	112,878.89	26
$D_{41}E_{15}O_{80}$	19,947.85	71d 0h 54m	49d 8h 14m	0.22	0.25	56	26.79	100	100	3,986.75	68,196.00	56,000	8,317.06	136,499.81	16
$D_{41}E_{30}O_{80}$	25,411.43	87d 6h 28m	61d 4h 11m	0.21	0.23	71	42.25	100	100	4,776.09	83,778.67	71,000	10,520.99	170,075.75	1
$D_{41}E_{41}O_{80}$	25,731.23	87d 14h 48m	61d 5h 56m	0.21	0.24	72	56.94	100	75.61	4,528.20	84,112.00	72,000	10,588.51	171,228.71	0
Orders$_{120}$															
$D_{41}E_0O_{120}$	16,648.83	54d 12h 8m	31d 17h 8m	0.34	0.38	37	0	NA	90.24	4,116.67	52,325.33	37,000	7,075.75	100,517.75	71
$D_{41}E_5O_{120}$	19,540.80	60d 13h 28m	34d 0h 33m	0.40	0.45	42	11.90	100	90.24	4,606.23	58,138.67	42,000	8,273.00	113,017.90	62
$D_{41}E_{15}O_{120}$	21,443.08	65d 13h 58m	38d 11h 8m	0.41	0.44	50	22.00	73.33	95.12	4,543.83	62,958.67	50,000	8,984.63	126,487.13	54
$D_{41}E_{30}O_{120}$	25,853.23	82d 14h 53m	50d 23h 18m	0.34	0.38	66	37.88	83.33	100	4,857.98	79,315.33	66,000	10,716.29	160,889.60	36
$D_{41}E_{41}O_{120}$	31,002.13	93d 15h 38m	56d 15h 23m	0.31	0.37	77	46.75	87.80	100	5,613.54	89,905.33	77,000	12,815.56	185,334.43	25

[1] Total Driving Distance [2] Total Time [3] Total Idle Time [4] Average Weight Utilization [5] Average Load meter Utilization [6] Total Trucks Used
[7] Electric/Diesel Ratio [8] Electric Ratio [9] Diesel Ratio [10] Total Toll Cost [11] Total Labor Cost [12] Total Fixed Cost [13] Total Kilometer Cost
[14] Total Cost [15] Unscheduled Orders after SA

Table 7.5: Performance Metrics Output of Experiments

Exp. ID	TDD[1]	TT[2]	TIT[3]	AWU[4]	ALU[5]	TTU[6]	E/D[7]	E[8]	D[9]	TTC[10]	TLC[11]	TFC[12]	TKC[13]	TC[14]	UO[15]
Orders$_{38}$															
$D_{41}E_0O_{38}$	11,825.69	16d 13h 19m	2d 0h 39m	0.27	0.30	22	0.00	NA	52.85	3,094.61	15,892.89	22,000	5,025.92	45,680.09	0
$D_{41}E_5O_{38}$	11,398.96	16d 5h 2m	2d 0h 21m	0.29	0.32	21	23.81	100.00	39.02	2,275.02	15,561.56	21,000	4,762.57	43,599.14	0
$D_{41}E_{15}O_{38}$	11,742.83	16d 5h 55m	1d 2h 11m	0.31	0.34	21	72.62	100.00	13.82	1,601.59	15,596.89	21,000	4,754.34	42,619.49	0
$D_{41}E_{30}O_{38}$	12,054.27	16d 9h 10m	1d 11h 49m	0.30	0.33	21	76.19	53.33	12.20	1,634.98	15,727.11	21,000	4,878.78	43,240.87	0
$D_{41}E_{41}O_{38}$	11,904.43	16d 7h 19m	1d 7h 19m	0.29	0.33	20	85.08	42.27	7.32	1,458.79	15,652.67	20,000	4,794.04	42,238.83	0
Orders$_{80}$															
$D_{41}E_0O_{80}$	15,928.01	38d 21h 27m	12d 8h 39m	0.53	0.59	28.50	0.00	NA	69.51	4,112.70	36,823.33	28,500	6,769.40	76,205.44	0
$D_{41}E_5O_{80}$	15,948.69	38d 38h 57m	9d 0h 46m	0.54	0.60	28.50	12.32	70.00	60.98	3,853.06	37,103.33	28,500	6,727.67	76,184.07	0
$D_{41}E_{15}O_{80}$	15,287.75	38d 3h 36m	12d 13h 46m	0.53	0.59	28.50	36.82	70.00	43.90	2,898.56	36,537.67	28,500	6,349.13	74,285.35	0
$D_{41}E_{30}O_{80}$	16,380.53	39d 17h 16m	19d 2h 27m	0.51	0.56	31.00	64.52	66.67	26.83	2,416.70	38,130.67	31,000	6,669.74	78,217.11	0
$D_{41}E_{41}O_{80}$	16,053.43	38d 11h 47m	17d 19h 27m	0.54	0.59	29.00	86.21	60.98	9.76	1,986.25	36,951.33	29,000	6,467.09	74,404.68	0
Orders$_{120}$															
$D_{41}E_0O_{120}$	20,688.26	40d 54h 26m	6d 23h 12m	0.67	0.75	41.00	0.00	NA	100.00	4,949.37	39,271.00	41,000	8,792.51	94,012.88	46
$D_{41}E_5O_{120}$	24,565.35	48d 1h 45m	10d 10h 2m	0.63	0.71	46.00	10.87	100.00	100.00	5,397.91	46,108.00	46,000	10,356.91	107,862.82	39
$D_{41}E_{15}O_{120}$	27,606.87	59d 33h 55m	15d 10h 35m	0.54	0.62	56.00	26.79	100.00	100.00	5,494.61	57,182.67	56,000	11,541.29	130,218.57	30
$D_{41}E_{30}O_{120}$	35,922.47	78d 11h 13m	15d 23h 44m	0.49	0.58	70.00	41.43	96.67	100.00	6,459.03	75,059.67	70,000	14,862.94	166,381.64	10
$D_{41}E_{41}O_{120}$	35,850.47	78d 31h 13m	21d 17h 58m	0.47	0.54	70.50	50.35	86.59	85.37	6,007.75	75,379.67	70,500	14,750.01	166,637.43	10

[1] Total Driving Distance [2] Total Time [3] Total Idle Time [4] Average Weight Utilization [5] Average Load meter Utilization [6] Total Trucks Used
[7] Electric/Diesel Ratio [8] Electric Ratio [9] Diesel Ratio [10] Total Toll Cost [11] Total Labor Cost [12] Total Fixed Cost [13] Total Kilometer Cost
[14] Total Cost [15] Unscheduled Orders after SA

Table 7.6: Performance Metrics Output of Experiments with Increased Range

Exp. ID	TDD[1]	TT[2]	TIT[3]	AWU[4]	ALU[5]	TTU[6]	E/D[7]	E[8]	D[9]	TTC[10]	TLC[11]	TFC[12]	TKC[13]	TC[14]	UO[15]
E_{500}	11,904.43	16d 7h 19m	1d 7h 19m	0.29	0.33	20	85.08	42.27	7.32	1,458.79	15,652.67	20,000	4,794.04	42,238.83	0
$E_{1,000}$	12,498.84	17d 0h 37m	1d 3h 57m	0.28	0.30	22	83.53	45.53	8.95	1,609.35	16,344.89	22,000	5,049.63	45,337.20	0
$E_{1,500}$	11,923.64	16d 11h 42m	1d 14h 44m	0.30	0.33	21	85.71	43.90	7.32	1,467.42	15,828.22	21,000	4,801.91	43,097.55	0

[1] Total Driving Distance [2] Total Time [3] Total Idle Time [4] Average Weight Utilization [5] Average Load meter Utilization [6] Total Trucks Used
[7] Electric/Diesel Ratio [8] Electric Ratio [9] Diesel Ratio [10] Total Toll Cost [11] Total Labor Cost [12] Total Fixed Cost [13] Total Kilometer Cost
[14] Total Cost [15] Unscheduled Orders after SA

7.3 Discussion of Findings

In the "Discussion of Findings" section, we elaborate on the strengths, limitations, robustness and implications of the proposed solution.

7.3.1 Strengths of the Proposed Solution

The proposed solution method provides Farm Trans with a complete solution to its specific VRP problem instance. Compared to the old method, the proposed solution incorporates breaks, recharging, and refuelling, thus creating a more complete solution. It also allows for scheduling breaks and recharging simultaneously, further improving the solution's quality. The proposed method also further enhances the routing decisions and grouping of orders, resulting in fewer trucks delivering the same number of orders and reducing the total driving distance, ultimately saving costs. Furthermore, it provides Farm Trans with a tool to schedule routes and provide insights during the transition from a diesel fleet to an electric or hybrid fleet, where managers can adapt input parameters and test possible fleet configurations to determine if and when an electric truck could be beneficial over a diesel truck.

7.3.2 Limitations and Areas for Improvement

The proposed method poses some limitations. Currently, the charging policy for an electric truck is to charge during all breaks, and when an additional charge is needed, we always fully charge. Many charging policies are available in the literature. Future research and experimentation could improve the current solution by incorporating alternative charging policies.

Several assumptions were made about the regulations concerning breaks. Dividing breaks into multiple, more minor breaks is impossible in the proposed method. However, this is allowed by law, as explained in Section 2.3.3. Additionally, maximum daily working times can vary during the week. The proposed method does not incorporate variable maximum daily working times. Incorporating these variable parameters could improve the quality of the solution.

Additionally, it is important to note that the outcomes of the experiments are based on costs. In this instance, electric trucks are favourable because they have lower overall costs. For some routes, diesel trucks are used since electric trucks are unable to adhere to the time windows due to longer charging times.

Finally, we use an API to determine travel distances and an average speed of 70 km/h to determine travel times. This is an approximation and can be further improved using other methods.

7.3.3 Robustness and Sensitivity Analysis

The proposed method provides Farm Trans with a robust solution. All input parameters can be altered to account for future changes. We tested against various order datasets and different fleet configurations to see if the method could provide a solution for different parameters. Furthermore, the experimentation shows that altering some input parameters of trucks still yields a feasible solution.

7.3.4 Practical Implications and Real-World Applicability

The main practical limitation of this research is that the current fuel and break locations are fictional and do not exist. Therefore, current solutions are not immediately operational. Further research is necessary to determine where fuel locations are and where a break can occur. Also, the dataset used for charging locations is not complete. CAPE's partner is still identifying and expanding their dataset on charging stations.

Additionally, the proposed method can reject orders if it is impossible to reach the delivery location due to time window constraints or the lack of sufficient breaks, fuel or charging locations.

Furthermore, the current solution schedules breaks according to international regulations and laws, but they do not account for traffic jams or other disturbances that result in delays.

7.4 Summary

Chapter 7 presents and analyzes the experimental results. First, the proposed solution is benchmarked against Farm Trans's current planning method, demonstrating improvements in driving distance, truck utilisation, and including breaks and fuel stops. The experimental analysis then explores how different fleet configurations and order sizes impact solution quality. Further comparisons are made between initial and final solutions to demonstrate the improvement achieved through SA. The discussion section highlights strengths (e.g., robustness, efficiency, scalability), acknowledges limitations (e.g., simplified charging policies, static traffic assumptions), and examines practical implications, particularly regarding the transition to electric fleets. The chapter concludes by emphasizing the method's adaptability and relevance to real-world logistics.

Chapter 8

Conclusions and Recommendations

This concluding chapter encapsulates the significance of this study, highlights the scope and limitations, and provides key insights, findings, and recommendations stemming from our comprehensive exploration of the VRP variant faced by Farm Trans.

8.1 Significance of the Study

Successfully resolving Farm Trans's problems helps the decision-making process between electric and diesel trucks. Furthermore, it can significantly impact the company's operations by reducing transportation costs, improving delivery efficiency, and improving its competitive position. Additionally, this research contributes to the broader combinatorial optimisation and logistics field by addressing a real-world problem with practical implications.

8.2 Scope and Limitations

It is essential to acknowledge the scope and limitations of this thesis. While we aim to provide a comprehensive solution to Farm Trans's problem instance, certain simplifications or assumptions may be necessary due to the complexity of the problem and data availability.

Farm Trans has many different transportation operations. This study focuses on the conditioned (Fresh & Frozen) transport. Furthermore, his study considers a limited time horizon when creating the solution. Farm Trans explained that orders continue to come in during the day. So, a planner determines a cut-off point and plans all known orders from this moment, and all others remain for the next cycle.

8.3 Summary of Findings

We have examined Farm Trans's VRP variant and obtained results from our extensive research and experimentation. The main findings are as follows:

- Our proposed solution demonstrates remarkable efficacy in optimising vehicle routing operations at Farm Trans. It outperforms Farm Trans's approach, showcasing significant improvements in solution quality.

- Experimental analyses provide insights into the use of electric trucks and possible future scenarios. Farm Trans can use the proposed solution to gain insights, model various future fleet configurations, and quickly adapt to technological advancements.
- Comparative assessments against the previous approach underscore our solution's advantages. It reduces costs, provides a more complete solution by incorporating breaks, refuelling, and recharging, reduces total travel distance, and enhances overall operational efficiency.
- The ability to schedule recharging and breaks simultaneously mitigates the impact of longer recharging times compared to refuelling.

8.4 Conclusions

This section draws overarching conclusions from our study of Farm Trans's VRP variant. Our work has shed light on several critical aspects:

- The proposed solution effectively addresses Farm Trans's VRP variant. It optimises vehicle routing and reduces operational costs, demonstrating its potential for significant impact.
- The adaptability of our solution to diverse operational scenarios positions it as a versatile tool for Farm Trans. Whether dealing with fluctuating demand, complex time windows, or evolving logistical challenges, the solution consistently results in a feasible solution.
- The comparative analysis reveals that our solution surpasses previous approaches. Its ability to provide cost-efficient routes while meeting customer expectations positions it as a valuable asset in Farm Trans's logistics operations.
- Experimental analysis also shows that Farm Trans can use the proposed method to support the decisions on fleet configuration by testing various scenarios.

8.5 Recommendations

This section provides Farm Trans with recommendations and actionable suggestions based on the research findings and insights. We propose the following recommendations for Farm Trans:

- **Implementation**: We recommend fully implementing our proposed solution into Farm Trans's logistics operations. This move will enable the company to reap the benefits of enhanced routing efficiency and cost savings. However, Farm Trans must acquire more insight into costs and input parameters before fully implementing this solution in real-world applications.
- **Operational Enhancements**: We suggest further research into the use of electric trucks. Experimental analysis has shown that electric trucks have cost advantages. However, further parameter tuning and research are necessary before purchasing additional electric trucks.

- **Integration with IT Infrastructure**: Integrating the solution with Farm Trans's IT infrastructure is crucial. This step ensures real-time monitoring, data exchange, and seamless adaptation to changing conditions.
- **Continuous Monitoring and Evaluation**: We recommend establishing a continuous monitoring and evaluation process. Regular assessments of the solution's performance will enable proactive adjustments and refinements. This also includes updating input parameters when they change to maintain an up-to-date solution method.

8.6 Future Research Directions

We have already named some areas for future research. Here, we identify promising avenues for further research in Farm Trans's VRP variant. Our study has highlighted areas that merit continued investigation:

- **Dynamic Routing Optimisation**: Exploring dynamic routing optimisation techniques to address real-time changes in demand and traffic conditions.
- **Charging Policies**: Currently, one charging strategy is used. Future research could explore the advantages of different strategies and possibly further improve the proposed solution.
- **Fuel- and break locations**: Further research in the specific locations of fuel and break locations is needed to create a real-world feasible solution.
- **Break regulations**: The proposed solution has some assumptions on break regulations. Further research could incorporate these assumptions to improve the proposed solution further.
- **Parameter Tuning**: Farm Trans needs to analyse specific costs for electric trucks and keep updating input parameters for their fleet to get realistic solutions.

These research directions will contribute to ongoing advancements in solving complex VRP variants and improving logistics management.

Appendix A

Definition of VRP Variants

Table A.1: Definitions of VRP Variants.

Acronym	Definition
1. VRP	Vehicle Routing Problem
2. CVRP	Capacitated Vehicle Routing Problem
3. VRPPD	Vehicle Routing Problem with Pickup and Delivery
4. VRPSPD	Vehicle Routing Problem with Simultaneous Pickup and Delivery
5. VRPB	Vehicle Routing Problem with Backhaul
6. VRPTW	Vehicle Routing Problem with Time Windows
7. VRPTW-P	Vehicle Routing Problem with Time Windows Probabilistic
8. D-VRPTW	Dynamic Vehicle Routing Problem with Time Windows
9. MDVRP	Multiple Depots Vehicle Routing Problem
10. TDVRP	Time Drive Vehicle Routing Problem
11. PTDVRP	Probabilistic Time Drive Vehicle Routing Problem
12. SVRP	Stochastic Vehicle Routing Problem
13. PVRP	Periodic Vehicle Routing Problem
14. LDVRP	Load Dependent Vehicle Routing Problem
15. DVRP	Distance - Constrained Vehicle Routing Problem
16. DCVRP	Distance and Capacity - Constrained Vehicle Routing Problem
17. EVRP	Electric Vehicle Routing Problem
18. MVRP	Multiple Vehicles Routing Problem
19. HF-VRP	Heterogeneous Fleet Vehicle Routing Problem
20. HF-VRPTW	Heterogeneous Fleet Vehicle Routing Problem with Time Windows

Appendix B

KPI's

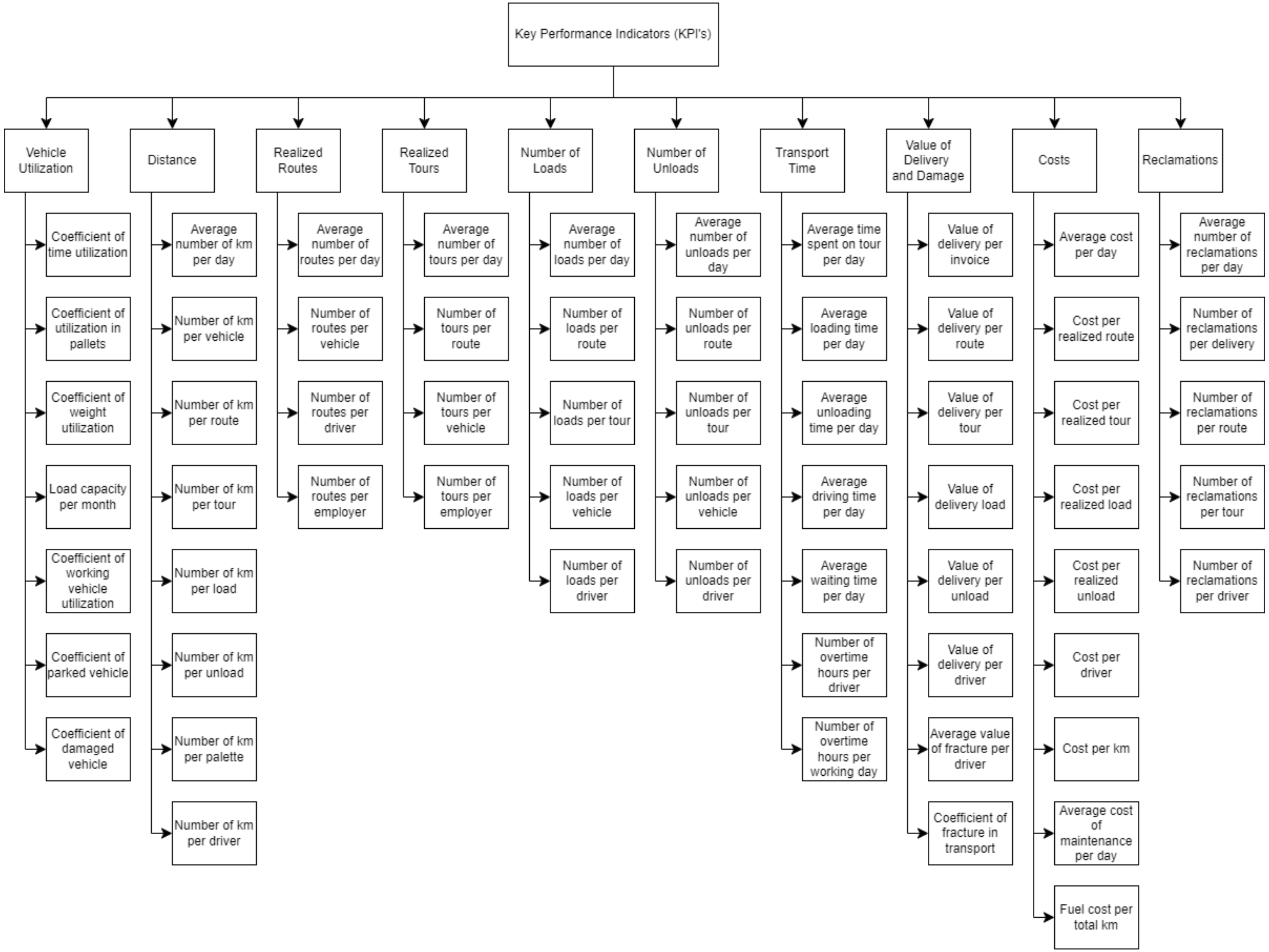


Figure B.1: Overview of KPIs in Categories

Appendix C

Python Packages and Descriptions

Table C.1: Description of Used Python Packages

Package	Description
`dataclasses`	Provides a decorator to create lightweight, immutable classes for data storage.
`datetime`	Handles date and time operations, including formatting and time calculations.
`folium`	Creates interactive maps using Leaflet.js, useful for geographic visualizations.
`geopandas` (`gpd`)	Extends pandas to handle geospatial data efficiently.
`geopy.distance` (`geodesic`)	Computes distances between geospatial coordinates using various methods.
`geopy.geocoders` (`Nominatim`)	Converts addresses into geographic coordinates and vice versa.
`global_land_mask`	Determines whether a given latitude/longitude point is on land or water.
`googlemaps`	Interfaces with the Google Maps API for geolocation and routing services.
`math`	Provides mathematical functions, including trigonometry, logarithms, and rounding.
`matplotlib.dates`	Supports formatting and handling dates in Matplotlib visualizations.
`matplotlib.pyplot`	Plots graphs and visualizations in Python using a MATLAB-like interface.
`numpy`	Supports numerical computations, including arrays, matrices, and mathematical operations.

Continued on next page

Package	Description
`openpyxl`	Reads, writes, and modifies Excel files in the `.xlsx` format.
`optuna`	Automates hyperparameter optimization using intelligent search strategies.
`pandas`	Manages and manipulates structured data efficiently using DataFrames and Series.
`pickle`	Serializes and deserializes Python objects for storage and transfer.
`random`	Generates pseudo-random numbers and selections for simulations and randomness.
`shapely.geometry`	Provides geometric objects and operations for spatial analysis.
`sys`	Interacts with the system, including command-line arguments and system paths.
`webbrowser`	Opens web pages in a browser from within a Python script.

Appendix D

Order Data

OrderID	CustomerID	Pallets	PalletType	Weight	Loadmeters	Temperature
1205	FT	13	EU	22275	13.2	-18
1206	CAPE	26	BL	19500	12.4	-2

Table D.1: Order Data Part 1

Pickup Address	Pickup Coordinates	Delivery Address	Delivery Coordinates	Pickup Start	Pickup End	Delivery Start	Delivery End	Pickup Handling Time	Delivery Handling Time
Address 1	(lat, long)	Address 2	(lat, long)	1-1-2025 9:00	1-1-2025 10:00	1-1-2025 13:00	1-1-2025 15:00	1:00	1:00
Address 2	(lat1, long1)	Address 3	(lat2, long2)	1-1-2025 7:00	1-1-2025 8:00	1-1-2025 16:00	1-1-2025 17:00	2:00	1:00

Table D.2: Order Data Part 2

Appendix E

Paramter Tuning 1

Trial Number	Initial Temperature	Cooling Rate	End Temperature	Markov Chain Length	Objective Value (€)	Running Time (min)
1	500	0.075	0.95	100	45,735.32	11.21
2	300	0.05	0.98	100	46,964.62	28.45
3	600	0.075	0.95	300	46,371.11	35.06
4	500	0.05	0.98	300	44,658.85	60.05
5	500	0.1	0.95	200	45,253.37	21.63
6	600	0.1	0.95	300	46,369.00	33.06
7	500	0.05	0.98	300	43,488.23	60.17
8	400	0.025	0.98	200	46,172.49	60.06
9	400	0.05	0.95	100	46,977.43	11.16
10	300	0.025	0.95	100	46,565.87	11.12
11	500	0.05	0.97	300	44,621.41	58.87
12	500	0.05	0.97	300	44,949.38	58.54
13	500	0.05	0.97	300	44,377.02	57.61
14	500	0.05	0.96	300	44,369.11	42.07
15	500	0.05	0.96	300	45,285.34	42.97
16	500	0.05	0.96	300	43,909.44	45.63
17	400	0.075	0.96	200	45,444.41	26.33
18	600	0.025	0.98	300	44,522.53	60.13
19	300	0.1	0.96	300	47,114.24	30.83
20	500	0.05	0.98	200	45,374.69	56.12

Table E.1: Parameter Tuning Trials

Appendix F

Parameter Tuning 2

Trial Number	Initial Temperature	Cooling Rate	End Temperature	Markov Chain Length	Objective Value (€)	Running Time (min)
21	500	0.98	0.05	300	44543.89	60.08
22	500	0.98	0.1	300	44492.56	60.06
23	500	0.98	0.5	300	44931.01	60.01
24	500	0.98	5	300	44905.21	41.11
25	500	0.98	50	300	46217.90	21.00

Table F.1: Parameter Tuning Trials for End Temperature

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