



Università degli studi di Genova

Department of Informatics, Bioengineering,
Robotics and Systems Engineering

**Models and methods for the optimal distribution in
logistics supply chains: application to the Decathlon
company**

by

Mohammad Javad Jafari



Finanziato
dall'Unione europea
NextGenerationEU



Ministero
dell'Università
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Piano Nazionale di Ripresa e Resilienza la Missione 4, componente 2 (*"Dalla
Ricerca all'Impresa"*)

Università degli studi di Genova

Department of Informatics, Bioengineering, Robotics and

Systems Engineering

Ph.D. Thesis in Computer Science and Systems

Engineering

Systems Engineering Curriculum

XXXVIII cycle

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April 2026

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PhD Thesis in Computer Science and Systems Engineering
Systems Engineering Curriculum (XXXVIII cycle)
(S.S.D. ING INF/04)

Submitted by Mohammad Javad Jafari DIBRIS, Univ. di Genova

Date of submission: March 24rd, 2026.

Title: Models and methods for the optimal route in logistics supply chains: application to the Decathlon company

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Acknowledgements

I want to thank all the people who have been close to me over the years. Starting of course with my family, thank you for being there and supporting me in all my decisions and difficulties.

I also thank my speakers for all the time they have given me and for the myriad of things they have allowed me to learn during this journey.

Sincere thanks also to my colleagues for being friends first, and then for helping me many moments.

Abstract

In the past decades, the vehicle routing problem has been a topic of interest to scientists, industrialists, industry owners, governments, and environmentalists, as new measures, policies, and technologies are being developed to reduce greenhouse gas emissions and, more broadly, air pollutants. This PhD, which is a joint project of the University of Genova and Decathlon Italy, aims to optimize the distribution between the final warehouses, called distribution centers, and the stores in the last two levels of the supply chain. To achieve this optimization, several objectives are considered, such as decreasing total distribution costs, reducing air pollution, and at the same time satisfying all demand without delays while considering all constraints of the supply chain, such as store delivery time windows and available trucks with different capacities.

To address this type of project, we used mathematical optimization, specifically referring to the capacitated vehicle routing problem. A set of mathematical models has been developed, each with distinct details and constraints to account for various problem scenarios. The first mixed-integer model aims to minimize total cost and emissions as a single objective, in which the costs are derived from a multiple regression model. The second version aims to minimize the total cost and emissions trade cost, in which a mixed fleet (internal combustion engine, electric and hydrogen vehicles) has been considered. The mixed fleet is applied in the mathematical model based on its performance in terms of energy consumption and the resulting costs and emissions. In this second version, emissions are expressed as emission trade costs using the carbon cap-and-trade mechanism. The third version of the model consists of a bi-objective optimization, in which total costs and total emissions are considered as distinct objectives.

In the third mathematical model, we consider a longer decision-making horizon, requiring future store demand. To estimate long-term demand, time-series and machine-learning forecasting methods are implemented and analysed. All models are piloted and tested on real cases from Decathlon Italy and France, and their results are compared with current procedures. Finally, analyses and managerial insights are provided to facilitate informed decision-making.

Table of Contents

Chapter 1: Introduction and motivation	8
1.1. Aim of the thesis and Industrial PhD	8
1.1.1. Decathlon company	8
1.2. Main Contributions	11
1.3. Thesis Organization	12
1.4. Publications and editorial activity	13
1.4.1. Papers:	13
1.4.2. Seminar:	14
1.4.3. Master's thesis co-advisor:	14
1.4.4. Organizational activities	14
1.4.5. Poster presentation	14
1.5. Visiting research period abroad	15
Chapter 2: Literature Review	16
2.1. Capacitated Vehicle Routing Problem (CVRP)	16
2.1.1. CVRP with time window (CVRPTW)	22
2.1.2. Green CVRP and Carbon emission Trade	23
2.1.3. CVRP with split delivery and scheduling arrival	26
2.1.4. Multi Objective Vehicle Routing Problem	28
2.2. Electric and Hydrogen Vehicle Routing problem	29
2.2.1. Electric vehicle routing problem	30
2.2.2. Hydrogen vehicle mechanism and routing problem	39
Chapter 3: Optimization Problems and Mathematical Modelling	45
3.1. Capacitated vehicle routing problem with split delivery and cost estimation	46
3.1.1. Problem definition	46
3.1.2. Cost estimation regression	47
3.1.3. Social Emission Effect Cost	48
3.1.4. Capacitated vehicle routing problem: mathematical model	49
3.2. Capacitated vehicle routing problem with Hybrid fleet	51
3.2.1. Energy/Fuel consumption of Hybrid fleet	53
3.2.2. Internal Combustion Engine (ICE)	54
3.2.3. Problem Definition	58
3.2.4. The overall cost function	61
3.2.5. Hybrid fleet capacitated vehicle routing problem mathematical model	64
3.3. Time dependent mathematical model and demand forecasting	66

3.3.1. Demand forecasting.....	66
3.4. Bi-objective and multi-period mathematical model	76
3.4.1. Torabi-Hassini method	77
Chapter 4: Cases and Results.....	80
4.1. Application to Decathlon case studies	80
4.1.1. Regression results for cost estimation.....	80
4.1.2. Routing result in Italy.....	81
4.1.3. Cost and CO2 Emissions Comparison	83
4.2. Result the distribution in a web app demo.....	85
4.3. Hybrid fleet routing results.....	87
4.3.1. Fuel, Energy and Hydrogen Cost Analysis.....	90
4.3.2. Emissions of electric and hydrogen vehicles	93
4.4. Forecasting demand results.....	96
4.4.1. Rolling forecast for Pallets and Items	96
4.4.2. Forecasting analysis	104
4.5. Bi objective multi-period problem results	106
Chapter 5: Conclusion and Future research	107
5.1. Conclusion.....	107

Acronyms

Acronym	Definition
VRP	Vehicle Routing Problem
CVRP	Capacitated Vehicle Routing Problem
CVRPTW	Capacitated Vehicle Routing Problem with Time Window
HF-CVRPTW	Hybrid fleet Capacitated Vehicle Routing Problem with Time Window
ICEs	Internal Combustion Engine Vehicles
DVs	Diesel Vehicles
EVs	Electric Vehicles
FCEVs	fuel cell electric vehicles
HVs	Hydrogen Vehicles
SSE	Sum Square Error
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
MLR	Multiple Linear Regression
GHGs	Greenhouse Gases

Chapter 1: Introduction and motivation

1.1. Aim of the thesis and Industrial PhD

Logistics and supply chain management have become crucial fields of investigation and development over the past decade, not only from an industrial perspective but also from a scientific point of view. Considering the necessity of studying supply chains and logistics and their variations in the real world, Decathlon Italy and the University of Genova established an agreement through a PNRR project to define a company-specific problem and propose a PhD position to research the topic over a three-year period, from November 1, 2022, to the end of October 2025. The overarching goal of this doctoral thesis is to compile a comprehensive account of all activities conducted during this period, encompassing studies, research endeavors, field missions, contributions, and other notable achievements.

An Industrial PhD (also known as an Industry PhD or Doctorate in collaboration with industry) is a doctoral program conducted in partnership between a university and a company. The PhD candidate works on research that is academically rigorous and industrially relevant, often spending time in both academic and corporate environments. Research is grounded in practical problems, increasing the relevance and potential impact of the work. The PhD candidates gain valuable work experience, expand professional network, and improve employability outside academia. The investigators have access to company-specific data, tools, or infrastructure that academic researchers typically can't use.

In this kind of PhD research topics could be defined by the company or an agreement between the university and company which can restrict exploration or publishing of certain results. In the industrial PhD balancing academic requirements and industrial deliverables can be challenging and time-consuming. A key feature of the Industrial PhD program is that the doctoral student is required to spend six months working on the company side, focusing on research and implementation activities. In addition, the student must complete a six-month visiting period abroad, outside Italy, at a university, research institution, or company, dedicated to research purposes.

1.1.1. Decathlon company

Decathlon, originally founded in 1976 by Michel Leclercq in France, has grown into one of the world's largest sporting goods retailers. Decathlon started with a vision to make sports accessible to everyone. The first store opened in Lille, France, offering a wide range of sports equipment and apparel under its own brands. Over the years, Decathlon expanded internationally, establishing a presence across Europe, Asia, Africa, and the Americas. It operates in over 70 countries worldwide. Known for its extensive product range across various sports categories, Decathlon designs, manufactures, and sells its own

brands, catering to both amateur and professional athletes. Decathlon operates over 1,600 stores globally, making it one of the largest sporting goods retailers in terms of physical presence. The company manages a network of warehouses and distribution centers worldwide to support its retail operations and online sales. Decathlon employs tens of thousands of people globally, with a significant workforce dedicated to retail, design, manufacturing, and logistics.

Decathlon entered the Italian market and has expanded significantly. They currently operate around 146 stores in Italy (Figure 2), supported by a workforce of over 7,000 to 8,000 employees that are working at the stores, warehouses, and some production centers. There are a lot of other workers that indirectly work with this company, such as some transportation companies, external warehouses for cross-docking, and some other manufacturers that distribute or sell their products through Decathlon. The company manages 4 logistics centers across the country (Figure 1) to ensure efficient distribution, along with 2 production sites contributing to local manufacturing. With a strong nationwide presence in both major cities and regional areas, Decathlon continues to grow its retail and online footprint in Italy, offering accessible and affordable sports equipment to millions of customers. The current thesis is part of an industrial PhD program established through a collaboration between Decathlon Italy and the University of Genoa.



Figure 1: Decathlon warehouse locations in Italy.



Figure 2: Distribution of stores across the country.

1.2. Main Contributions

The main contributions of the thesis can be listed as follows:

- Forecasting daily demand and orders of Decathlon for store deliveries using machine learning and time series models.
- Formulating a mathematical model for the Green Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) based on real-world case assumptions, considering scheduled arrival times and split deliveries among trucks.
- Developing a Mixed-Integer Linear Programming (MILP) model for the Hybrid Fleet Vehicle Routing Problem with Time Windows (HF-VRPTW).
- Integrating carbon cap-and-trade emissions into the model and comparing them with other transportation cost components.

- Proposing a pricing methodology for internal combustion engine vehicles (ICEs), electric vehicles (EVs), and hydrogen vehicles (HVs), taking into account energy and fuel consumption factors.
- Developing a bi-objective MILP vehicle routing problem model that considers both total cost and emissions as objectives.
- Implementing and validating the mathematical model through a real-world case study, analyzing the daily distribution system of Decathlon Italy and Decathlon France.
- Proposing a demo for developing software to support distribution planning at Decathlon, based on the optimization models provided in this thesis.

1.3. Thesis Organization

This thesis is structured into six chapters, starting with the introduction and state of the art, followed by the presentation of optimization problems and various approaches to address them, including an extensive analysis of different real cases, and concluding with a summary and several managerial insights. More specifically, the contents of the chapter are listed below.

Chapter 1: Introduction and motivation

This chapter outlines the thesis' aim and motivation and provides information about the industrial PhD and the partner company. It also listed the publications, missions, and all other activities that have been done in the PhD period.

Chapter 2: Literature Review

Chapter 2 provides an extensive literature review of studies from the past decade, with a focus on the Capacitated Vehicle Routing Problem (CVRP) and its variants. It also includes studies that incorporate green factors, time windows, CO₂ emissions, and energy consumption of mixed fleets with respect to propulsion, as well as their relationship to the CVRPTW.

Chapter 3: Optimization Problems and Mathematical Modelling

In Chapter 3, all the problems are defined, and the approaches to address them are presented. These problems include: forecasting demand using machine learning and time series methods; solving a CVRPTW MILP model by estimating costs through multiple regression; addressing the CVRPTW with a hybrid fleet considering carbon trading, energy consumption, and emissions based on energy

calculations for each fleet type; developing a pricing method for distributed products; and finally, by separating cost and emissions, a multi-objective CVRPTW model is introduced.

Chapter 4: Cases and Results

This chapter investigates a set of real cases from Decathlon's distribution system in two countries, Italy and France, taking into account the specific features and assumptions of each case and each country.

Chapter 5: Analysis

Chapter 5 explores a variety of analyses on the mathematical model and the real cases, considering both economic and environmental aspects

Chapter 6: Conclusion and Future research

This chapter summarizes the overall contributions of the thesis and concludes the findings, along with a list of managerial insights. In the final part, a couple of future opportunities for further research are presented.

1.4. Publications and editorial activity

In this section, a comprehensive list of research activities, including conference and journal publications, conference presentations, seminars, and organizational activities during the PhD program is provided.

1.4.1. Papers:

- Jafari, M. J., Ferro, G., Magni, A., Mereu, A., Minciardi, R., Paolucci, M., & Robba, M. (2024). Optimizing a Capacitated Vehicle Routing Problem with Scheduled Arrival, Split Deliveries within Time Windows and Emission Consideration. *IFAC-PapersOnLine*, 58(2), 180-185.
- Jafari, M. J., Parodi, L., Ferro, G., Minciardi, R., Paolucci, M., & Robba, M. (2025). Mixed-Fleet Goods-Distribution Route Optimization Minimizing Transportation Cost, Emissions, and Energy Consumption. *Energies*, 18(19), 5147.
- Farina, L., Ferro, G., Jafari, M. J., Parodi, L., & Robba, M. (2025). Optimal Siting and Sizing of Electric Vehicles Charging Stations in a Logistic Network. *IFAC Workshop on Smart Energy Systems for Efficient and Sustainable Smart Grids and Smart Cities*.

1.4.2. Seminar:

- Mathematical modelling of Decathlon distribution system, for the course “Methods and models for logistics” November 2023 Semester, Genova, Italy
- Mathematical modelling of Decathlon distribution system, for the course “Methods and models for logistics” October 2024 Semester, Genova, Italy

1.4.3. Master’s thesis co-advisor:

- “Heavy-duty electric vehicles: feasibility analysis and optimization model for the electrification of a company fleet” by Francesco Suprani, The university of Genova, 2024
- “Safety engineering for transport, logistics, and production” by Ginevra Roggero, The university of Genova, 2025

1.4.4. Organizational activities

- National Organizing Committee member of the Integrated Assessment Modeling for Environmental Systems (IAMES) conference, Savona, Italy, May 29–31, 2024.
- Co-organized the Open Invited Track " Advanced Methods for Sustainable Energy and Mobility Integration" at the IFAC Workshop on Smart Energy Systems for Efficient and Sustainable Smart Grids and Smart Cities (SENSYS 2025), Bari, May 18–20, 2025.
- Co-chaired the Special Session " Sustainable mobility and air pollution" at the 3rd IFAC Workshop on Integrated Assessment Modeling for Environmental Systems (IAMES), Savona, Italy, May 29–31, 2024.

1.4.5. Poster presentation

- Jafari, M. J., Ferro, G., Magni, A., Mereu, A., Minciardi, R., Paolucci, M., & Robba, M. (2024). Optimizing a Capacitated Vehicle Routing Problem with Scheduled Arrival, Split Deliveries within Time Windows and Emission Consideration. 2024 IEEE ITSS R8 Chapters Meeting: Poster Session Competition.
- Jafari, M. J., Parejo, A., Leon, C., Ferro, G. & Robba, M. (2024)., Store-Level Demand Forecasting Using Time Series and Machine Learning Methods, XII R&D&I Conference & 4th International Workshop on STEM and IX Conference of the ISI Doctoral Program

1.5. Visiting research period abroad

Based on the contract of this PNRR PhD position, certain requirements had to be fulfilled over the three-year period. One of them is an in-person stay at the site of the partner company for at least six months. Another requirement is a six-month research stay outside of Italy, either at a university, scientific organization, or company. These periods could be completed either continuously or in split intervals. According to these PNRR PhD regulations, the list of visits to the company site and abroad is as follows:

- 3-month internship entitled “Optimization of Routes and Scheduling Arrival Times for the Last Mile Delivery Operations of Our Company – Case Study” at the headquarters of Decathlon, Lille, France, May – August 2024
- 3-month visiting stay with the research title “Forecasting the Demand Using Time Series and Machine Learning Methods” at the University of Seville, Seville, Spain, June – September 2025.
- 6-month in-person participation on-site at the Decathlon warehouse in Basiano, with the title “Implementation of the Vehicle Routing Problem Mathematical Model for the Real Case of Basiano Distribution Centre,” January – May 2025, Basiano, Italy.

Chapter 2: Literature Review

Logistics involves organizing, moving, and storing materials and people to ensure that the right products reach the right place at the right time. Originally in a military term, logistics has expanded to include business and service operations, covering everything from manufacturing components to hospital supplies. It integrates functions like procurement, warehousing, and distribution to deliver value efficiently. With rising customer expectations, companies face pressure to deliver faster, cheaper, and more accurately, making logistics increasingly complex. As a result, logistics management now plays a crucial role in planning and supporting decisions at every level of operations (Ghiani et al., 2013).

Vehicle Routing problem (VRP)), whose purpose is to find the most efficient set of routes for a fleet of vehicles to deliver goods or services to a group of customers, is considered one of the most significant and extensively researched problems in the field of combinatorial optimization and is a key part of logistics and supply chain (Toth et al., 2014). In the following a vast literature review about VRP and its variations is presented.

To better visualize the structure of the systematic literature review of this thesis, Figure 3 is provided, in which the breakdown of the literature and its relation using a chart is shown.

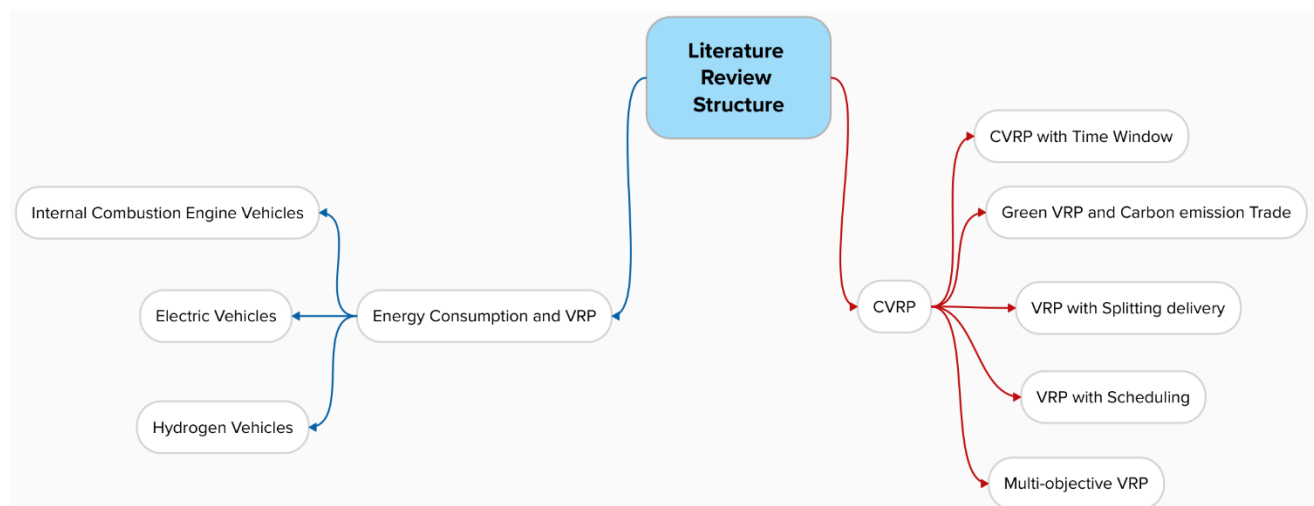


Figure 3: Literature structure breakdown

2.1. Capacitated Vehicle Routing Problem (CVRP)

Over 60 years have passed since Dantzig and Ramser first introduced the Vehicle Routing Problem (VRP) in 1959 (Dantzig & Ramser, 1959), using a real-world case involving gasoline deliveries to service stations. They also developed the first mathematical model and algorithm for solving it. In 1964, Clarke and Wright introduced a more efficient greedy heuristic, marking another major advancement.

Since then, hundreds of models and algorithms (both exact and approximate) have been developed to tackle various versions of the VRP (Clarke & Wright, 1964). Today, many software packages are available for solving practical VRP applications. The problem continues to draw interest due to its real-world importance and computational complexity, as exact methods still struggle with instances involving more than 50 customers (Toth et al., 2014).

The Capacitated Vehicle Routing Problem (CVRP) is widely recognized as the most extensively studied version of the VRP. In Figure 4 a sample CVRP is shown in which the vehicles satisfy the demand of the stores and then return to the depot. In the following sections, we present a selection of recent studies and investigations related to the Capacitated Vehicle Routing Problem (CVRP) and its variants.

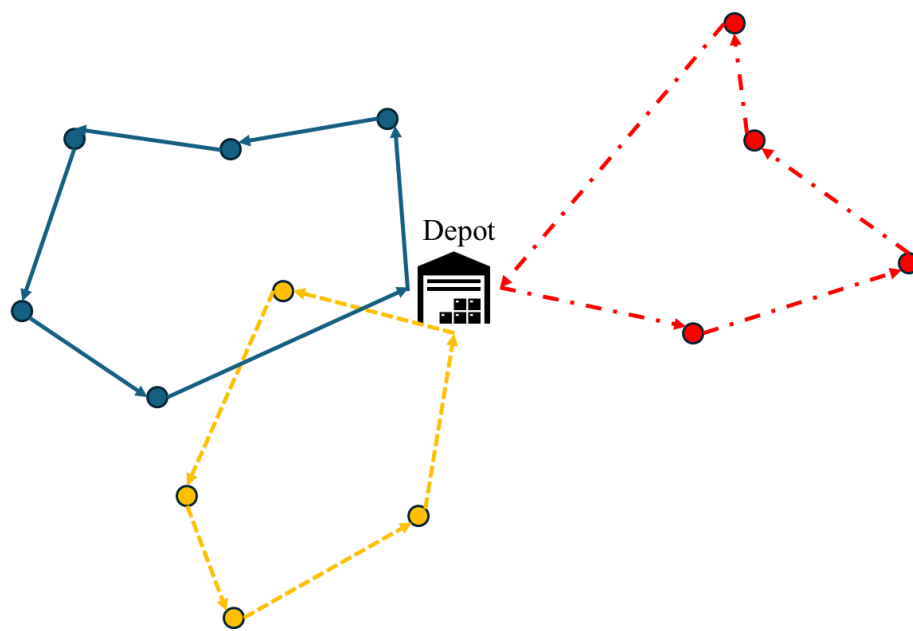


Figure 4: Capacitated vehicle routing problem example

In the last decade in 2013, Jepsen et al presented an exact solution method for the symmetric two-echelon capacitated vehicle routing problem (2E-CVRP). This problem involves the distribution of goods from a central depot to customers via intermediate satellite locations. The approach is based on an edge flow model, which is a relaxation of the original problem and provides a valid lower bound. To find feasible solutions, the authors introduce a tailored branching scheme. The method's effectiveness is demonstrated using a benchmark set of 93 instances, of which it successfully solves 47 to optimality. This outperforms previous exact algorithms in terms of both solution quality and computational reach (Jepsen et al., 2013).

In 2014 Lysgaard & Wøhlk addressed the Cumulative Capacitated Vehicle Routing Problem (CCVRP), which is a variant of the classic Vehicle Routing Problem (VRP). Rather than minimizing the total distance or travel time, the CCVRP aims to minimize the sum of customer arrival times. The authors

introduce a branch-and-cut-and-price algorithm, the first exact solution method published for this problem. Using standard CVRP benchmark instances, they conduct computational experiments to explore how much varying the number of available vehicles affects solution quality and performances. The results demonstrate the effectiveness of the proposed approach in solving CCVRP instances optimally (Lysgaard & Wøhlk, 2014).

Another study is Santos et al. in 2015, that introduce a branch-and-cut-and-price algorithm for solving the two-echelon capacitated vehicle routing problem (2E-CVRP). This approach uses a q-route reformulation to address symmetry issues found in earlier models and incorporates several classes of valid inequalities to strengthen solutions. In a CVRP, a q-route is a route in which customers are allowed to be visited more than once, as long as the vehicle capacity constraint is respected. The proposed method significantly outperforms previous exact approaches, including two branch-and-price algorithms and a branch-and-cut method. Notably, this study provides ten new optimality certificates and eight new best-known upper bounds, as well as improved lower bounds for all instances in the most challenging test set available in the literature. (Santos et al., 2015).

Comert et al. also study the capacitated vehicle routing problem (CVRP) by focusing on minimizing total travel distance while delivering to customers with specific demands from a central warehouse, all while considering vehicle capacity constraints. Because the problem is NP-hard, the authors use a hierarchical solution strategy known as the cluster-first, route-second approach. Three clustering methods, K-means, K-medoids, and random clustering, are used to group customers while considering vehicle capacity. Routing within each cluster is then solved using a branch-and-bound algorithm. The methodology is tested through a case study involving a supermarket chain. Analyzing the numerical results with paired-sample t-tests shows that the K-medoids clustering method produces better results than the other methods (Comert et al., n.d.).

In recent years (2021) a paper of Accorsi & Vigo introduces FILO (Fast Iterative Local Optimization), a metaheuristic designed to solve large-scale instances of the capacitated vehicle routing problem (CVRP) quickly and effectively. Based on the Iterated Local Search (ILS) framework, FILO uses proven acceleration techniques and innovative strategies to localize and adapt the optimization process to specific instances. FILO uses a simulated annealing-based acceptance criterion to maintain solution diversity and encourage broad exploration of the search space. Extensive experiments on well-known benchmark instances demonstrate that FILO rivals state-of-the-art algorithms in terms of solution quality and computational efficiency. To promote reproducibility and facilitate further research, the authors provide open-source access to the algorithm, along with implementation guidelines and a library of reusable components (Accorsi & Vigo, 2021).

Again in 2021 another study addresses the capacitated vehicle routing problem (CVRP) in the context of smart logistics and smart cities. The authors propose a novel crossover operator called Giant Tour Best Cost Crossover (GTBCX) within a multi-objective genetic algorithm based on NSGA-II to minimize total distance and longest route. The CVRP is modeled as a symmetric graph and tested on 88 benchmark instances. The results demonstrate that GTBCX outperforms existing operators (NNX and EAX) in terms of solution quality, route balance, and the number of Pareto-optimal solutions. This shows its effectiveness for solving large-scale CVRP problems. (Sajid et al., 2021).

Many recent works have applied Machine learning and Deep learning for VRP. In 2022 Li et al. present the heterogeneous capacitated vehicle routing problem (HCVRP), in which vehicles have varying capacities. This scenario is more reflective of real-world logistics than the homogeneous fleet assumed in most existing deep reinforcement learning (DRL) approaches. The authors propose a novel DRL method that uses an attention mechanism and incorporates two decoders: one for vehicle selection and another for node selection. This enables the model to make dynamic decisions that account for fleet diversity and route construction. The model is evaluated using randomly generated instances and standard benchmarks (CVRPLib). The results show that the model outperforms existing DRL methods and conventional heuristics and produces results comparable to those of leading heuristic methods, such as slack induction by string removal (J. Li et al., 2022).

There is another investigation stream that considers learning methods in CVRP in which a hybrid algorithm that combines machine learning and integer linear programming (ILP) is presented for addressing large-scale Capacitated Vehicle Routing Problems (CVRP). The strategy addresses the drawbacks of end-to-end learning techniques, which frequently encounter scalability issues and constraint violations. These concerns are addressed by decomposing the CVRP into smaller subproblems appropriate for a trained machine-learning heuristic, which yields multiple potential solutions. A set partitioning ILP model is then used to combine these, guaranteeing that fleet-size restrictions are met. The proposed approach outperforms current learning-based heuristics, achieving solution gaps of less than 3% relative to the best-known solutions on difficult benchmarks with hundreds to thousands of nodes. Additionally, it demonstrates encouraging generalization to similar issues such as the Green Vehicle Routing Problem (Fitzpatrick et al., 2024).

Chin et al. introduce FM-MCVRP, a novel deep learning-based approach for solving the Montreal Capacitated Vehicle Routing Problem (MCVRP). MCVRP is a variant of the Capacitated Vehicle Routing Problem (CVRP) defined on a fixed, city-like graph. The authors frame the MCVRP as a natural language processing (NLP) task and leverage a transformer-based foundation model trained on suboptimal solutions. Despite being trained on suboptimal data, FM-MCVRP generalizes well to larger instances and achieves near-optimal results, within 2% of the benchmark, for 400-customer cases.

Unlike many existing models, FM-MCVRP is unified and robust across varying instance sizes and vehicle capacities. FM-MCVRP offers a scalable, high-performing alternative for real-world CVRP applications (Chin et al., 2024).

Another study that considers Machine learning in VRP is (Asín-Achá et al., 2024) which proposes machine learning (ML) approaches for automatically selecting and configuring fast algorithms to solve the capacitated vehicle routing problem (CVRP) with unit demands. The framework integrates the selection and configuration of algorithms across a portfolio that includes the sweep algorithm, the Clarke and Wright heuristic, and the initial solution generator of a hybrid genetic search. Predicting the best-performing method for a given instance enables the approach to consistently produce high-quality, feasible solutions in very short runtimes. These results demonstrate the potential of ML to enhance combinatorial optimization methods, especially for real-time applications and initializing global solvers. (Asín-Achá et al., 2024).

Nourmohammadi et al. (2025) also propose a data-driven optimization framework for learning decision-makers' preferences in multi-objective vehicle routing problems using historical last-mile delivery data. The approach currently under consideration centers on the capacitated vehicle routing problem with time windows (CVRPTW). The model integrates supervised learning, sampling, and optimization to infer preference weights for objectives. A review of the extant literature reveals that delivery planners often prioritize factors such as workload balance and reduced fleet size over minimal travel distance. The research provides valuable insights into human-influenced routing decisions and supports more informed, human-centered logistics optimization (Nourmohammadi et al., 2025).

From now on we focus on the CVRP studies of the last two years in which Hamdi (2024) addresses the cumulative capacitated vehicle routing problem (CCVRP) with a focus on post-disaster humanitarian aid delivery. It introduces a hybrid delivery model that uses trucks and unmanned aerial vehicles (UAVs). In this model, drones perform tasks independently and periodically return to their base truck to swap batteries. A mathematical model is developed and solved using CPLEX for small instances. For larger problems, a heuristic based on the cluster-first, route-second strategy is proposed. The heuristic is further enhanced and paired with a minimum spanning tree-based lower bound. Computational experiments using benchmark instances demonstrate the heuristic's strong performance and efficiency in solving large-scale cases (Hamdi, 2024).

In 2024 Bernardino and Paia's study discusses the family capacitated vehicle routing problem (F-CVRP), which is a generalization of both the traveling salesman problem and the capacitated vehicle routing problem. The F-CVRP is relevant to warehouse management involving dispersed storage. The authors introduce modified valid inequalities and present and contrast various mixed-integer linear programming (MILP) formulations. They also use a branch-and-cut approach to solve certain models.

Using a new dataset, the authors evaluate performance, emphasizing the challenges and limitations of precise methods. The authors present an Iterated Local Search (ILS) technique for solving unresolved cases. This approach effectively identifies high-quality solutions and surpasses the upper bounds of exact methods within a limited amount of computational time (Bernardino & Paias, 2024).

Zhang et al. (2024) investigate a novel two-echelon, capacitated vehicle routing problem with shared satellite resources (2E-CVRPSSR). This problem is inspired by the growth of e-commerce and the sharing economy. In this model, second-echelon vehicles can begin and end routes at different satellites, which enhances flexibility. They develop a mixed integer linear programming (MILP) formulation and propose an adaptive large neighborhood search (ALNS) algorithm with customized operators to solve the problem. The results demonstrate the algorithm's effectiveness, showing an average transportation cost reduction of 6.29% through satellite sharing. Geographic analysis reveals that the spatial configuration of depots, satellites, and customers significantly impacts cost savings (Zhang et al., 2024).

Within recent studies of CVRP, a study by (Hao et al., 2025) addresses a gap in the existing research by incorporating truck platooning technology into the capacitated vehicle routing problem with time windows (CVRPTW). Recognizing the necessity for trucks to serve multiple customers in real-world scenarios, the authors propose a novel modeling framework based on a road network that reflects realistic platooning operations. The objective is to minimize total operational costs, including fixed dispatch and energy costs, while satisfying all delivery time windows. The authors develop a three-stage solution algorithm that combines a route-then-schedule approach, dynamic programming, and a modified insertion heuristic. Numerical experiments confirm the effectiveness of the model and algorithm and demonstrate the operational benefits of incorporating truck platooning into CVRPTW scenarios.

Chi et al. in 2025 address the three-dimensional (3D) loading-capacitated vehicle routing problem (3L-CVRP) by combining vehicle routing and container loading. The study focuses on relocation-ban constraints, which prohibit the repositioning of items during transport. While these constraints streamline operations, they also reduce vehicle space utilization and increase costs. To balance operational complexity and cost, the authors propose two relaxed relocation constraints and develop a mixed-integer linear programming (MILP) model for the pickup scenario. They use an improved branch-and-price algorithm combined with backward dynamic programming and enhanced label-correcting techniques to generate optimized routing and loading plans. Experiments demonstrate that enabling limited relocations can increase volume utilization by up to 36.48% and reduce overall transportation costs by up to 13.08%. These results underscore the practical value of controlled relocations in 3L-CVRP settings (Chi et al., 2025).

2.1.1. CVRP with time window (CVRPTW)

The Vehicle Routing Problem with Time Windows (VRPTW) expands on the Capacitated Vehicle Routing Problem (CVRP) by requiring that each customer's service starts within a specified time window. These time windows can be either hard, where early arrivals force a vehicle to wait, or soft, where late arrivals incur penalty costs but early arrivals are acceptable. Applications of VRPTW include security patrols, postal deliveries, and school bus routing, among others (Toth et al., 2014). In this section our focus is on the recent studies on Capacitated Vehicle Routing Problem with Time Window (CVRPTW). The following papers are some of the studies whose main focus is on time window issues.

Integration of time window and VRP has been studied for decades. Lau et al. in 2003 present a variant of the Vehicle Routing Problem with Time Windows (VRPTW) called the m-VRPTW, where the number of vehicles is limited. In this setting, feasible solutions may leave some customers unserved or allow relaxed time windows with penalties for lateness. The authors propose a tabu search algorithm featuring a holding list and a strategy to densely pack routes. Customer insertions are guided by a hierarchical objective that balances multiple goals. Computational tests show the method performs competitively against top VRPTW solutions and achieves near-optimal results for m-VRPTW cases. As vehicle numbers decrease, routes become more densely packed, demonstrating the approach's effectiveness in both solution quality and stability (Lau et al., 2003).

A paper by (Repoussis et al., 2007) has the same assumption considered in this thesis, referring to the Open Vehicle Routing Problem with Time Windows (OVRPTW). In this case, vehicles do not return to the depot after completing their routes. In this paper, capacitated vehicles must serve within specified time windows. A detailed mathematical model incorporates practical constraints, and a greedy look-ahead heuristic is developed to construct routes. This heuristic uses composite customer selection and route-insertion rules that leverage the time window constraints to determine visit sequences. Computational tests on benchmark problems show strong performance and suggest the approach's practical usefulness in real-world routing scenarios.

In recent years, Azadi et al. (2024) present a sustainable multi-objective electric vehicle routing problem (EVRP) that integrates economic, environmental, and social objectives. The model considers vehicle capacity constraints, partial recharging, and both hard and soft delivery time windows. Its goal is to minimize system costs, electricity consumption, and customer waiting times, thereby balancing operational efficiency with sustainability and service quality. The problem is formulated as a multi-objective integer linear program and solved using two main approaches: Preemptive Fuzzy Goal Programming (PFGP) with CPLEX for small-scale instances, and four hybrid metaheuristics—Modified Simulated Annealing (MOSA), Multi-Objective Grey Wolf Optimization (MOGWO), Multi-Objective Particle Swarm Optimization (MOPSO), and Non-Dominated Sorting Genetic Algorithm II

with Teaching-Learning-Based Optimization (NSGA-II-TLBO)—for larger cases. The performance of the system is examined using four metrics, such as solution time, Mean Ideal Distance (MID), Mean of Constraint Violations (MOCV), and Hypervolume (HV). The results demonstrate that MOSA provides the most efficient solutions, while NSGA-II-TLBO achieves the highest-quality results across MID, MOCV, and HV. The study underscores the trade-offs between minimizing cost, electricity usage, and delivery times, showing that enhancements in one objective frequently result in compromises in others. The judicious management of time windows is imperative for the mitigation of penalties and the enhancement of customer satisfaction. (Azadi et al., 2024).

2.1.2. Green CVRP and Carbon emission Trade

Due to environmental and social concerns about the recent emissions caused by road transportation in the industrial distribution of companies, a significant amount of research has been conducted to find ways to reduce greenhouse gas emissions from this process. One method that some cities and countries have implemented is called carbon cap-and-trade. In this section, we will review some of the latest research conducted in this field but before it is better to see what the carbon cap-and-trade mechanism is.

The carbon cap-and-trade system operates on a straightforward principle: companies that emit less carbon than a predefined cap during a given timeframe can retain the surplus as carbon credits and trade them in the carbon market. Conversely, if a company exceeds the allowed carbon limit, it must pay for the excess emissions. The European Union is currently the leading region implementing such an emissions trading system, with similar frameworks also adopted in places like New Zealand, Chicago (USA), and Montreal (Canada) (Sadati-Keneti et al., 2023).

In Figure 5, which illustrates the cap-and-trade mechanism, companies that emit less than their allocated carbon allowances can sell the surplus to others. This creates a financial incentive to reduce emissions. Conversely, companies that exceed their emission limits must purchase additional allowances on the market, allowing them some flexibility, but at a cost.

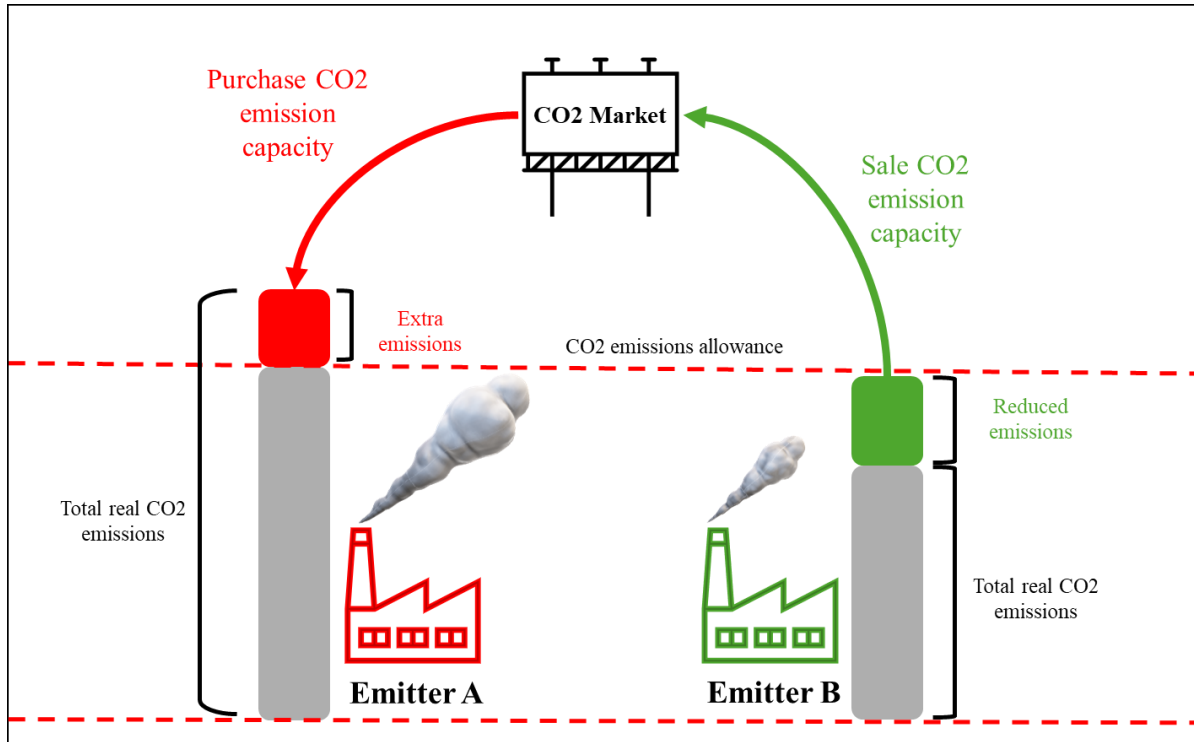


Figure 5: Cap-and-trade mechanism

One of the papers that considered CVRP and carbon emission is (Zhou et al., 2020) in which they study on integrating carbon emissions considerations into distribution network operations to advance energy conservation and emissions reduction goals. The research adopts on a robust optimization approach within the multi-capacity hierarchical location-routing framework. Initially formulated as a mixed-integer nonlinear programming model, the study uses strong duality theory to convert it into a linear robust equivalent. GUROBI software facilitates practical implementation and analysis. Key findings underscore the efficacy of carbon trading policies in curbing emissions. The study demonstrates a notable decline in carbon output with lower emissions caps and higher trading prices. The study also shows how uncertainties in freight volumes affect businesses' optimal decision-making and emphasizes that increasing vehicle availability can mitigate carbon emissions. Recommendations include setting emissions caps that align with market dynamics and encouraging enterprises to incorporate robust decision-making parameters that account for carbon trading policies into their strategic planning and adjustment processes.

Another study is (Kumari et al., 2023) presents an integrated approach to sustainable supply chain decision-making that emphasizes cost-effectiveness over traditional sequential strategies. This study considers a supply chain network involving one vendor and multiple buyers, incorporating the vendor's trade credit policy. The model accounts for carbon emissions from production, vehicle routing, and storage and applies a cap-and-trade policy to encourage reducing CO2 emissions. In their paper a mathematical model is developed to minimize total system cost while meeting various operational

constraints. This includes optimizing production, shipment schedules, and vehicle routing. To solve this complex problem, the study introduces a hybrid metaheuristic algorithm, GA-RR, which combines a genetic algorithm with a ruin-and-recreate phase to improve performance.

(Bi et al., 2024) examine the distinctive operational challenges associated with electric vehicles (EVs) in logistics. They focus specifically on the impact of speed variations on vehicle range and routing decisions. The researchers introduce a novel EV routing model, EVRP-SVR-TW-PR, which incorporates speed-varying range (SVR) and allows for partial en-route recharging within a time-windowed delivery framework. To solve this NP-hard problem, the researchers use a deep reinforcement learning (DRL) approach, specifically an actor-critic model with automated entropy regularization (AC-AER). This framework optimizes routing decisions and dynamically adapts speed and charging strategies. The entropy regularization component helps prevent premature convergence to suboptimal routes, thereby improving the quality of the solution by exploring more potential policies. Empirical results demonstrate that the DRL model outperforms traditional optimization tools (e.g., OR-Tools) by enabling faster deliveries and more effective use of recharging opportunities. The model's strength lies in its flexibility, efficiently navigating the trade-off between speed and energy consumption, a challenge for traditional methods. This research provides valuable insights into electric vehicle routing, especially under environmental and operational constraints. It is particularly relevant to hybrid fleet vehicle routing problems involving time windows and emission limits because it emphasizes the need for adaptive decision-making frameworks that account for real-world electric vehicle (EV) limitations, such as range variability and charging logistics.

In their 2024 study, (Lou et al., 2024) address the growing need for environmentally conscious logistics. The researchers develop a vehicle routing problem (VRP) model that considers time window constraints and carbon emissions. The study's primary objective is to minimize carbon emissions while ensuring timely customer service. To achieve this goal, the authors design a time-sensitive, emission-aware VRP model that incorporates real-world traffic dynamics, such as time-dependent speeds, speed variability, and road conditions. A key innovation in their methodology is the use of a graph convolutional network (GCN) to predict traffic speeds over time. This approach captures complex spatial-temporal traffic patterns, enabling more precise emission estimates and route planning. To solve the resulting high-dimensional optimization problem, the authors implement a hybrid genetic algorithm enhanced with an adaptive variable neighborhood search to ensure computational efficiency and solution quality. When tested with actual traffic and logistics data from Jingzhou, China, the model reduces carbon emissions by 10.15% and improves emission outcomes by 23.39% compared to traditional approaches. The study underscores the value of integrating real-time traffic data and predictive modeling into routing decisions, especially when environmental goals are involved.

Ferreira et al. (2024) present an enhanced green vehicle routing model that integrates two-dimensional loading constraints with split delivery, with the objective of minimizing CO₂ emissions rather than merely minimizing distance. The model, designated as the Green 2D Loading Split Delivery Vehicle Routing Problem (G2L-SDVRP), addresses the dual objectives of routing efficiency and loading feasibility. It does so by conceptualizing customer demands as rectangular items, with the requirement that these items be accommodated within the confines of vehicle loading areas. To address this intricate challenge, the authors devise a Variable Neighborhood Search (VNS) metaheuristic. The algorithm under consideration incorporates multiple neighborhood structures, local search via Random Variable Neighborhood Descent (RVND), and a set partitioning refinement phase. Specialized procedures are developed to ensure the feasibility of 2D loading, including a constraint programming packing validator. A series of computational experiments demonstrate that the VNS-based approach consistently yields optimal results in numerous benchmark instances, thereby enhancing the existing best-known solutions for both G2L-SDVRP and related two-dimensional loading problems. The efficacy of the proposed approach is substantiated by its ability to deliver high-quality solutions within a reasonable computation time frame. (Ferreira et al., 2024).

In 2024, (Su et al., 2024) introduce a multi-depot green vehicle routing problem with time windows (MDGVRPTW-CS) that integrates customer satisfaction as a main objective alongside environmental and operational efficiency. The study proposes a hybrid optimization algorithm, termed the Lightweight Genetic Algorithm with Variable Neighborhood Search (LGAVNS), which integrates a genetic algorithm for global search with a selective variable neighborhood search applied to key genes for localized enhancement. This approach is further improved by an advanced crossover operator that facilitates gene transfer between parent solutions, thereby ensuring the maintenance of solution quality with minimal computational overhead. Parameter tuning ensures the method's effectiveness across both small- and large-scale scenarios. The experimental results demonstrate that LGAVNS surpasses six benchmark algorithms in terms of convergence speed and solution quality, particularly in the context of large problem instances. The algorithm's lightweight design also makes it scalable and adaptable, enabling it to optimize not only routes but also the number and placement of depots. Their work tends to lower operational costs and achieve greater efficiency. The integration of customer satisfaction factors, and the considering the delivery time window preferences, ensures the model's congruence with the overarching objectives of sustainable and service-oriented logistics. The study further suggests improvements in genetic operators and neighborhood search strategies.

2.1.3. CVRP with split delivery and scheduling arrival

A set of assumptions can be introduced into the classic CVRP to make the problem more representative of real-world scenarios. Splitting deliveries and scheduling arrival times are among the assumptions we applied, based on the conditions observed in the real case. For an instance, Figure 6 shows an example

in which a delivery to one store is split among the trucks and each truck must be scheduled to arrive after unloading the previous truck.

In this section, some papers are reviewed that focus on split deliveries and arrival time scheduling.

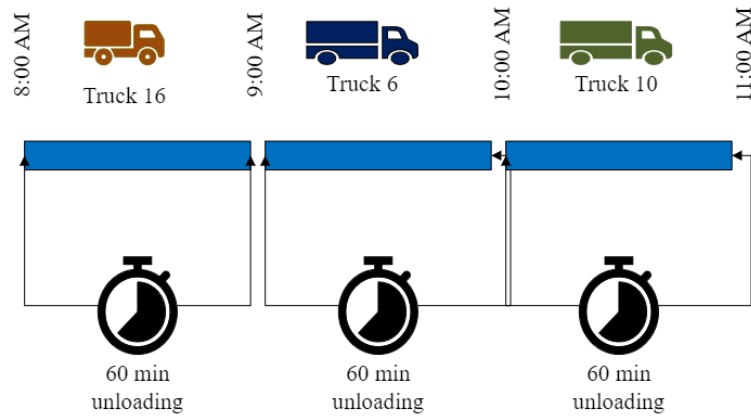


Figure 6: Scheduled arrival times for split deliveries

Decades ago (Belenguer et al., 2000) studied on Split Delivery Vehicle Routing Problem (SDVRP), a variant of the Capacitated Vehicle Routing Problem (CVRP) that allows a single customer's demand to be fulfilled by multiple vehicles, thus offering more flexibility in routing. The authors define what constitutes a feasible solution for the SDVRP and analyze the structure of the solution space by showing that the convex hull of its incidence vectors forms a polyhedron (denoted as PSDVRP). They examine how the dimensionality of this polyhedron changes depending on whether each visiting vehicle must deliver at least one unit of demand. Furthermore, the study introduces a partial linear description of PSDVRP and proposes a new family of valid inequalities to strengthen the model. These developments enable the computation of a strong lower bound, whose effectiveness is demonstrated through computational experiments. Notably, the authors report solving a well-known benchmark instance with 50 clients to optimality, which, to their knowledge, is the largest such instance solved to date (Belenguer et al., 2000).

In recent years, Aguayo et al. (2025) investigate the Vehicle Routing Problem with Transfers (VRP-T), an extension of the Split Delivery VRP (SDVRP) wherein customer locations can serve as transfer points for load exchanges between vehicles. The allowance of such transfers is demonstrated to reduce routing costs by up to 50%. The authors propose a two-index mixed-integer programming model alongside a heuristic based on Multi-start Local Search (MSLS). The heuristic solutions warm-start the MIP solver, leading to significant cost savings and reductions in the number of vehicles necessary. The

findings suggest that load transfers are at least as effective as split deliveries in reducing operational costs (Aguayo et al., 2025).

2.1.4. Multi Objective Vehicle Routing Problem

In most cases in VRP, there is more than one objective to be taken into account. If we can prove that the objectives can have conflict with each other like by improving one of them, the other one gets worse, then we can consider the problem as a multi-objective problem. Multi-objective optimization can be used to enhance traditional logistics models, which typically focus only on minimizing cost. By considering additional objectives, the models become more practical and relevant to real-world applications where other factors also matter. In the following there some potential objectives other than economic cost are listed (Jozefowicz et al., 2008):

Driver workload: A vehicle routing problem extension that aims to balance tour lengths to promote fairness among drivers.

Customer satisfaction: A vehicle routing problem with time windows to improve delivery timing, thereby enhancing customer satisfaction.

Commercial distribution: This objective focuses on the periodic vehicle routing problem, particularly in the context of the food and beverage industry. Their model includes objectives related to cost, fairness, and marketing. Like driver workload, they emphasize the importance of balanced driver schedules, which can help strengthen customer relationships and boost sales.

Green Objectives: This can also be considered as CO₂ and other greenhouse gas emission reduction, which nowadays play a key role.

Now we are going to see some recent papers which dealt with on multi objectives vehicle routing problem.

In 2022 (De Jonge et al., 2022) worked on a problem applied multi-objective optimization to the combination of automated negotiation and vehicle routing. The study focused on cooperation among competing logistics companies that try to improve efficiency by exchanging truckloads. The study addressed the challenge of identifying load exchanges that are Pareto-optimal and individually rational. This enables each company to get benefits without disclosing its private cost models to a central authority. The study proposed a new heuristic algorithm to generate these exchanges based on separate order sets for each company. This algorithm facilitates automated negotiation for selecting which

exchanges to execute. The paper also introduced a novel, multi-objective variant of the And/Or search approach.

Most of the recent studies of this field have tried to make heuristics, metaheuristics and exact algorithms to cope with these problems. One of the papers in this category is (C. Wang et al., 2023). In this paper, the authors work on CVRP with a focus on workload balancing by formulating it as a multi-objective optimization problem (MO-CVRP). The objective is to minimize both the total route length and the variance in load assignments among vehicles to ensure fair workload distribution. To overcome the slow convergence issues typical of many existing multi-objective evolutionary algorithms (MOEAs), the study proposes a co-evolutionary genetic algorithm with knowledge transfer. This approach leverages solutions from a simplified Traveling Salesman Problem (TSP), which ignores vehicle capacity constraints, to accelerate the search for optimal solutions in the MO-CVRP. A denoising autoencoder is used to build a transformation between TSP and CVRP solutions, enabling effective information sharing. Furthermore, an adaptive migration strategy and an improved split operator ensure solution feasibility and adaptability during the optimization process. Experimental comparisons with four state-of-the-art MOEAs across various MO-CVRP instances demonstrate that the proposed method achieves faster convergence and superior solution quality.

Another work that also focused on MODM and VRP is (Chen et al., 2025). This study addresses the complex issue of vehicle routing in logistics by presenting a new intelligent optimization method: the Multi-Objective Capacity Adjustment Ant Colony Optimization (MCAACO) algorithm. Recognizing the importance of optimizing vehicle capacity allocation for improving routing efficiency and service coverage, the authors integrate advanced multi-objective strategies, such as capacity adjustment and crossover operators, into the ant colony framework. The algorithm uses pheromone updating and Pareto front optimization to resolve conflicts between capacity constraints and multi-objective goals. Dynamic pheromone updates, elite retention, and adaptive parameter adjustment strategies are also introduced to improve global exploration and local exploitation. Comparisons with MOPSO, NSGA-II, and the multi-objective sparrow search algorithm (MOSSA) reveal that MCAACO reduces travel distances by an average of 3.05% and improves service coverage by 3.2%, while maintaining compliance with vehicle capacity limits. These results demonstrate the algorithm's effectiveness in overcoming the high cost and low efficiency of real-world logistics and distribution systems.

2.2. Electric and Hydrogen Vehicle Routing problem

This section of the literature review focuses on the different types of fleet propulsion systems. First, we briefly examine how they function in terms of energy or fuel consumption. Then, we examine papers that studied each type of fleet separately, as well as hybrid fleets (comprising internal combustion, electric, and hydrogen fuel cell vehicles).

2.2.1. Electric vehicle routing problem

Electric vehicles (EVs) can be categorized into three main types based on their primary energy source: Battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs). The figure illustrates the energy flow for each of these EV types.

BEVs operate entirely on electrical energy stored in batteries. They rely solely on external electricity supplied via the power grid for recharging because they have no internal system for generating electricity. BEVs typically have battery packs ranging from 20 kWh to 80 kWh, which provide a driving range of up to 663 kilometers. Since all the energy must come from the battery, BEVs require larger, higher-capacity battery systems than other EV types. In Figure 7 we can see the mechanism of BEVs (Guo et al., 2021).

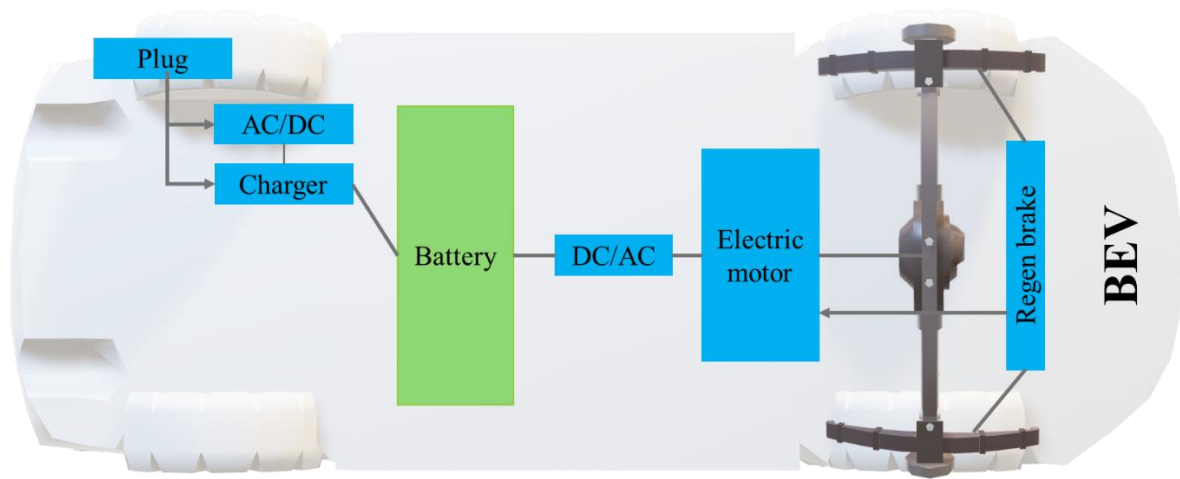


Figure 7: Battery Electric Vehicles (BEV) mechanism

HEVs are the most widespread EV type, featuring a combination of an internal combustion engine (ICE) and an electric motor, showed in Figure 8. These vehicles are powered by fossil fuels only, while the battery is recharged through regenerative braking. The electric motor can support the ICE, for example while idling at traffic signals, or power the vehicle independently over short distances. HEVs have relatively small battery capacities, typically between 1.3 kWh and 1.6 kWh, and do not include a plug-in option for grid charging. This design focuses on improving fuel efficiency with minimal battery requirements (Guo et al., 2021).

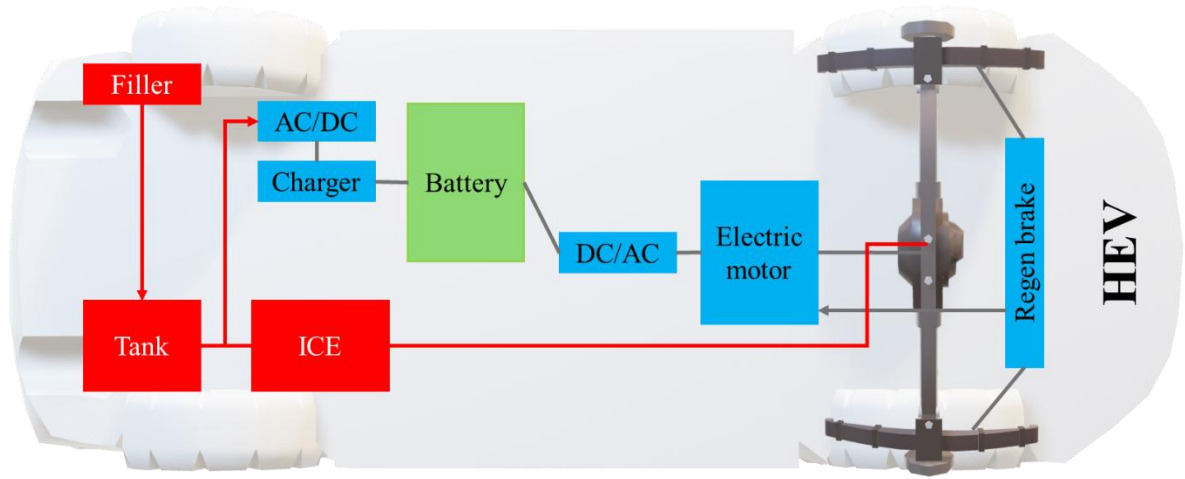


Figure 8: Hybrid Electric Vehicles (HEV) mechanism

PHEVs have a similar powertrain configuration to HEVs and incorporate both an ICE and an electric motor. However, PHEVs can be connected to external charging sources, such as EV charging stations. Like HEVs, PHEVs use regenerative braking to recharge the battery (Figure 9). PHEVs have larger battery capacities, usually between 4.5 kWh and 10 kWh, allowing for longer electric-only driving ranges. Traditionally, PHEVs use a balanced mix of energy sources, with approximately 50% of the power coming from gasoline and 50% from electricity (Guo et al., 2021).

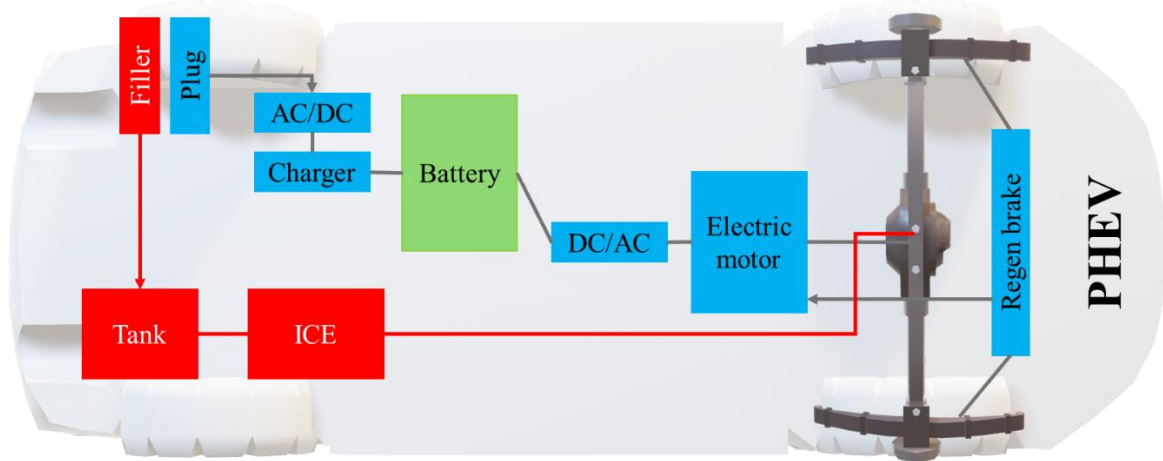


Figure 9: Plug-In Hybrid Electric Vehicles (HEV) mechanism

One of the key studies that focuses on mixed fleets such as electric and internal combustion vehicles for the routing problem is Goeke and Schneider (2015), who introduce the Electric Vehicle Routing Problem with Time Windows and Mixed Fleet (E-VRPTWMF), to optimize routing for a mixed fleet of electric commercial vehicles (ECVs) and conventional internal combustion commercial vehicles (ICCVs). Unlike previous models that assume an energy consumption linearly proportional to distance, the study incorporates a realistic energy consumption model considering the speed, slope of the road,

and cargo load distribution, which are crucial factors for accurately determining ECV driving range and charging times. To solve their problem, the authors develop an Adaptive Large Neighborhood Search algorithm enhanced with a local search for solution intensification. Through numerical experiments on newly designed E-VRPTWMF test instances, the study explores how considering actual load distribution affects solution quality and structure, examines the impact of different objective functions on solution characteristics and ECV contribution to routing costs, and validates the algorithm's performance on benchmark instances of related VRPTW and E-VRPTW problems (Goeke & Schneider, 2015).

Following the previous research, there is also another paper that considers mixed fleet VRP. Hiermann et al. (2016) introduce the Electric Fleet Size and Mixed Fleet VRP with Time Windows and Recharging Stations (E-FSMFTW) model to address decisions related to fleet composition, vehicle routing, and recharging time and location selection. The model accounts for different vehicle types that differ in transport capacity, battery size, and acquisition cost. It also incorporates time windows at customer locations, reflecting a common real-world constraint. They solve the problem using the branch-and-price method and then a hybrid heuristic that mixes an adaptive large neighborhood search with an embedded local search and labeling procedure for intensification. Examining the approach on a newly created benchmark set for E-FSMFTW and existing single-vehicle-type benchmarks using an exact method, the authors demonstrate the effectiveness of the proposed solution approach (Hiermann et al., 2016).

In the same line as the last two papers, a key investigation that focuses on considering alternative fuel vehicle fleets in the vehicle routing problem, such as biodiesel and electricity, is provided in the paper by Andelmin and Bartolini (2017). In this paper, the authors present an exact algorithm for the Green Vehicle Routing Problem (G-VRP) that optimizes routes for alternative fuel vehicle fleets while accounting for fuel autonomy and refueling constraints. The researchers model the problem as a set partitioning problem using a multigraph. This approach naturally excludes suboptimal refueling paths, eliminating the need for explicit modeling of refueling stops. The authors strengthen the formulation with valid inequalities, such as k-path and subset-row cuts. Some of these cuts are Chvátal-Gomory cuts that are solved using mixed-integer linear programming to improve lower bounds. When tested on benchmark and new instances, the algorithm efficiently solves problems with up to 110 customers, providing tight bounds and effectively pruning the solution space. This improves computational efficiency and route feasibility by integrating strategic refueling (Andelmin & Bartolini, 2017).

Ashtineh and Pishvae (2019) examine the economic and environmental impacts of alternative fuels in the context of the Vehicle Routing Problem (VRP), incorporating a life cycle assessment (LCA) of fuel emissions. Their study aims to optimize fuel consumption and reduce emissions by accounting for the

broader environmental footprint of transportation fuels. To do so, they use Tank-to-Wheel (TTW) and Well-to-Wheel (WTW) models, which consider the entire process from fuel production to combustion. The authors formulate mixed-integer programming (MIP) models that integrate key variables affecting fuel economy and pollutant intensity, such as distance, vehicle load, speed, and transmission gear ratio. The authors then conduct a comparative analysis of various alternative fuels, including biodiesel, hydrogen, and petroleum diesel. They evaluate these fuels' greenhouse gas (GHG) emissions and air pollutants throughout their life cycles. The WTW analysis examines emissions from extraction, refining, distribution, and combustion, while the TTW analysis focuses solely on emissions during vehicle fuel consumption. Experimental validation through numerical tests highlights the influence of fuel type, gear selection, and driving behavior on fuel efficiency and emissions. The study finds that although biodiesel combustion emissions are similar to petroleum diesel, the full life cycle analysis indicates a 37% reduction in GHG emissions with biodiesel, though benefits depend on production methods and regional factors. Although hydrogen has zero emissions at the vehicle level, it has significant greenhouse gas emissions during production, so its sustainability depends on the production process. Furthermore, the research emphasizes the previously overlooked role of the transmission gear ratio in affecting vehicle speed, fuel consumption, and emissions. This highlights the importance of developing routing models that incorporate transmission dynamics to enhance energy efficiency (Ashtineh & Pishvaei, 2019).

Seyfi et al. (2022) introduce the Multi-Mode Hybrid Electric Vehicle Routing Problem (MM-HEVRP), an influential version of the Hybrid Electric Vehicle Traveling Salesman Problem (HEV-TSP). The MM-HEVRP is designed to more accurately reflect the operational realities of HEV logistics. The MM-HEVRP considers the multi-mode nature of HEVs, which can alternate between electric and internal combustion engine (ICE) modes. The hybrid vehicle in this paper refers to one vehicle with two propulsion technologies, which is different from our thesis assumption, which considers three different fleets with different propulsion technologies. It aims to minimize total travel costs by selecting the most efficient drive mode for each route segment. Their problem is modeled as a mixed integer linear programming (MILP) that accounts for drive mode selection, vehicle capacity constraints, customer demands, and shift length restrictions requiring vehicles to return to the depot within a working day. To solve this complex optimization problem, the authors develop a matheuristic approach that combines variable neighborhood search (VNS) with mathematical programming techniques. Specifically, VNS explores customer route sequences while the Fixed-Route Vehicle Mode Selection Problem (FRVMSP) allocates the optimal drive mode along each route. For small-scale instances (three to ten customers), the model is validated using the CPLEX solver to benchmark the matheuristic's performance. Computational results show that the proposed approach efficiently generates high-quality solutions, particularly for larger instances where exact MILP solvers become impractical. The key findings underscore the substantial cost savings achieved through optimal mode switching and the influence of

vehicle speed and battery capacity on routing flexibility and overall efficiency. The study's sensitivity analysis emphasizes the importance of operational parameters in developing cost-effective HEV deployment strategies. The MM-HEVRP is a meaningful advancement in sustainable logistics because its multi-mode modeling approach more accurately reflects HEV capabilities. The authors suggest several areas for future research: dynamic routing based on real-time traffic or battery conditions; the incorporation of emissions-based objectives to improve sustainability metrics; and the adaptation of the model to other vehicle types, such as plug-in hybrids and fully electric vehicles (Seyfi et al., 2022).

Froger et al. (2022) address an advanced variant of the Electric Vehicle Routing Problem (E-VRP) by incorporating capacitated charging stations (CSs) into the optimization model, resulting in what they define as the E-VRP-NL-C. This model introduces critical real-world constraints that are often overlooked, such as the limited number of EVs that can charge simultaneously at a station, nonlinear charging functions, and the presence of multiple charging technologies. The primary objective is to optimize EV routes while minimizing costs and effectively managing charging infrastructure limitations. The E-VRP-NL-C is formulated as a continuous-time, path-based model that incorporates nonlinear charging behaviors, where the rate of charge depends on the current battery level, as well as varying charging technologies, such as fast and standard charging, restricted capacity at charging stations, and flexible charging quantities depending on route demands. To solve this complex problem, the authors propose a two-step solution framework. First, an Iterated Local Search (ILS) metaheuristic is used to generate high-quality routes by solving an uncapacitated version of the problem, forming a diverse pool of candidate solutions. Second, a branch-and-cut algorithm assembles feasible solutions by combining these routes while managing CS capacities. This solution method adjusts vehicle charging schedules and quantities and considers waiting times to resolve CS congestion. The study evaluates four strategies for handling CS capacity: basic capacity checks, incorporation of waiting times, adjustment of charging amounts, and a combined strategy integrating both delays and charging adjustments. Their experimental results of 120 benchmark instances show that the framework produces new best-known solutions for 80 cases, solves all small-sized problems optimally, and consistently outperforms commercial MILP solvers for larger instances. Notably, the combined strategy of charging and timing adjustments proves the most effective without substantially increasing computational time. Key findings emphasize the importance of accurately modeling CS capacity constraints, as ignoring them risks infeasibility. The study also demonstrates that more advanced CS management approaches reach significantly better results and that high-quality initial routes generated by the ILS contribute meaningfully to the overall solution quality (Froger et al., 2022).

Nolz et al. (2022) examine a consistent electric vehicle routing problem involving backhauls and charging management. They focus on improving operational reliability by implementing time- and driver-consistent scheduling while addressing the limitations of the recharging infrastructure. The study

is based on a real-world parcel delivery scenario in which electric vehicles (EVs) can only recharge at a depot with a restricted number of charging slots between morning delivery and afternoon pickup tours. The researchers try to minimize total costs, including fixed vehicle costs, operational time, and penalties for deviations from consistent driver assignments and arrival times. They formulate the problem mathematically to account for driver and time consistency, charging slot limitations, and cost optimization. For the sake of this complex routing and scheduling challenge, the researchers develop a hybrid solution framework integrating three components: Template-Based Adaptive Large Neighborhood Search (ALNS) for exploring and refining solutions; Constraint Programming (CP) for scheduling charging slots efficiently; and Quadratic Programming (QP) for refining delivery and pickup schedules to ensure time consistency. The authors test their approach using data from an Austrian parcel delivery company and evaluate its effectiveness under some constraints. The results show that management of recharging resources significantly impacts vehicle availability and overall delivery performance. Including time and driver consistency constraints results in more predictable and stable routing schedules, improving cost efficiency and driver satisfaction. (Nolz et al., 2022).

Barletta et al. (2023) present a solution to the Hybrid Fleet Capacitated Vehicle Routing Problem (HF-CVRP), which involves optimizing deliveries using a heterogeneous fleet comprising electric vehicles (EVs) and internal combustion engine (ICE) vehicles. The central objective is to optimize the efficiency of parcel delivery while taking into account the capacity limitations of vehicles and the restricted driving range of electric vehicles (EVs). In order to address this challenge, the authors propose a two-phase heuristic framework. In the clustering phase, a capacitated k-median algorithm groups customer locations according to proximity and parcel weight. Concurrently, a hierarchical constrained minimum weight matching algorithm ensures that clusters respect the range limitations of electric vehicles (EVs). This approach not only simplifies the routing phase but also synchronizes cluster formation with the operational limits of electric vehicles (EVs). In the routing phase, a flexible Monte Carlo Tree Search (MCTS) heuristic is employed, guided by a custom objective function that prioritizes EV usage, a rollout policy that promotes efficient routing, and tree pruning techniques for computational efficiency. Then Tabu Search is employed to improve route quality and enhance the overall solution. The proposed method demonstrates high scalability, effectively handling real-world instances with thousands of deliveries and hundreds of vehicles, and performs particularly well in scenarios with spatially clustered customers. However, challenges emerge in the context of randomly distributed networks or the presence of natural obstacles, such as mountains or bodies of water, which the current clustering mechanism does not account for. The approach is noteworthy for its emphasis on electric vehicles (EVs), integrating operational efficiency with environmental sustainability. Its pertinence to hybrid fleet routing under carbon cap-and-trade systems is substantial, as it furnishes pragmatic strategies for emissions reduction while accommodating real-world constraints in intricate fleet routing environments. (Barletta et al., 2023a).

Again in 2023, Kumar et al. (2023) investigate the Electric Vehicle Routing Problem with Time Windows (EVRPTW) by proposing a novel metaheuristic framework combining the Firefly Algorithm and the Ant Colony Algorithm (ACA) to solve the problem. This framework incorporates multiple recharging options and time-of-use (ToU) energy pricing. The study aims to optimize EV routing by minimizing total travel and recharging costs, especially under operational constraints like limited battery range and varying recharging needs. The core of the methodology is a hybrid metaheuristic in which the ACA serves as the primary optimization engine and the Firefly Algorithm facilitates extensive exploration of the solution space to avoid local optima. The model supports multiple recharging options, including battery swapping, partial charging, and various charging levels, allowing for flexible energy management. Furthermore, the model enables cost-aligned charging schedules that capitalize on low-price time periods by integrating ToU energy pricing. This approach's performance is benchmarked using the Schneider test set and compared with other established algorithms, such as Variable Neighborhood Search (VNS) and Ant Colony Optimization with Local Search (ACO-LS). The results demonstrate that the hybrid algorithm provides near-optimal solutions and improves convergence rates by about 50%. It also reduces deviations from optimal costs by 20–25%, outperforming other methods. Significant reductions in transportation costs are achieved by using multiple recharging strategies, which underscores the benefits of adaptable charging logistics. Despite its strengths, the study acknowledges that, as a metaheuristic, the algorithm cannot guarantee global optimality due to inherent stochastic processes. Future research could explore new combinations of metaheuristics or integrate them with exact algorithms to enhance reliability. The authors also recommend incorporating real-time data (Kumar et al., 2023).

In another study similar to the previous one, (Bruglieri et al., 2023) propose a matheuristic approach to the Electric Vehicle Routing Problem with Time Windows (E-VRPTW). Like the current study, they also attempt to compute realistic energy consumption modeling by integrating vehicle speed and payload into the optimization process. They propose a mixed integer linear programming (MILP) model that departs from traditional methods by eliminating the need for cloned charging stations, allowing recharging at the same station without duplicating nodes. This simplifies the model while maintaining accuracy. The MILP formulation models vehicle speed as a continuous variable within set bounds and incorporates payload-dependent energy consumption. This leads to a more realistic depiction of energy usage in EV routing. To improve scalability for larger instances, the authors develop a Random Kernel Search (RKS) matheuristic that focuses computational effort on a "kernel" of promising solutions. This approach is complemented by the Random k-Degree Search (RkDS) sub-heuristic, which generates initial feasible solutions, crucial for effective performance in complex scenarios. They examine the proposed methodology on scaled versions of Schneider's benchmark instances, ranging from 25 to 100 customers. The results show that RKS outperforms the cloneless MILP in both speed and solution quality, particularly for medium and large problem sizes. Specifically, RKS achieves better solutions in

just 30 minutes than the standalone MILP does in two hours, demonstrating its computational efficiency and robustness to parameter variation. While RkDS is not a complete solver, its role in generating feasible initial solutions is critical to the success of RKS.

There is another paper that addresses the challenge of minimizing total inspection energy consumption (TIEC) in unmanned aerial vehicle (UAV)-based automatic inspections of large-scale offshore wind farms, aided by mobile edge computing (MEC). The study develops system and energy consumption models that incorporate UAVs, MEC servers, and near-Earth satellites. The problem is formulated as a distance-constrained capacitated vehicle routing problem (DCVRP), and an improved hybrid heuristic algorithm using K-means clustering, smallest enclosing circle (SEC), and Lin-Kernighan-Helsgaun (LKH-3) is proposed. Simulation results from a wind farm with 86 turbines demonstrate that the proposed approach reduces TIEC by up to 51.8% while requiring only four UAV airfields, thereby outperforming existing methods (Huang & Wang, 2024).

Gülmez, Emmerich, and Fan (2024) present a novel green vehicle routing model that incorporates flexible time windows for last-mile deliveries. The model's optimization of three objectives is notable. These objectives include the reduction of travel costs, the promotion of electric vehicle use over traditional fuel-based options, and the maximization of customer satisfaction through the provision of multiple preferred delivery time slots. This flexibility endows route planners with greater autonomy to devise efficient, eco-friendly delivery schedules. The study introduces the Green Vehicle Routing Problem with Flexible Time Windows, which allows customers to express their delivery time preferences. Four advanced evolutionary algorithms are employed to solve this multi-objective problem: Non-dominated Sorting Genetic Algorithm II (NSGA-II), NSGA-III, Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D), and S-Metric Selection Evolutionary Multi-objective Algorithm (SMS-EMOA). The efficacy of these algorithms is determined by their capacity to generate high-quality Pareto-optimal solutions, which reflect trade-offs between cost, emissions, and service quality (Gülmez et al., 2024).

In 2023 (Fan et al., 2023) study the electric vehicle routing problem considering energy differences of charging stations (EVRPEDCS), taking into account environmental impact and economic viability in EV-based logistics distribution. The study emphasizes that charging stations vary in their carbon emissions due to the different sources of electricity generation, ranging from fossil fuels to renewable energy. To do so, the authors develop a mixed integer programming (MIP) model that incorporates energy consumption and emission calculations based on the energy source of each charging station. To solve this model efficiently, especially for large-scale logistics scenarios, the authors apply an improved ant colony algorithm (IACA), which enhances solution quality and computational performance. Numerical experiments demonstrate that the EVRPEDCS framework significantly reduces emissions

and operational costs, cutting carbon emissions by an average of 89.69% and charging expenses by 41.26%. These results highlight the importance of energy source variability, showing that EVs powered by cleaner sources at distributed new energy charging stations (NECSs) contribute far less to environmental degradation. Furthermore, the study suggests that the wider adoption of NECSs, which are powered by solar or wind energy, supports sustainability goals and reduces the need for costly grid expansions (Bruglieri et al., 2023).

Eslamipoor (2024) presents a bi-objective optimization model for the Hybrid Vehicle Routing Problem (HVRP) that, like our current thesis, simultaneously addresses direct and indirect emissions within a pickup and delivery system. The model incorporates load-dependent energy consumption and vehicle capacity constraints, aiming to minimize total cost and customer waiting time while considering time windows and electric vehicle charging considerations. The problem is formulated as a Hybrid Vehicle Routing Problem with Time Windows (HVRPTW), taking into account the energy consumption based on vehicle load, direct and indirect emissions aligned with green logistics principles, multiple depots for dynamic pickup and delivery, and time-window constraints to enhance operational efficiency. To solve this complex problem, the study applies two multi-objective metaheuristics: Multi-Objective Particle Swarm Optimization (MPSO), which uses swarm intelligence to improve solution quality and convergence, and the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), which leverages evolutionary computing to produce diverse, well-distributed solutions balancing trade-offs between objectives. The model is validated using the General Algebraic Modeling System (GAMS) on medium-size instances, and these tests confirm the accuracy of the formulation and the effectiveness of the heuristics. Experimental results show that both the multi-particle swarm optimization (MPSO) and non-dominated sorting genetic algorithm-II (NSGA-II) effectively approximate optimal solutions. MPSO performs better than NSGA-II in convergence speed and solution quality, while NSGA-II has better performance in maintaining diversity across the Pareto front. (Eslamipoor, 2024).

In another work in 2024, Li et al. develop an electric vehicle routing model made for cold chain logistics. This model aims to minimize total operational costs while addressing carbon emissions from electricity consumption. The model integrates sector-specific cost components, including refrigeration, product damage, and queuing at charging stations, as well as dynamic factors like time-varying speeds, electricity prices, and multiple distribution centers. To address this challenge, the authors propose a hybrid Crow Search Algorithm, which integrates Opposition-Based Learning and Taboo Search methodologies. This approach is designed to enhance the quality of solutions obtained and to circumvent the occurrence of local optima. A comparative analysis reveals that the hybrid algorithm demonstrates superior performance in terms of speed and accuracy when compared to traditional methods, including the genetic algorithm and particle swarm optimization. The study's key findings

include the advantages of joint distribution across centers for reducing cost and emissions, and the positive impact of larger battery capacities on sustainability performance (Y. Li et al., 2024).

2.2.2. Hydrogen vehicle mechanism and routing problem

To understand the function and significance of hydrogen vehicles (HVs), especially in heavy-duty applications, it is essential to examine their powertrain architecture and energy systems in detail. As shown in Figure 10, the standard configuration of a fuel cell-powered heavy-duty truck shares several key features with battery electric vehicles (BEVs), particularly in the electric drivetrain design. At the core of the propulsion system lies an electric motor that is directly connected to the driven axle through a differential, bypassing the need for a traditional multi-speed gearbox. This direct-drive configuration not only simplifies the mechanical complexity of the drivetrain but also minimizes energy losses due to friction and gear shifting, thereby increasing the overall mechanical efficiency of the vehicle (Bernard et al., 2009). Consequently, it has been demonstrated that this configuration increases the overall mechanical efficiency of the vehicle.

The electric motor is engineered for bidirectional functionality, thereby operating as both a propulsion unit and a generator during braking phases (a feature that is imperative for regenerative braking systems). During deceleration or downhill movement, the motor converts kinetic energy back into electrical energy and stores it in the battery. This process significantly improves energy efficiency and reduces overall energy consumption over time (Pramuanjaroenkij & Kakaç, 2023). The vehicle's energy storage and generation systems contain three major components: a high-voltage lithium-ion battery pack, a hydrogen fuel cell stack, and high-pressure hydrogen storage tanks. The battery functions as an auxiliary power unit, managing peak power demands, such as rapid acceleration, and storing energy recovered from regenerative braking. Conversely, the fuel cell stack functions as the primary power source, generating electricity through the continuous electrochemical conversion of hydrogen gas stored in onboard tanks with oxygen from the ambient air, yielding only water vapor as a byproduct. This reaction has been demonstrated to facilitate the generation of energy in a manner that is both clean and efficient, with no concomitant production of harmful byproducts.

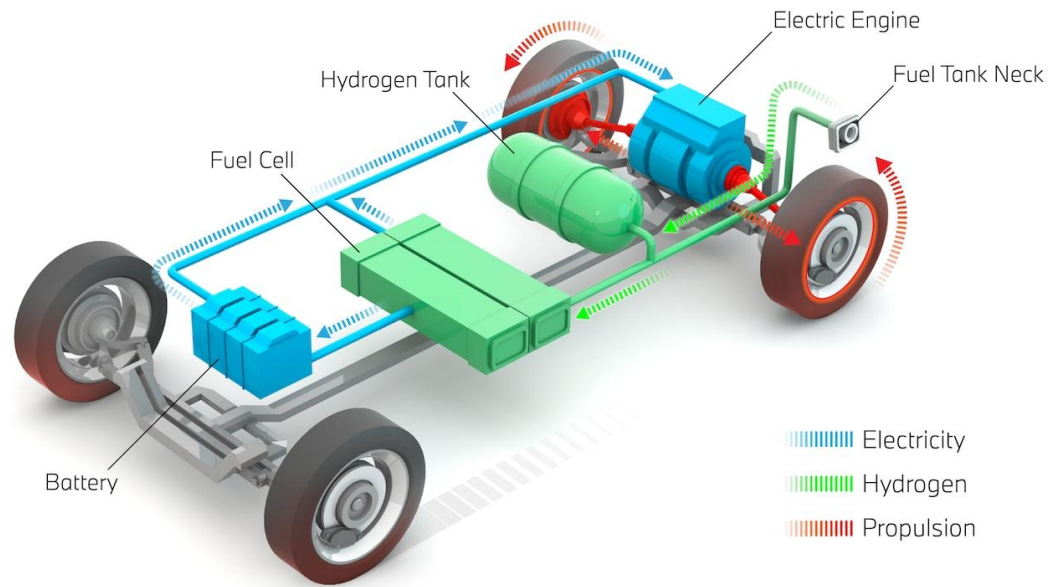


Figure 10: The standard configuration of the powertrain in a fuel cell-powered vehicle ([BMW](#))

There are a few investigations that connect vehicle routing and hydrogen vehicles. One of them is the investigation by Ren et al. (2024) on a hydrogen fuel cell vehicle (HFCV) routing model incorporating unmanned aerial vehicles (UAVs) and variable drone speeds, proposed to optimize last-mile delivery operations. The model, known as the Time-Dependent HFCV Routing Problem with Drones and Variable Drone Speeds, aims to minimize total cost and makespan by coordinating vehicle-drone operations under time windows and dynamic speed constraints. A mixed-integer programming model is developed and solved using a customized Non-Dominated Sorting Genetic Algorithm III with Intelligent Selection. This approach integrates multiple UAV speed adjustment strategies and route construction phases to improve energy efficiency and service timing. Results show that incorporating variable drone speeds reduces total cost by up to 19.35%, makespan by 3.85%, and UAV hover waiting time by 5.66%. The HFCV-UAV delivery system also achieves substantial carbon emission reductions, outperforming both electric and fossil-fueled vehicle systems. Furthermore, flexible time windows and intelligent speed adjustments significantly enhance operational performance. This study offers important insights into energy-aware logistics, especially for hybrid delivery systems using UAVs. Its findings are highly relevant to vehicle routing problems under carbon regulation, demonstrating how hydrogen-powered fleets and UAV coordination support cost-effective, low-emission delivery (Ren et al., 2024).

There is also another recent investigation of the Hydrogen Vehicle Routing Problem in which Abibou et al. (2024) work on the Hydrogen VRP with Time Windows (H-VRPTW) and consider vehicle

capacity, focusing on optimizing hydrogen vehicle routing within sustainable transportation networks. Their objectives are to minimize total driving costs, penalties for time window violations, and vehicle capacity constraints while accounting for the limited travel range of hydrogen vehicles and their fuel costs. The problem is designed to balance route distance and penalty costs, recognizing that exceeding travel limits increases fuel expenses. To solve their problem, a genetic algorithm (GA) is developed. Their GA starts from a randomly generated population and iteratively applies selection, crossover, and mutation to evolve optimal or near-optimal routes. The GA effectively manages multi-objective constraints, delivering time-efficient and cost-effective solutions. The robustness of the approach is proven in minimizing penalties and accounting for capacities, demonstrating practical applicability in hydrogen distribution logistics. This research underscores the role of hydrogen vehicle routing in reducing greenhouse gas emissions and managing operational challenges, offering a scalable and adaptable framework for future hydrogen supply chain optimization. As regards vehicle type, they do not mention fuel cell vehicles; their hydrogen vehicles are internal combustion engines (ICEs) that consume hydrogen, and they name it a hydrogen fleet (Abibou et al., 2024).

Knowing that utilizing each fleet type has pros and cons and in order to better categorize and understand the three fleet types considered in this thesis, Table 2.1 is provided, which shows the advantages and disadvantages of different propulsion systems inspired by (Cunanan et al., 2021). Table 2.1 categorizes the advantages and disadvantages of ICEs, EVs, and HVs across three main aspects: economic, functional, and environmental. Each aspect highlights merits or drawbacks observable for each fleet type.

Table 2.2 also shows the comparison between the current work and recent literature. In the taxonomy table, the main focus was on recent papers, mainly after 2022, aiming to compare the current thesis with other research in terms of features such as types of decisions made, fleet type and capacity, objectives to be satisfied, solution methods, mathematical model approaches, and some vehicle routing and emission features. The taxonomy table in recent literature illustrates that various papers exhibit one or a combination of features and objectives, as presented in the table. The current study identified this gap and incorporates all of these features and objectives within a single real-world case problem.

Table 2.1: Merits and drawbacks of the DVs, EVs and HVs

Category	Aspect	Powertrain technology		
		DVs	EVs	HVs
Merits	Economical	- Large market with widely available parts and vehicles. - Low initial cost - No infrastructure investment - Widely available parts and vehicles	- Lower refueling and maintenance costs - Lower infrastructure requirements than HVs	-
	Functional	- Faster refueling time than EVs - Long range and high payload	- Higher energy efficiency compared to diesel	- Higher energy efficiency - Faster refueling than EVs
	Environmental	-	- Low greenhouse gas emissions - Low local air pollution	- Low greenhouse gas emissions
Drawbacks	Economical	- High refueling and maintenance cost	- Significant infrastructure investment required - High vehicle costs than DVs	- High cost of hydrogen fuel - Substantial infrastructure investment required - Highest vehicle cost compared to alternatives
	Functional	- Low energy efficiency	- Weight and size of the large battery - Reduced cargo capacity - Limited range of travelling - Long recharging time	- Slower development of supporting technology
	Environmental	- High greenhouse gas emissions	- Emissions from electricity generation - Batteries components which are harmful for the environment - Batteries are in the category of hazardous materials for transportation	- Emissions associated with hydrogen production - Flammability and Explosiveness of the Hydrogen tanks

Table 2.2: Literature review of the last decade on VRP, E-VRP and HF-VRP

Study	(Ashtineh et al., 2023)	(Barletta et al., 2023)	(Fan et al., 2023)	(Bezzi et al., 2023)	(Kumar et al., 2023)	(Bruglieri et al., 2023)	(Nolz et al., 2022)	(Seyfi et al., 2022)	(Froger et al., 2022)
Operational Decision	Routing	✓	✓	✓	✓	✓	✓	✓	✓
	Scheduling	-	-	-	-	-	✓	-	✓
Fleet Type	DVs	✓	✓	-	-	-	-	✓	-
	EVs	-	✓	✓	✓	✓	✓	✓	✓
	HVs	-	-	-	-	-	-	-	-
Features	Cap and Trade Mechanism	-	-	-	-	-	-	-	-
	Time Window	✓	-	-	-	✓	✓	-	✓
	Split delivery	-	-	-	-	-	-	✓	-
Fleet Capacity	Homogeneous	✓	-	✓	✓	✓	✓	✓	✓
	Heterogeneous	-	✓	-	-	-	-	-	-
Time Horizon	Single	✓	✓	✓	✓	✓	-	✓	✓
	Multi	-	-	-	-	-	✓	-	-
Objective	Min Cost	✓	-	✓	✓	✓	✓	✓	-
	Min Emission	✓	-	✓	-	-	-	-	-
	Min Time	-	-	-	-	-	-	-	✓
Model Approach	MIP	-	MIP	MIP	Dynamic programming	MILP	MILP	MILP	MILP
Solution Approach	CPLEX	Monte-Carlo Tree Search	Improved Ant Colony Algorithm	Branch-and-price method	Firefly and Ant Colony Algorithm	a Random Kernel Search (RKS) mat-heuristic approach	template-based Adaptive Large Neighborhood	Variable Neighborhood Search	A two-part algorithmic framework (local search and branch-

Table 2.3: Literature review of the last decade on VRP, E-VRP and HF-VRP

Study	(Lou et al., 2024)	(Gülmez et al., 2024)	(Y. Li et al., 2024)	(Ferreira et al., 2024)	(Azadi et al., 2024)	(Ren et al., 2024)	(Su et al., 2024)	(Eslamipoor, 2024)	This study 2025
Operation Decision									
Routing	✓	✓	✓	✓	✓	✓	✓	✓	✓
Scheduling	-	-	-	-	-	✓	-	-	✓
Fleet Type									
DVs	✓	✓	-	✓	✓	-	-	✓	✓
EVs	-	✓	✓	-	-	-	✓	✓	✓
HVs	-	-	-	-	-	✓	-	-	✓
Cap and Trade Mechanism	-	-	-	-	-	-	-	✓	✓
Features									
Time Window	✓	✓	✓	-	✓	-	✓	-	✓
Split delivery	-	-	-	✓	-	-	-	-	✓
Fleet Capacity									
Homogeneous	✓	✓	✓	-	-	✓	-	✓	-
Heterogeneous	-	-	-	✓	✓	-	✓	-	✓
Time Horizon									
Single	-	✓	✓	✓	✓	✓	✓	✓	✓
Multi	✓	-	-	-	-	-	-	-	-
Objective									
Min Cost	-	✓	✓	-	✓	✓	✓	✓	✓
Min Emission	✓	-	✓	✓	✓	-	-	✓	✓
Model Approach	MILP	MILP	MILP	-	-	MILP	MILP	MINLP	MILP
Solution Approach	genetic algorithm	Meta-heuristics for MODM	Crow search algorithm	Variable neighborhood search	Goal Programming and Meta-heuristics for MODM	NSGA-III with Intelligent Selection	Genetic with Variable neighborhood search (VNS) algorithm	MPSO and NSGA-II	Gurobi

Chapter 3: Optimization Problems and Mathematical Modelling

This chapter introduces the main optimization problems and the methodologies and approaches used to address them. These optimization tasks entail developing mathematical models and forecasting certain inputs while incorporating real-world features based on the Decathlon case study. Next, the section formulates a mathematical model for the Capacitated Vehicle Routing Problem with Split Deliveries and cost estimation (Jafari et al., 2024). Next, a mathematical model is developed for a hybrid fleet, considering energy consumption, fuel usage, and fleet emissions (Jafari et al., 2025). Lastly, a forecasting model is introduced to predict demand, which is one of the inputs of the models. This enables the optimization models to be applied over a longer planning horizon.

The following provides a summary of Chapter 3, organized by subsection.

Section 3.1: This section develops a CVRPTW model in which deliveries may be split among multiple trucks, and truck arrival times are explicitly scheduled. The model's cost function is estimated using a multivariate regression approach and is integrated with social emission costs to capture both economic and environmental impacts.

Section 3.2: This section presents a CVRPTW model considering three different fleet types distinguished by their propulsion systems. The model is linearized prior to solution. Energy consumption is explicitly modeled for each fleet type, and the corresponding fuel use and emissions are calculated to identify the optimal fleet composition. A carbon cap-and-trade mechanism is incorporated to account for the trade-off between operational costs and emissions.

Section 3.3: This section applies forecasting methods based on stochastic time-series analysis and machine learning to predict demand over a long-term horizon.

Section 3.4: Subsequently, in this section a bi-objective mathematical model is developed to address a periodic routing problem, in which cost and emissions are treated as two distinct and competing objectives.

3.1. Capacitated vehicle routing problem with split delivery and cost estimation

The first optimization model in this thesis is the capacitated vehicle routing problem with time windows (CVRPTW), in which deliveries to a certain destination can be split among several trucks. The objective function of the model (to be minimized) represents the total costs of the routing problem. An estimation model based on multi-regression is investigated to better compute the economic cost of the routing. This estimation is necessary owing to the lack of precise cost data for all possible routes, in the information provided by the company. The cost function includes a component, which is the social emission effect cost, which will be described in the following sections. After describing the problem, the MILP mathematical model is presented.

3.1.1. Problem definition

The decision problem involves delivering products from a warehouse or distribution center (DC) to several stores spread over a certain territory. Specifically, the optimal route for each vehicle must be defined to deliver the products. The system under consideration is part of a distribution company's overall supply chain, and the association of stores to DCs is assumed to be fixed. This means that if there are multiple DCs, each of them corresponds to a separate delivery problem that must be solved independently of the other delivery problems (relevant to the other DCs).

Each DC receives a set of orders from the associated stores on a daily basis. Each order includes the store's name and location, the aggregate demand volume, the deadline for fulfilling the demand, and the delivery time window. Each store can place one order per day. However, it is possible to fulfill an order for a single store with more than one visit when the delivery volume (i.e., the number of pallets) exceeds a single truck's capacity. Additionally, it may be convenient to split deliveries to a single store using different trucks to optimize truck fleet utilization. Actually, split deliveries are a key feature of the model. When a split delivery occurs for a store, it is important to note that the store cannot accommodate more than one truck at a time. To ensure this, it is necessary to schedule the arrival times of trucks at the same store so that the time interval between two subsequent arrival times is greater than or equal to the time needed for the first truck to unload. In the proposed model, the demand for a given store is treated as the volume of a single category of items (pallets), even when it refers to different product classes. Each pallet is assumed to have a standard volume.

Deliveries must be made using a fleet of trucks belonging to different specific categories. Each category has specific features, including the propulsion mechanism (ICE, EV, or HV), capacity, consumption rate, and emission rate. When using EVs and HVs, it is necessary to consider that the total consumption on a given route cannot exceed the trucks' battery capacity. There may be limitations in associating truck categories with stores, as some stores may be accessible only to certain truck categories. The

number of available trucks for each category is limited. The time required to unload each truck at a store is determined by the volume (i.e., the number of pallets) to be unloaded and the type of truck. Each truck to which a set of deliveries is assigned (within the considered day) departs from the distribution center (DC) and ends the trip at the last customer on the route. The final store is the last node in the model because, after the day's deliveries, vehicles are assigned to other missions outside the scope of this model.

The delivery service for a truck within a single day has a maximum duration, which varies by truck category. The duration of a delivery service (movements plus unloading operations), hereinafter referred to as a route, can be determined based on the set of stores to be served within the route and the truck category involved. Then, the problem to be solved is that of determining the set of routes that minimize the overall cost to be paid for the considered day, fulfilling completely the demand and the various constraints above mentioned. It should be mentioned that the proportion of vehicle types is not constrained, and traffic congestion is neglected in the current model.

Since the prices for all possible routes between nodes are not available, and only historical data for frequently used routes exist, a suitable approach is needed to develop a convenient structure for the economic cost of the routes. In the following section, a method is applied to estimate the total economic cost. At a later stage (section 3.2.43.2.4), a pricing formula will be developed; however, for the current stage, cost estimation for all links is preferred.

3.1.2. Cost estimation regression

In the real case under consideration, the costs of all node-to-node connections in the network are not fully known, except for a limited subset of links. Moreover, there is no clear evidence regarding the rule or mechanism by which these available cost values can be generated. To address this data gap and the absence of a suitable model, Multiple Linear Regression (MLR) was applied to estimate the missing costs using available real data (Uyanık & Güler, 2013). Regression analysis is a statistical method used to estimate the relationship between variables that exhibit cause-and-effect dynamics. A key focus is univariate regression, which involves examining the relationship between a dependent variable and a single independent variable to formulate a linear equation that captures their interdependence.

When a model includes one dependent variable and multiple independent variables, it is called multiple linear regression (Uyanık & Güler, 2013). Clearly, the cost of each route for each truck depends on factors such as the distance between nodes and the travel time between them. In this section, we provide a multiple linear regression based on distances, travel time, and fixed costs. Based on real data, this regression was accomplished within three different models. That is:

- Based on the distance between nodes ($dist_{ij}[km]$) and fixed cost,
- Based on travel time between nodes ($t_{ij}[hour]$) and fixed cost,
- Based on the distance, travel time and fixed cost.

This analysis is performed separately for each type of truck. The estimation relies on minimizing the Sum of Squared Errors (SSE) between the estimated values and the available real costs, as shown in (3.2). The numerical analysis is presented in section 4.1. Equation (3.1) represents the linear regression in which $K1_h$ [€/km], $K2_h$ [€/hour] and $K3_h$ [€] are the coefficient of distance of the link (i, j) , coefficient of travel time of link (i, j) and fixed cost of using each type of vehicle h , respectively, and c_{ijh}^{real} is the available real cost of the link (i, j) by vehicle h . The cost of path from i to node j by vehicle type h , (c_{ijh}) is defined as the following:

$$c_{ijh} = K1_h \cdot dist_{ij} + K2_h \cdot t_{ij} + K3_h \quad \forall i \in N, j \in J, h \in H \quad (3.1)$$

$$Min E_h = \sum_{i \in N} \sum_{j \in N} \left(c_{ijh}^{real} - K1_h \cdot dist_{ij} - K2_h \cdot t_{ij} - K3_h \right)^2 \quad \forall h \in H \quad (3.2)$$

3.1.3. Social Emission Effect Cost

Since controlling pollutant emissions, particularly carbon dioxide (CO₂), is essential to addressing large-scale problems, this section employs a method from the literature to calculate emissions and convert them into monetary costs. CO₂ is selected as the most representative pollutant, and its emission cost is quantified. Integrated assessment models (IAMs), of which there are about 36 in the literature, have been extensively studied for estimating the social cost of emissions. (P. Wang et al., 2019) analyzed 578 scientific works and determined that the average social cost of CO₂ is approximately 0.0000536[€/gCO₂]. Their method for calculating emission costs considers CO₂ emission rates for three types of diesel-engine vehicles: delivery vans, medium-duty trucks, and heavy-duty vehicles. These emission rates were reported as 252, 450, and 678 [gCO₂/km], respectively (Krause et al., 2020).

Equation (3.3) is used to calculate the social emission cost for CO₂ which represented by $EC_v^{CO_2}$ based on the type of truck (v) per kilometer of travel. In Equation (3.3), $e_v^{CO_2}$ [gCO₂/km] denotes the emission of truck v (per unit distance), and EP^{CO_2} [€/gCO₂] indicates the social emission price of one gram of CO₂.

$$EC_v^{CO_2} = EP^{CO_2} e_v^{CO_2} \quad \forall v \in V \quad (3.3)$$

3.1.4. Capacitated vehicle routing problem: mathematical model

In this section, a Mixed-Integer Linear Programming (MILP) model based on real-case assumptions (section 3.1.1), is proposed (Jafari et al., 2024). The model has the following main features:

- Consideration of time windows for each store.
- Use of heterogeneous vehicles with different delivery capacities.
- Allowance for split deliveries between trucks to fulfill store orders.
- Scheduling the arrival times for split deliveries.

In this section, before presenting the mathematical model, we define the notations used, including sets, parameters (representing input and known information), and decision variables (representing the model's outputs after optimization). All the aforementioned elements are presented in Table 3.1.

Table 3.1 Sets, parameters and decision variables

Notation	Definition
<i>Sets</i>	
N	The set of all nodes (DC and Stores), $\forall i, j \in N$
$J \subseteq N$	A subset of N that include only store nodes $\forall i, j \in J$
V	The set of all trucks with different characteristics and capacities $\forall v \in V$
<i>Parameters</i>	
c_{ijv}	Cost of path from i to node j by vehicle v , $\forall i, j \in N, v \in V$
$dist_{ij}$	Distance of path from i to node j , $\forall i, j \in N$
t_{ij}	Travel time between nodes i and j $\forall i, j \in N$
d_j	Aggregate demand of the customer j $\forall j \in J$
Q_v	Capacity of truck v , $\forall v \in V$
a_j	Earliest possible arrival time at the node j , $\forall j \in J$
b_j	Latest possible arrival time at the node j , $\forall j \in J$
S_{jv}	Service/unloading time at the node j , by truck v , $\forall j \in J, v \in V$
UV	Upper bound for the number of visits in each tour
M	A large number
<i>Decision Variables</i>	
x_{ijv}	Binary variable equal to 1 if truck v includes link (i, j) , 0 otherwise

z_{ijv}	Load of truck v transferred between link (i,j)
w_{jv}	Arrival time at the node j by truck v
g_{jvl}	Binary variable equal to 1 if truck v arrives at node j before truck l , 0 otherwise

The objectives of the routing problem are defined as follows:

- Minimizing the total economic cost incurred on a given day;
- Minimizing the total social emission cost of CO2 in relation to the designated routes.

By considering the objectives, the constraints and assumptions mentioned, we have developed the following mathematical model:

$$\begin{aligned} \text{Min } Z = & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V} x_{ijv} (K1_v \text{dist}_{ij} + K2_v t_{ij} + K3_v) + \\ & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V} x_{ijv} \text{dist}_{ij} EP^{CO_2} e_v^{CO_2} \end{aligned} \quad (3.4)$$

Subject to

$$\sum_{j \in J} x_{1jv} \leq 1 \quad \forall v \in V \quad (3.5)$$

$$\sum_{\substack{i \in N \\ i \neq j}} \sum_{v \in V} x_{ijv} \geq 1 \quad \forall j \in J \quad (3.6)$$

$$z_{ijv} \leq x_{ijv} Q_v \quad \forall i \in N, j \in J, i \neq j, v \in V \quad (3.7)$$

$$\sum_{\substack{i \in N \\ i \neq j}} z_{ijv} \geq \sum_{\substack{k \in J \\ k \neq j}} z_{ikv} \quad \forall j \in J, v \in V \quad (3.8)$$

$$\sum_{i \in N} \sum_{v \in V} z_{ijv} = d_j + \sum_{k \in J} \sum_{v \in V} z_{jkv} \quad \forall j \in J \quad (3.9)$$

$$\sum_{\substack{i \in N \\ i \neq j}} x_{ijv} \geq \sum_{\substack{k \in J \\ k \neq j}} x_{jkv} \quad \forall j \in J, v \in V \quad (3.10)$$

$$w_{iv} + t_{ij} + S_{jv} - w_{jv} \leq (1 - x_{ijv}) M \quad \forall i \in N, j \in J, i \neq j, v \in V \quad (3.11)$$

$$w_{jv} \geq a_j \sum_{i \in N} x_{ijv} \quad \forall j \in J, v \in V \quad (3.12)$$

$$w_{jv} \leq b_j \sum_{i \in N} x_{ijv} \quad \forall j \in J, v \in V \quad (3.13)$$

$$w_{jv} \geq w_{jl} + S_{jl} - (1 - g_{jlv})M \quad \forall l, v \in V, l \neq v, j \in J \quad (3.14)$$

$$g_{jvl} + g_{jlv} \leq 1 \quad \forall l, v \in V, l \neq v, j \in J \quad (3.15)$$

$$g_{jvl} + g_{jlv} \geq \sum_{\substack{i \in N \\ i \neq j}} x_{ijv} + \sum_{\substack{i \in N \\ i \neq j}} x_{ijl} - 1 \quad \forall l, v \in V, l \neq v, j \in J \quad (3.16)$$

$$\sum_{\substack{i \in N \\ i \neq j}} \sum_{\substack{j \in J \\ j \neq l}} x_{ijv} \leq UV \quad \forall v \in V \quad (3.17)$$

$$\begin{aligned} x_{ijv} &\in \{0,1\}, z_{ijv} \in \mathbb{R}_+ \quad \forall i, j \in N, \forall v \in V \\ g_{jvl} &\in \{0,1\} \quad \forall j \in N, \forall v, l \in V \\ w_{jv} &\in \mathbb{R}_+ \quad \forall j \in N, \forall v \in V \end{aligned} \quad (3.18)$$

The cost to be minimized in equation (3.4) is composed of two parts: the economic cost incurred by the total transportation over one day, and the social emission cost generated by the transportation during the time horizon. Constraints (3.5) specify that each trip must start from the warehouse node, which serves as the initial node. To ensure that all store demands are met, constraints (3.6) require that each customer is visited at least once. This constraint allows for multiple deliveries to the same store, enabling split deliveries when necessary. Constraints (3.7) limit the total product volume carried by each truck, ensuring it does not exceed the truck's capacity. Constraints (3.8) ensure the balance between the inflow and outflow of load at customer node j for each truck. Moreover, (3.9) represents flow conservation, calculating the load that each truck must transfer between nodes while accounting for the demand of each customer. Constraints (3.10) govern the inflow and outflow of trucks at each customer node. Constraints (3.11)-(3.13) ensure that deliveries to customers occur within their specified time windows. Constraints (3.14)-(3.16) handle cases where a store's delivery is split among multiple trucks, ensuring that these trucks do not arrive simultaneously. Constraints (3.17) set an upper limit on the number of visits per tour, applicable when a truck is not allowed to make more than a specified number of stops for deliveries. Lastly, constraints (3.18) define the type of decision variables in the model.

3.2. Capacitated vehicle routing problem with Hybrid fleet

As electric and hydrogen-powered vehicles are increasingly adopted in the logistics and transportation sectors, companies worldwide are reevaluating the efficiency and suitability of these alternative fleets. This raises the question: which type of fleet (electric, hydrogen, or diesel) is the most effective when considering economic, environmental, and social factors? As the production and deployment of vehicles with new propulsion technologies expands in the industry, logistics companies must carefully consider

the benefits of each technology for their distribution networks. Two critical criteria, cost efficiency and environmental impact, are consistently considered when evaluating fleet composition for industrial distribution. For this reason, a pricing method has been proposed that considers transportation costs and green factors in the supply chain using the carbon cap-and-trade mechanism (Xu et al., 2017). Figure 11 shows all costs related to a mixed fleet. This work considers different types of vehicles, and, to calculate costs and emissions, it is necessary to quantify energy consumption and the resources (power, hydrogen, and fuel) required to cover it. Then, the costs and emissions required to provide these resources must be calculated. The results show that energy consumption, costs, and emissions are functions of the decision variables (e.g., routing, type of vehicle selected, mass, etc.).

In this thesis, part of the cost refers to the cost of carbon emissions. The Emissions Trading Scheme (ETS) operates on two main concepts: allowances and the cap-and-trade system. An allowance grants the right to emit a specific amount of greenhouse gases (GHGs), typically measured as one ton of carbon dioxide equivalent (CO_2e), during a certain period. Governments set a cap on total emissions, and companies that emit below their cap earn tradable carbon credits. Companies that exceed the cap must purchase these credits or face penalties. Examples of ETS programs around the world include the EU ETS (the largest program), the New Zealand ETS, the Chicago Climate Exchange, and the Montreal Climate Exchange. The cap-and-trade system encourages businesses to reduce emissions through supply chain changes or purchase credits. Emission reductions can occur at various stages of the supply chain, including product design, manufacturing, transportation, and recycling. A structured decision-making approach is essential for managing the supply chain in a cost-effective and sustainable way while meeting GHG targets (Chaabane et al., 2011). Refer to section 2.1.2 for a more detailed explanation of the carbon cap-and-trade mechanism.

On the other hand, Figure 11 shows that another category of cost in this study is transportation cost. This category includes expenses related to fuel/energy consumption, depreciation, maintenance, and driver wages for different paths in the distribution system. Fuel consumption, in particular, depends on various factors, such as the characteristics of the routes, which are similar for all hybrid fleets. Additionally, factors specific to different vehicle types exist, varying based on powertrain configurations, as well as differences in size and capacity within each category (Ehsani et al., 2017).

This part of the thesis proposes a mathematical optimization problem based on a real-world case to minimize the total distribution cost from a warehouse to a group of pre-assigned stores. The mathematical formulation incorporates key features such as split delivery and scheduling arrival times within specific time windows for each store. The costs addressed by the problem include total transportation costs and CO_2 emission trade costs, which are calculated using a carbon cap-and-trade mechanism. Energy and fuel consumption, as well as carbon emissions, are computed for different

vehicle types, including Internal Combustion Engine (ICE) vehicles, Diesel Engine (DE) vehicles, Electric (EV) vehicles, and Hydrogen (HV) vehicles. The costs are considered separately for each class of vehicles. The mathematical model is implemented for a real-world case, and the results demonstrate the percentage usage of each fleet type, highlighting the trade-off between transportation and emission costs. The findings are analyzed, and the managerial insights derived from the results are discussed. The highlights of this version of the model's contribution could be listed as follows:

- Development of a Mixed-Integer Linear Programming (MILP) model for the Hybrid Fleet Vehicle Routing Problem with Time Windows (HF-VRPTW), incorporating constraints on arrival times and allowing split deliveries to stores.
- Integration of carbon cap-and-trade emissions into the model and comparison with other transportation cost components.
- Proposal of a pricing formula for internal combustion engine (ICE) vehicles, electric vehicles (EVs), and hydrogen vehicles (HVs), accounting for energy consumption, fuel usage, and emissions.
- Implementation and validation of the mathematical model through a real-world case study, focusing on the daily distribution system of Decathlon.

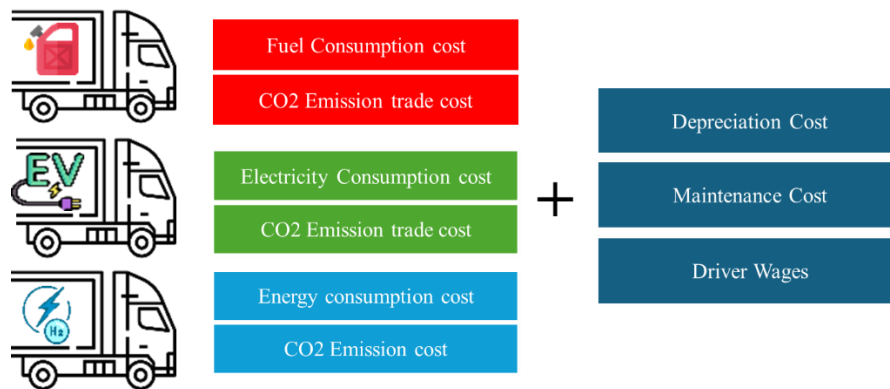


Figure 11. Hybrid fleet transportation cost breakdown.

3.2.1. Energy/Fuel consumption of Hybrid fleet

This section calculates the energy required and emissions for a given vehicle type (ICEs, EVs, and HVs) over the logistics network. These calculations are fundamental to define optimal routes based on cost and emissions while considering each vehicle's driving range. For EVs in particular, energy consumption is calculated for each network link as a function of specific road and vehicle

characteristics. Of course, the total consumption along the entire route must not exceed the available energy, since en-route charging EVs and HVs is not included in this mathematical model. Additionally, the overall energy consumption is supplied by the electrical grid, which entails costs and emissions. In this case, emissions depend on the energy mix used to generate electricity on the grid. Similarly, for hydrogen-based vehicles, the power required to operate an electrolyzer to produce the hydrogen needed by the fuel cell must be calculated. This should be calculated for each link in the network and for each vehicle type. For internal combustion engines (ICEs), energy consumption and emissions are calculated based on fuel consumption per unit of the distance. Several factors influence this calculation, including vehicle type and efficiency, road characteristics, and emission factors, which will be discussed in subsequent subsections.

3.2.2. Internal Combustion Engine (ICE)

3.2.2.1. ICE energy consumption

In this section, we propose a method based on (Bektaş & Laporte, 2011; Qiu et al., 2017) to calculate the energy consumption and corresponding fuel usage of ICE vehicles, which are considered as transportation modes within the current model and distribution system as shown in Equation (3.19). This method computes the total energy consumption, denoted by E_{ijv}^{DVs} [kWh] on arc (i,j) , based on a vehicle-specific constant for consumption of ICE truck v on arc (i,j) and an arc-specific (route-specific) constant for ICE truck v consumption on arc (i,j) , denoted as α_{ijv}^{DVs} [kWh/m] and β_{ijv}^{DVs} [kWh/kg·m], respectively. The first coefficient reflects the relationship between consumption, vehicle type, and the specific characteristics of the link. The second coefficient additionally accounts for the vehicle's weight and the weight of the transported load. In the following, the methods for computing the coefficients are presented.

To calculate α_{ijv}^{DVs} that is shown by equation (3.20), the following information is considered: the speed of a vehicle over arc as l_{ij}/t_{ij} [m/s]. It should be noted that the velocity is assumed to be independent of the vehicle type. The other elements are as the frontal surface area of vehicle v , namely A_v [m²], the coefficient of drag for vehicle v , namely C_v^d , the air density ρ [kg/m³], and P_v^{acc} [kWh] that represents the internal power consumption (like air conditioner consumption) of the vehicle v .

In order to compute β_{ijv}^{DVs} (see equation (3.21)), various aspects are taken into account, such as ac_v , that represents the acceleration of the vehicle [m/s²], and g , C_v^r and θ_{ij} , that are the gravity acceleration [m/s²], the coefficient of rolling resistance for vehicle v , and the angle of the mean slope of the arc (i,j) , respectively. The total weight of a truck on each arc (i,j) must be considered when calculating the total energy consumption. This weight is given by $(z_{ijv}\bar{\omega} + m_v^o)$ where m_v^o is the weight of the empty truck v [kg] and $\bar{\omega}$ is the weight of an standard pallet [kg] that could be multiplied by the number of pallet

z_{ijv} carried out by the vehicle on the considered link. In fact, z_{ijv} , is one of the main decision variables in the mathematical model, as will be discussed in the upcoming sections.

$$E_{ijv}^{DVs} = \left(\alpha_{ijv}^{DVs} + \beta_{ijv}^{DVs} (z_{ijv} \bar{\omega} + m_v^o) \right) l_{ij} \quad i, j \in N; v \in V^{DVs} \quad (3.19)$$

$$\alpha_{ijv}^{DVs} = \frac{(l_{ij})^2 C_v^d A_v \rho}{2(t_{ij})^2} + \frac{P_v^{acc} t_{ij}}{l_{ij}} \quad i, j \in N; v \in V^{DVs} \quad (3.20)$$

$$\beta_{ijv}^{DVs} = ac_v + g \left(C_v^r \cos \theta_{ij} + \sin \theta_{ij} \right) \quad i, j \in N; v \in V^{DVs} \quad (3.21)$$

3.2.2.2. . ICEs Fuel consumption and emission

To convert energy consumption into fuel consumption, expressed in F_{ijv}^{DVs} [kg], a simple conversion rule is applied, as represented by Equation (3.22). In this equation, LHV^{DVs} [kWh/kg] represents the lower heating value of the fuel used by ICE vehicles and η^{DVs} is the overall operating efficiency of the ICE fleet. The amount of emissions, expressed in C_{ijv}^{DVs} [kgCO₂], is derived using a coefficient that represents the unit carbon emission of ICE vehicles, measured in F^{DVs, CO_2} [kg/kW]. By multiplying the total energy consumption by the unit carbon emission per unit of energy consumption, the CO₂ emission of the ICE vehicles is obtained, as shown in Equation (3.23).

$$F_{ijv}^{DVs} = \frac{E_{ijv}^{DVs}}{\eta^{DVs} LHV^{DVs}} \quad i, j \in N; v \in V^{DVs} \quad (3.22)$$

$$C_{ijv}^{DVs} = F^{DVs, CO_2} E_{ijv}^{DVs} \quad i, j \in N; v \in V^{DVs} \quad (3.23)$$

3.2.2.3. Electric Vehicle

The electricity consumption of electric vehicles along a path depends on both vehicle characteristics and path properties. Emissions are then calculated based on the energy mix of the electrical grid supplying the charging stations. To quantify consumption, the following parameters must be defined and incorporated into the overall optimization problem:

- Distance between nodes l_{ij} [m].
- Travel time between the nodes t_{ij} [s].
- The speed of the EVs l_{ij}/t_{ij} [km/h] (considered as independent from the type of vehicle).

- The total weight of truck v , $(z_{ijv}\bar{\omega} + m_v^o)$ including the curb mass of the truck v , m_v^o [kg] and the load of the truck (z_{ijv} is the number of pallets and $\bar{\omega}$ is the average weight of one pallet [kg]).
- The slope of the arc θ_{ij} (the gradient of the terrain).
- Efficiency coefficients associated with different energy conversions: , including transmission efficiency, η_v^{te} , electric motor efficiency η_v^e , and the power converter efficiency of each vehicle η_v^{in} .
- The regenerative braking power coefficient for each vehicle K_v .

The energy consumption E_{ijv}^{EVs} [kWh] can be calculated on the basis of models already introduced in the two recent works (Ehsani et al., 2018; Ferro et al., 2020) as follows:

$$E_{ijv}^{EVs} = \left(\alpha_{ijv}^{EVs} + \beta_{ijv}^{EVs} (z_{ijv}\bar{\omega} + m_v^o) \right) t_{ij} \quad i, j \in N; v \in V^{EVs} \quad (3.24)$$

$$\alpha_{ijv}^{EVs} = \left(\frac{(l_{ij})^3 C_v^d \rho A_v}{\eta_v^{te} \eta_v^e \eta_v^{in} (t_{ij})^3} + P_v^{acc} \right) S^d + \left(\frac{(l_{ij})^3 K_v \eta_v^{te} \eta_v^e \eta_v^{in} C_v^d \rho A_v}{2(t_{ij})^3} - P_v^{acc} \right) S^c \quad i, j \in N; v \in V^{EVs} \quad (3.25)$$

$$\beta_{ijv}^{EVs} = \left(\left(\frac{l_{ij} g}{\eta_v^{te} \eta_v^e \eta_v^{in} t_{ij}} \right) (C_v^r \cos \theta_{ij} + \sin \theta_{ij}) \right) S^d + \left(\left(\frac{K_v l_{ij} \eta_v^{te} \eta_v^e \eta_v^{in} g}{2 t_{ij}} \right) (C_v^r \cos \theta_{ij} + \sin \theta_{ij}) \right) S^c \quad i, j \in N; v \in V^{EVs} \quad (3.26)$$

where:

- equation (3.24) represents the consumption of EVs over arc (i,j) ,
- α_{ijv}^{EVs} [kW] in Equation (3.25) is the baseline electricity consumption coefficient for truck v on arc (i,j) which is a function of drag C_v^d for vehicle v and ρ as the air density [kg/m³], and A_v as the frontal surface area of vehicle v [m²]. P_v^{acc} represents the internal power consumption of the vehicle v .

- equation (3.26) defines the electricity consumption coefficient associated with the cargo mass on arc (i,j) , measured in β_{ijv}^{EVs} [kW/kg]. For each arc in the graph, the terrain's gradient can be divided into two components, denoted as S^c indicates the energy contributing to battery recharging along the arc, whereas S^d represents the energy resulting in battery discharge ($0 \leq S^c, S^d \leq 1$ and $S^c + S^d = 1$). K and g in the equation (3.26) are the regenerative braking power coefficient for each vehicle v and the gravity constant [m/s²], respectively.

To calculate the indirect CO₂ emissions C_{ijv}^{EVs} [kgCO₂] incurred by the charging the EVs (located the depot), equation (3.27) is used in which F^{EVs, CO_2} [kg/kWh] is the CO₂ emission factor of EVs.

$$C_{ijv}^{EVs} = F^{EVs, CO_2} E_{ijv}^{EVs} \quad i, j \in N; v \in V^{EVs} \quad (3.27)$$

3.2.2.4. Hydrogen Vehicle

This section focuses on determining the energy and hydrogen consumption of hydrogen vehicles (HVs). Like battery electric vehicles (BEVs), HVs have a powertrain consisting of an electric motor directly coupled to the chassis. This eliminates the need for a conventional gearbox and enables regenerative braking. The energy system comprises a high-voltage battery, a fuel cell, and a hydrogen tank. The battery handles sudden power demands while the fuel cell converts hydrogen into electricity. This provides high energy density and rapid refueling for an extended driving range. Advanced power electronics manage the flow of energy between these components to ensure efficiency and reliability. For more detailed explanation of this fleet type refer to section 2.2.2 and Figure 10.

The energy consumption of HVs is computed using the same methodology as EVs, with parameter values tailored to the characteristics of HVs. E_{ijv}^{HVs} [kWh] denotes the total energy consumed by using HV v on arc (i,j) in equation (3.28) where terms α_{ijv}^{HVs} [kW] and β_{ijv}^{HVs} [kW/kg] are calculated as in equations (3.29) and (3.30), respectively. Since the drivetrain configuration of fuel cell electric vehicles (FCEVs) or HVs is similar to that of EVs, the method for computing energy consumption is also similar (Waseem et al., 2023).

$$E_{ijv}^{HVs} = \left(\alpha_{ijv}^{HVs} + \beta_{ijv}^{HVs} (z_{ijv} \bar{\omega} + m_v^o) \right) t_{ij} \quad i, j \in N; v \in V^{HVs} \quad (3.28)$$

$$\alpha_{ijv}^{HVs} = \left(\frac{(l_{ij})^3 C_v^d \rho A_v}{\eta_v^{te} \eta_v^e \eta_v^{in} (t_{ij})^3} + P_v^{acc} \right) S^d + \left(\frac{(l_{ij})^3 K_v \eta_v^{te} \eta_v^e \eta_v^{in} C_v^d r A_v}{2(t_{ij})^3} - P_v^{acc} \right) S^c \quad i, j \in N; v \in V^{HVs} \quad (3.29)$$

$$\begin{aligned} \rho_{ijv}^{HVs} = & \left(\left(\frac{l_{ij} g}{\eta_v^{te} \eta_v^e \eta_v^{in} t_{ij}} \right) (C_v^r \cos \theta_{ij} + \sin \theta_{ij}) \right) S^d \\ & + \left(\left(\frac{K_v l_{ij} \eta_v^{te} \eta_v^e \eta_v^{in} g}{2 t_{ij}} \right) (C_v^r \cos \theta_{ij} + \sin \theta_{ij}) \right) S^c \end{aligned} \quad i, j \in N; v \in V^{HVs} \quad (3.30)$$

To calculate the cost associated with hydrogen consumption in the hydrogen fleet, the total amount of hydrogen used must first be determined. In order to convert the energy to H₂ and compute the total H₂ consumption which defined as (F_{ijv}^{HVs} [kg]) the lower heating value of the hydrogen fleet LHV^{H2} [kWh/kg] and the overall operating efficiency of the hydrogen fleet η^{H2} must be used in equation (3.31) that computes the H₂ consumption in it (Ennassiri et al., 2023). Hydrogen production for HVs can be achieved through multiple methods, such as coal gasification, electrolysis powered by the grid, hydro, solar, wind, or nuclear sources, biomass gasification, and steam reforming of natural gas (Dulău, 2023). All these hydrogen production methods generate CO₂ emissions, which will be analyzed in detail later in the thesis to assess how differences in production affect total emissions in a real case study. To compute the total CO₂ emission incurred by using HVs, equation (3.32) can be used, in which F^{HVs, CO_2} [kgCO₂/kWh] is the coefficient that provides the CO₂ emission per unit of energy.

$$F_{ijv}^{HVs} = \frac{E_{ijv}^{HVs}}{\eta^{H2} LHV^{H2}} \quad i, j \in N; v \in V^{HVs} \quad (3.31)$$

$$C_{ijv}^{HVs} = F^{HVs, CO_2} E_{ijv}^{HVs} \quad i, j \in N; v \in V^{HVs} \quad (3.32)$$

3.2.3. Problem Definition

Before examining the details of the mathematical model, Table 3.2 presents definitions for the notations used, including sets, parameters (representing input and known information), and decision variables (whose values are to be determined through the optimization process).

The developed mathematical model of the real case scenario involves two types of nodes, warehouses and stores, which are distributed across multiple cities. Stores are assigned to distribution centers in advance, and this assignment is a part of the data input. Thus, the model focuses exclusively on deliveries from warehouses to their associated stores. Each store issues orders either the night before or at the beginning of each day. Vehicle categories and driver-related constraints also limit the number of stores that can be served on a single route. Each truck begins its route at a designated depot and ends at the final store. All the other assumptions of the problem are defined in detail in section 3.1.1.

Table 3.2. Sets, parameters and decision variables.

Notation	Definition
<i>Sets</i>	

N	The set of all nodes (DC and Stores), $\forall i, j \in N$
$DC \subseteq N$	A subset of N that includes only DC nodes $\forall i, j \in DC$
$J \subseteq N$	A subset of N that includes only store nodes $\forall i, j \in J$
$V = V^{DVs} \cup V^{EVs} \cup V^{HVs}$	The set of all trucks with different characteristics and capacities $\forall v \in V$
$V^{DVs} / V^{EVs} / V^{HVs}$	A subset of V that includes only DVs/ EVs/ HVs
<i>Parameters</i>	
E_{ijv}^{DVs}	The energy consumption of traveling from i to node j by ICE vehicle v , [kWh], $\forall i, j \in N, v \in V$
E_{ijv}^{EVs}	The energy consumption of traveling from i to node j by Electric vehicle v , [kWh], $\forall i, j \in N, v \in V$
E_{ijv}^{HVs}	The energy consumption of traveling from i to node j by hydrogen vehicle v , [kWh], $\forall i, j \in N, v \in V$
α_{ijv}^{DVs}	Vehicle-specific constant for consumption of ICE truck v on arc (i, j) [kWh/m], $\forall i, j \in N, v \in V$
β_{ijv}^{DVs}	Arc-specific constant for ICE truck v consumption on arc (i, j) [kWh/kg·m], $\forall i, j \in N, v \in V$
α_{ijv}^{EVs}	Baseline electricity consumption coefficient for truck v on arc (i, j) [kW], $\forall i, j \in N, v \in V$
β_{ijv}^{EVs}	Sensitivity coefficient for electricity consumption relative to the mass of the cargo on arc (i, j) , [kW/kg], $\forall i, j \in N, v \in V$
α_{ijv}^{HVs}	Baseline hydrogen consumption coefficient for truck v on arc (i, j) [kW], $\forall i, j \in N, v \in V$
β_{ijv}^{HVs}	Sensitivity coefficient for hydrogen consumption relative to the mass of the cargo on arc (i, j) [kW/kg], $\forall i, j \in N, v \in V$
F_{ijv}^{DVs}	Amount of fuel consumption of ICT vehicle v on arc (i, j) [kg], $\forall i, j \in N, v \in V$
F_{ijv}^{HVs}	Amount of H ₂ consumption of HV vehicle v on arc (i, j) [kg], $\forall i, j \in N, v \in V$
C_v^d	Coefficient of drag for vehicle v , $\forall v \in V$
C_v^r	Coefficient of rolling resistance for vehicle v , $\forall v \in V$
A_v	Frontal surface area of vehicle v , $\forall v \in V$ [m ²]
ρ	Air density, which is a constant and does not vary by vehicle [kg/m ³]
ac_v	Represents the acceleration of the vehicle in meters per second, $\forall v \in V$, [m/s ²]
g	Gravity constant, [m/s ²]
θ_{ij}	The angle of the arc (i, j) , $\forall i, j \in N$
η_v^{te}	The transmission efficiency of each vehicle v , $\forall v \in V$
η_v^e	The electrical motor efficiency of each vehicle v , $\forall v \in V$
η_v^{in}	The power converter efficiency of each vehicle v , $\forall v \in V$
p_v^{acc}	The internal power consumption of the vehicle v , $\forall v \in V$, [kWh]
LHV^{DVs}	the lower heating value for ICE vehicle [kwh/kg]
η^{DVs}	overall operating efficiency of the ICE fleet
η^{H2}	overall operating efficiency of the fuel cell
LHV^{H2}	the lower heating value for hydrogen vehicle [kwh/kg]
S^d	The contribution to discharge the battery on arc (i, j) , $\forall i, j \in N$

S^c	The contribution to recharge the battery $(i,j) \forall i,j \in N$
K_v	Regenerative braking power coefficient for each vehicle $v \forall v \in V$
l_{ij}	Distance of path from i to node $j, \forall i,j \in N$
t_{ij}	Travel time between nodes i and $j \forall i,j \in N$
d_j	Aggregate demand of the customer $j \forall j \in J$
Q_v	Capacity of truck v , [number of pallets] $\forall v \in V$
a_j	Earliest possible arrival time at the node $j, \forall j \in J$
b_j	Latest possible arrival time at the node $j, \forall j \in J$
S_{jv}	Service/unloading time at the node j , by truck $v, \forall j \in J, v \in V$ [h]
$u_v^{EVs, cap}$	The maximum battery capacity of the vehicle $v, \forall v \in V$ [kWh]
$u_v^{HVs, cap}$	The maximum H ₂ capacity of the vehicle $v, \forall v \in V$ [kg]
$p^{DVs, fuel}$	Unit price of the fuel [€]
$p^{DVs, dep}$	ICE truck depreciation price [€/km]
$p^{DVs, ma}$	ICE truck maintenance price [€/km]
$p^{DVs, drive}$	ICE truck driver price [€/h]
$p^{Electricity}$	Unit price of the electricity for charging an electric vehicle [€]
$p^{EVs, dep}$	Electric truck depreciation price [€/km]
$p^{EVs, ma}$	Electric truck maintenance price [€/km]
$p^{EVs, drive}$	Electric truck driver price [€/h]
p^H	Unit price of the Hydrogen [€]
$p^{HVs, dep}$	Hydrogen truck depreciation price [€/km]
$p^{H, ma}$	Hydrogen truck maintenance price [€/km]
$p^{HVs, drive}$	Hydrogen truck driver price [€/h]
F^{DVs, CO_2}	CO ₂ emission factor of ICE trucks [kg/kWh]
F^{EVs, CO_2}	CO ₂ emission factor of charging electric trucks [kg/kWh]
F^{HVs, CO_2}	CO ₂ emission factor of charging hydrogen trucks [kg/kWh]
E^{cap}	Maximum free capacity of CO ₂ emission [kg]
p^{CO_2}	Unit CO ₂ market price [€/kgCO ₂]
E^{max}	Upper bound for carbon emission [kg]
$Cost^{DVs}$	Transportation costs related to DVs [€]
$Cost^{EVs}$	Transportation costs related to EVs [€]
$Cost^{HVs}$	Transportation costs related to HVs [€]
$Emission^{DVs}$	Emission related to DVs over link (i,j) using vehicle $v, \forall i,j \in N, v \in V$ [kg]
$Emission^{EVs}$	Emission related to EVs over link (i,j) using vehicle $v, \forall i,j \in N, v \in V$ [kg]
$Emission^{HVs}$	Emission related to HVs over link (i,j) using vehicle $v, \forall i,j \in N, v \in V$ [kg]
ω	Weight of each pallet [kg]
m_v^o	weight of empty truck $v, \forall v \in V$ [kg]

UV	Upper bound for the number of visits on each tour
M	A large number
<i>Decision Variables</i>	
x_{ijv}	Binary variable equal to 1 if truck v includes link (i,j) , 0 otherwise, $\forall i,j \in N, v \in V$
z_{ijv}	Load of truck v transferred between link (i,j) , $\forall i,j \in N, v \in V$
w_{jv}	Arrival time at the node j by truck v , $\forall i,j \in N, v \in V$
y_{ijv}	Auxiliary decision variable for the linearization, $\forall i,j \in N, v \in V$
λ_{jvl}	Binary variable equal to 1 if truck v arrives at node j before truck l , 0 otherwise, $\forall j \in N, v, l \in V$

3.2.4. The overall cost function

A key aspect of this thesis, and of its industrial case, is the definition of a comprehensive cost function. As discussed earlier in Section 3.1.2, forecasting (multi linear regression) was used to estimate costs. Here, we propose a detailed formula for computing costs that incorporates all aspects of energy consumption across the different fleet types. The optimization problem considered in this section focuses on the total cost composed of:

- Transportation expenses
- Costs associated with CO₂ emissions trading in the carbon market.

In the following subsections, transportation and emissions costs are presented and analyzed separately.

3.2.4.1. Transportation costs

Transportation costs depend on several factors, including fuel or energy consumption for each vehicle type, driver wages, depreciation over a given time horizon, and maintenance expenses. These costs vary by vehicle type, particularly with respect to the powertrain, and may also differ across a heterogeneous fleet with varying capacities and sizes. These factors are linearly related to two key elements:

- a. the travel time between nodes;
- b. the distance between nodes.

For example, driver wages depend on both driving and stoppage hours (time dependent), while maintenance costs are largely determined by the distance to travel (distance dependent). The depreciation cost of each vehicle is to be derived for each kilometer of traveling. Fuel consumption is

calculated differently for the fleets: for ICE vehicles, it is based on distance traveled, whereas for EVs and HVs, it is based on the travel time along the routes. Taking the aforementioned factors into account, Equation (3.33) presents the total transportation cost, while Equations (3.34), (3.35) and (3.36) define the transportation costs for each of the three fleets individually. All notations have been introduced in the Table 3.2.

$$\text{Transportation cost} = \text{Cost}^{DV's} + \text{Cost}^{EV's} + \text{Cost}^{HV's} \quad (3.33)$$

$$\text{Cost}^{DV's} = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DV's}} \left(F_{ijv}^{DV's} P^{fuel} + P^{DV's,dep} l_{ij} + P^{DV's,ma} l_{ij} + P^{DV's,drive} (t_{ij} + S_{jv}) \right) x_{ijv} \quad (3.34)$$

$$\text{Cost}^{EV's} = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EV's}} \left(F_{ijv}^{EV's} P^{Electricity} + P^{EV's,dep} l_{ij} + P^{EV's,ma} l_{ij} + P^{EV's,drive} (t_{ij} + S_{jv}) \right) x_{ijv} \quad (3.35)$$

$$\text{Cost}^{HV's} = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HV's}} \left(F_{ijv}^{HV's} P^{H2} + P^{HV's,dep} l_{ij} + P^{HV's,ma} l_{ij} + P^{HV's,drive} (t_{ij} + S_{jv}) \right) x_{ijv} \quad (3.36)$$

3.2.4.2. Emission trade cost (Carbon Cap and Trade Mechanism)

In this thesis, the cost of CO₂ emissions is evaluated using a cap-and-trade mechanism. Under this system, a maximum limit (cap) is imposed on greenhouse gas emissions. Companies must either reduce their emissions to remain within the cap or purchase tradable carbon credits from others who emit less, thereby creating an incentive for cost-effective emission reductions (see section 2.1.2). On this basis, Equation (3.37) is applied to evaluate carbon cap-and-trade emissions. If total emissions exceed the allocated capacity, the equation yields a positive value that is added to the transportation cost. Conversely, if emissions are below the assigned capacity, Equation (3.37) yields a negative value, allowing the surplus capacity to offset transportation costs according to the prevailing carbon market price. In the carbon cap-and-trade mechanism, the fluctuating market price of carbon plays a critical role. When the carbon unit price is high, companies are incentivized to remain within their emission limits. To achieve this, they may make a fleet transition towards greener technologies or reduce production and delivery activities, as the trade-off between production and emissions costs forces them to limit overall output. Depending on the case, fluctuations in carbon prices can lead to different outcomes, such as the selection of alternative fleet types and sizes, or variations in the optimal routes generated by the model that is observable in the upcoming section. To better understand the total emission separately, the components of the total emission are shown in the equation (3.38). Then the detailed emission computation based on the energy consumption is showed in the equations (3.39), (3.40) and (3.41) for ICEs, EVs and HVs respectively.

$$\text{Emission trade cost of } CO_2 = P^{CO_2} (Total\ Emission - E^{cap}) \quad (3.37)$$

$$Total\ Emission = Emission^{DVs} + Emission^{EVs} + Emission^{HVs} \quad (3.38)$$

$$Emission^{DVs} = F^{DVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} E_{ijv}^{DVs} x_{ijv} \quad (3.39)$$

$$Emission^{EVs} = F^{EVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} E_{ijv}^{EVs} x_{ijv} \quad (3.40)$$

$$Emission^{HVs} = F^{HVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} E_{ijv}^{HVs} x_{ijv} \quad (3.41)$$

By combining the transportation cost described in section 3.2.4.1 with the emission trading cost derived from the cap-and-trade mechanism in Section 3.2.4.2, the total cost can be calculated as shown in Equation (3.42). A detailed breakdown of the total cost incorporating all factors of pricing is presented in (3.43). As can be seen in equation (3.43), in the formula involving two decision variables x_{ijv} (binary) and z_{ijv} (continues), certain terms are multiplied, which results in the mathematical model becoming nonlinear. This aspect will be addressed in the section 3.2.5.

$$Total\ Cost = Transportation\ cost + Emission\ trade\ cost\ of\ CO_2 \quad (3.42)$$

$$\begin{aligned} Total\ cost = & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left(P^{DVs, fuel} \frac{\alpha_{ijv}^{DVs} l_{ij}}{\eta_{DVs} LHV^{DVs}} + P^{DVs, fuel} \frac{\beta_{ijv}^{DVs} l_{ij} (z_{ijv} \omega + m_v^{\circ})}{\eta_{DVs} LHV^{DVs}} + P^{DVs, dep} l_{ij} + P^{DVs, ma} l_{ij} + P^{DVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv} + \\ & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left[P^{Electricity} \alpha_{ijv}^{EVs} t_{ij} + P^{Electricity} \beta_{ijv}^{EVs} t_{ij} (z_{ijv} \omega + m_v^{\circ}) + P^{EVs, dep} l_{ij} + P^{EVs, ma} l_{ij} + P^{EVs, drive} (t_{ij} + S_{jv}) \right] x_{ijv} + \\ & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left(P^{HVs} \frac{\alpha_{ijv}^{HVs} t_{ij}}{\eta_{H_2} LHV^{H_2}} + P^{HVs} \frac{\beta_{ijv}^{HVs} t_{ij} (z_{ijv} \omega + m_v^{\circ})}{\eta_{H_2} LHV^{H_2}} + P^{HVs, dep} l_{ij} + P^{HVs, ma} l_{ij} + P^{HVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv} + \\ & \left[\begin{aligned} & F^{DVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left[\alpha_{ijv}^{DVs} l_{ij} x_{ijv} + \beta_{ijv}^{DVs} l_{ij} (z_{ijv} \omega + m_v^{\circ}) x_{ijv} \right] + \\ & F^{EVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left[\alpha_{ijv}^{EVs} t_{ij} x_{ijv} + \beta_{ijv}^{EVs} t_{ij} (z_{ijv} \omega + m_v^{\circ}) x_{ijv} \right] + \\ & F^{HVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^*} \left[\alpha_{ijv}^{HVs} t_{ij} x_{ijv} + \beta_{ijv}^{HVs} t_{ij} (z_{ijv} \omega + m_v^{\circ}) x_{ijv} \right] \end{aligned} \right] - E^{cap} P^{CO_2} \end{aligned} \quad (3.43)$$

3.2.5. Hybrid fleet capacitated vehicle routing problem mathematical model

This section presents the overall optimization model, following the structure proposed by (Jafari et al., 2025). Before introducing the mathematical model, the issue of nonlinearity highlighted earlier (at the end part of section 3.2.4.2) is revisited along with the approach adopted to handle it.

Referring to equation (3.43) which is the breakdown of the cost function, we observe a multiplication of binary decision variable x_{ijv} (representing the routes) and continuous variable z_{ijv} (representing the truck loads on the arcs). In order to linearize the non-linear terms $x_{ijv}z_{ijv}$ before solving the problem the following process is applied.

The linearization process consists in introducing an auxiliary variable $y_{ijv} = x_{ijv}z_{ijv}$ in the model. Each occurrence of the non-linear term ($x_{ijv}z_{ijv}$) is replaced by this auxiliary variable y_{ijv} , while two additional constraints, namely Equations (3.57) and (3.58), are imposed to preserve equivalence.. Equation (3.57) prevents any artificial inflation of y_{ijv} beyond z_{ijv} . Equation (3.58), a big M constraint, is used for linearization to enforce dependencies between decision variables and ensures that y_{ijv} can take the value of z_{ijv} only when the corresponding binary variable x_{ijv} is active ($x_{ijv}=1$).

This procedure transforms nonlinear relationships into a linear form. After linearization, the resulting formulation becomes a Mixed-Integer Linear Programming (MILP) model for the capacitated vehicle routing problem, which can be expressed as follows:

$$\begin{aligned}
 & \min Z \\
 & = \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} \left[\left(P^{DVs, fuel} \left(\frac{l_{ij} (\alpha_{ijv}^{DVs} + \beta_{ijv}^{DVs} m_v^o)}{\eta^{DVs} LHV^{DVs}} \right) + P^{DVs, dep} l_{ij} + P^{DVs, ma} l_{ij} + P^{DVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv} + P^{DVs, fuel} \frac{\beta_{ijv}^{DVs} l_{ij} \omega}{\eta^{DVs} LHV^{DVs}} y_{ijv} \right] + \\
 & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} \left[\left(P^{Electricity} (t_{ij} (\alpha_{ijv}^{EVs} + \beta_{ijv}^{EVs} m_v^o)) + P^{EVs, dep} l_{ij} + P^{EVs, ma} l_{ij} + P^{EVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv} + P^{Electricity} \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv} \right] + \\
 & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} \left[\left(P^{HVs} \left(\frac{t_{ij} (\alpha_{ijv}^{HVs} + \beta_{ijv}^{HVs} m_v^o)}{\eta^{HVs} LHV^{HVs}} \right) + P^{HVs, dep} l_{ij} + P^{HVs, ma} l_{ij} + P^{HVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv} + P^{HVs} \frac{\beta_{ijv}^{HVs} t_{ij} \omega}{\eta^{H2} LHV^{H2}} y_{ijv} \right] + \\
 & \left[\left(F^{DVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} [(\alpha_{ijv}^{DVs} + \beta_{ijv}^{DVs} m_v^o) l_{ij} x_{ijv} + \beta_{ijv}^{DVs} l_{ij} \omega y_{ijv}] + \right. \right. \\
 & \left. F^{EVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} [(\alpha_{ijv}^{EVs} + \beta_{ijv}^{EVs} m_v^o) t_{ij} x_{ijv} + \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv}] + \right. \\
 & \left. F^{HVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} [(\alpha_{ijv}^{HVs} + \beta_{ijv}^{HVs} m_v^o) t_{ij} x_{ijv} + \beta_{ijv}^{HVs} t_{ij} \omega y_{ijv}] \right) - E^{cap} \right] P^{CO_2}
 \end{aligned} \tag{3.44}$$

Subject to

$$\sum_{j \in J} x_{ijv} \leq 1 \quad \forall i \in DC, v \in V \quad (3.45)$$

$$\sum_{\substack{i \in N \\ i \neq j}} \sum_{v \in V} x_{ijv} \geq 1 \quad \forall j \in J \quad (3.46)$$

$$z_{ijv} \leq x_{ijv} Q_v \quad \forall i \in N, j \in J, i \neq j, v \in V \quad (3.47)$$

$$\sum_{\substack{i \in N \\ i \neq j}} z_{ijv} \geq \sum_{\substack{k \in J \\ k \neq j}} z_{jkv} \quad \forall j \in J, v \in V \quad (3.48)$$

$$\sum_{i \in N} \sum_{v \in V} z_{ijv} = d_j + \sum_{k \in J} \sum_{v \in V} z_{jkv} \quad \forall j \in J \quad (3.49)$$

$$\sum_{\substack{i \in N \\ i \neq j}} x_{ijv} \geq \sum_{\substack{k \in J \\ k \neq j}} x_{jkv} \quad \forall j \in J, v \in V \quad (3.50)$$

$$w_{iv} + t_{ij} + S_{jv} - w_{jv} \leq (1 - x_{ijv}) M \quad \forall i \in N, j \in J, i \neq j, v \in V \quad (3.51)$$

$$w_{jv} \geq a_j \sum_{i \in N} x_{ijv} \quad \forall j \in J, v \in V \quad (3.52)$$

$$w_{jv} \leq b_j \sum_{i \in N} x_{ijv} \quad \forall j \in J, v \in V \quad (3.53)$$

$$w_{jv} \geq w_{jl} + S_{jl} - (1 - \lambda_{jvl}) M \quad \forall l, v \in V, l \neq v, j \in J \quad (3.54)$$

$$\lambda_{jvl} + \lambda_{jlv} \leq 1 \quad \forall l, v \in V, l \neq v, j \in J \quad (3.55)$$

$$\lambda_{jvl} + \lambda_{jlv} \geq \sum_{\substack{i \in N \\ i \neq j}} x_{ijv} + \sum_{\substack{i \in N \\ i \neq j}} x_{ijl} - 1 \quad \forall l, v \in V, l \neq v, j \in J \quad (3.56)$$

$$y_{ijv} \leq z_{ijv} \quad \forall i \in N, j \in J, v \in V \quad (3.57)$$

$$y_{ijv} \geq z_{ijv} - (1 - x_{ijv}) M \quad \forall i \in N, j \in J, v \in V \quad (3.58)$$

$$\sum_{i \in N} \sum_{j \in J} \alpha_{ijv}^{EVs} t_{ij} x_{ijv} + \sum_{i \in N} \sum_{j \in J} \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv} \leq u_v^{EVs, cap} \quad \forall v \in V^{EVs} \quad (3.59)$$

$$\sum_{i \in N} \sum_{j \in J} \alpha_{ijv}^{HVs} t_{ij} x_{ijv} + \sum_{i \in N} \sum_{j \in J} \beta_{ijv}^{HVs} t_{ij} \omega y_{ijv} \leq u_v^{HVs, cap} \quad \forall v \in V^{DVs} \quad (3.60)$$

$$F^{DVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} (\alpha_v^{DVs} l_{ij} x_{ijv} + \beta_{ijv}^{DVs} l_{ij} \omega y_{ijv}) + F^{EVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} (\alpha_{ijv}^{EVs} t_{ij} x_{ijv} + \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv}) + F^{HVs,CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} (\alpha_{ijv}^{HVs} t_{ij} x_{ijv} + \beta_{ijv}^{HVs} t_{ij} \omega y_{ijv}) \leq E^{\max} \quad (3.61)$$

$$\sum_{i \in N} \sum_{\substack{j \in J \\ i \neq j}} x_{ijv} \leq UV \quad \forall v \in V \quad (3.62)$$

$$\begin{aligned} x_{ijv} &\in \{0,1\}, z_{ijv}, y_{ijv} \in \mathbb{R}_+ & \forall i, j \in N, \forall v \in V \\ \lambda_{jvl} &\in \{0,1\} & \forall j \in N, \forall v, l \in V \\ w_{jv} &\in \mathbb{R}_+ & \forall j \in N, \forall v \in V \end{aligned} \quad (3.63)$$

Equation (3.44) defines the total cost to be minimized, which includes both transportation costs and carbon emission trading costs, arising from the trade-off between the allocated carbon capacity and the actual carbon emitted. Constraints (3.45) ensure that each trip must initiate from the DC node. To ensure demand satisfaction, constraints (3.46) require that every customer is visited at least once, while still allowing the possibility of split deliveries.. Constraints (3.47) define an upper bound for the total product volume carried, ensuring it does not exceed the capacity of each truck. Constraints (3.48) balance the inflow and outflow of the total product to be delivered by each truck at customer node j . Considering customer demand, equation (3.49) enforces flow conservation by accounting for the truck load that must be transferred between nodes. Constraint (3.50) regulates the inflow and outflow of trucks at customer nodes. The arrival of trucks within the designated stores time windows is enforced by constraints (3.51)-(3.53) . In case of split delivery would be needed for a store, constraints (3.54)-(3.56) schedule non-simultaneous truck permanence by considering unloading time as the minimum difference between two arrival times. Constraints (3.57) and (3.58) are applied to linearize the model. Constraints (3.59)-(3.60) ensure that if an electric or hydrogen vehicle is selected for delivery, the total energy consumption along the route does not exceed the truck's battery capacity or the hydrogen tank capacity. Constraints (3.61) impose an upper bound for the total CO₂ emission over the whole problem horizon. Constraints (3.62) impose a limit on the number of visits per route, ensuring that each truck does not exceed the maximum number of deliveries allowed by the carrier company. Lastly, constraints (3.63) define the type of decision variables in the mathematical model.

3.3. Time dependent mathematical model and demand forecasting

3.3.1. Demand forecasting

Since the primary objective of this thesis is to formulate a mathematical model for routing optimization in a distribution company, a critical parameter to be considered is the reliability of expected store

demand. In the initial development of the mathematical model, one of the key assumptions was that it would be applied on a day-to-day basis. Consequently, the model was designed to be executed daily to generate results specific to each day. This assumption was primarily necessary owing to the absence of reliable long-term demand forecasts. The objective of this section is to develop a dependable demand forecasting approach at the store level for a defined future time horizon. Establishing such forecasts would enable optimization to be carried out over an extended planning horizon, rather than restricting the process to daily optimization.

The following points outline the main advantages of forecasting future demand:

- a) It enables the identification of the required number, type, and capacity of trucks needed for upcoming days and weeks.
- b) It improves planning and organization within the warehouse, including workforce allocation across different sectors and the timely preparation of orders.
- c) By anticipating future demand, and when early or delayed deliveries are permitted, it becomes possible to optimize vehicle routing and truck utilization over a longer planning horizon.

The complete process for forecasting demand is presented in the following section, after which the updated mathematical model for a longer planning horizon is introduced.

3.3.1.1. Data Description

The dataset used in this section is derived from Decathlon Italy and contains store-level demand data from early 2023 to mid-2025, covering a period of two and a half years. The dataset includes the following columns: shipment date, store name and ID, number of items to be delivered, and number of pallets to be delivered. A sample of the data is provided in Table 3.3. The data are recorded on a daily basis. For each day, if a store has an order, a corresponding delivery record is included; if a store has no orders on a given day, no entry is present in the dataset for that store on that day.

Table 3.3. A sample of the initiating data of stores' demands.

Stores	Date of loading	Total pallets	Total items
2701 Venaria	2/1/2023	22	3,578.00
2701 Venaria	3/1/2023	10	1,242.00
2701 Venaria	5/1/2023	20	3,566.00
2701 Venaria	6/1/2023	15	1,819.00
2701 Venaria	9/1/2023	24	4,262.00

Given that the dataset is affected by several criticalities, a preprocessing phase was essential. The following list summarizes the actions taken to clean and prepare the data:

- c. Since some of the numerical data are stored as floats or objects, all variables must be converted to numerical values before they can be used in the forecasting model.
- d. For the column containing both store name and ID, the two should be separated, and only the store ID will be used during the training phase of the models.
- e. Standardizing the store names to ensure that each store has a unique name and corresponding ID.
- f. Standardizing the date format.
- g. As mentioned earlier, if a store has no orders on a given day, no record is present in the dataset for that store. However, for the training phase, in order to forecast days with no demand, these missing days should be explicitly added to the dataset with a value equal to zero orders.
- h. To improve the modeling process and better capture trends, additional features can be derived from the data, such as the day of the year, the week of the year, and the month of the year.
- i. Detecting cases where two deliveries are recorded for the same store on the same day, and, if such cases occur, integrating them into a single delivery by summing the quantities.

After the first stage of data preprocessing, a sample of the cleaned dataset is presented in Figure 12:

Store_ID	Data di carico	Negozi	Settimana	Giorno di carico	Totale bancali	Totale articoli	Mese
2701	2025-01-11	2701 Venaria	2	6	0.0	0.0	1
2701	2025-01-12	2701 Venaria	2	7	0.0	0.0	1
2701	2025-01-13	2701 Venaria	3	1	16.0	3719.0	1
2701	2025-01-14	2701 Venaria	3	2	0.0	0.0	1
2701	2025-01-15	2701 Venaria	3	3	12.0	2773.0	1
2701	2025-01-16	2701 Venaria	3	4	0.0	0.0	1
2701	2025-01-17	2701 Venaria	3	5	9.0	1879.0	1
2701	2025-01-18	2701 Venaria	3	6	0.0	0.0	1
2701	2025-01-19	2701 Venaria	3	7	0.0	0.0	1
2701	2025-01-20	2701 Venaria	4	1	12.0	2809.0	1
2701	2025-01-21	2701 Venaria	4	2	0.0	0.0	1
2701	2025-01-22	2701 Venaria	4	3	14.0	4776.0	1
2701	2025-01-23	2701 Venaria	4	4	0.0	0.0	1

Figure 12. The shape of the data after cleaning and processing (“Data di carico”: Loading date; “Negozio”: store; “Settimana: week”, “Giorno di carico: day of loading”, Totale bancali: “total pallets”, “Totale articoli: total items”, “Mese: months”)

To gain a better understanding of the data before starting the forecasting process, a subset of five stores in the Piemonte region was selected. A preliminary analysis of the demand for these stores is presented below. Figure 13 shows the distribution of total pallets to be delivered to each store. The box plot in Figure 13 illustrates the following: the median (the middle line within the box), the interquartile range (IQR, represented by the box spanning from Q1 to Q3, i.e., the middle 50% of the data), whiskers (typically extending to $1.5 \times \text{IQR}$ from the quartiles), and outliers (points falling outside the whiskers). Figure 14 and Figure 15 show, respectively, the average number of pallets sent on each day of the week over the 2.5-year period and the average number of pallets sent in each month during the same period.

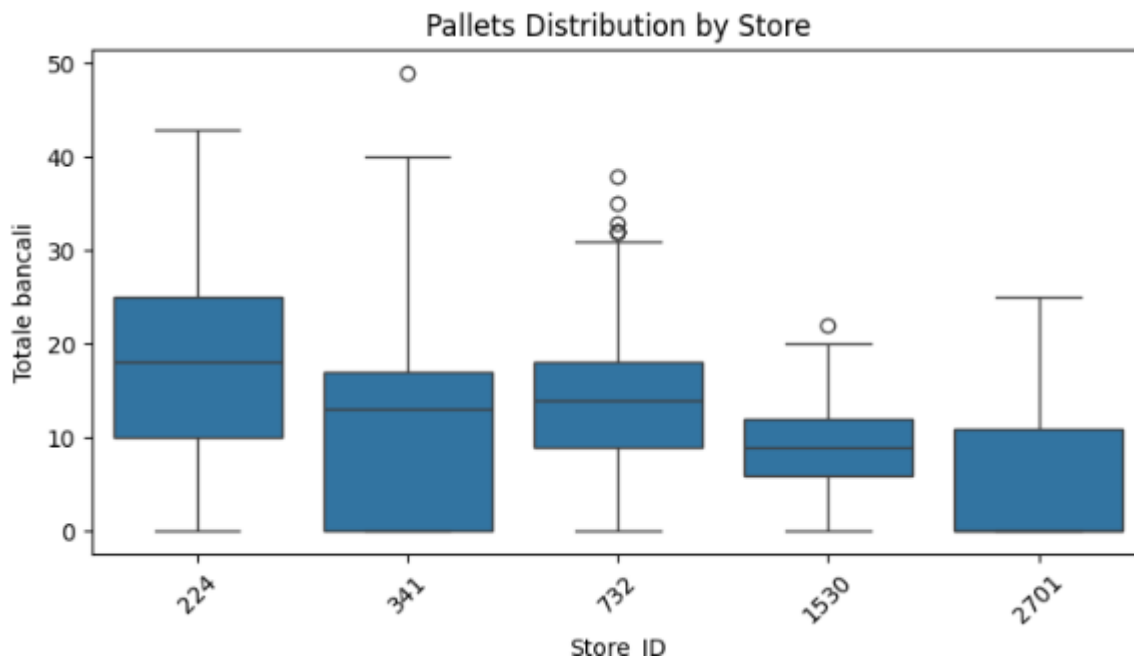


Figure 13. Distribution of the number of pallets delivered to each store.

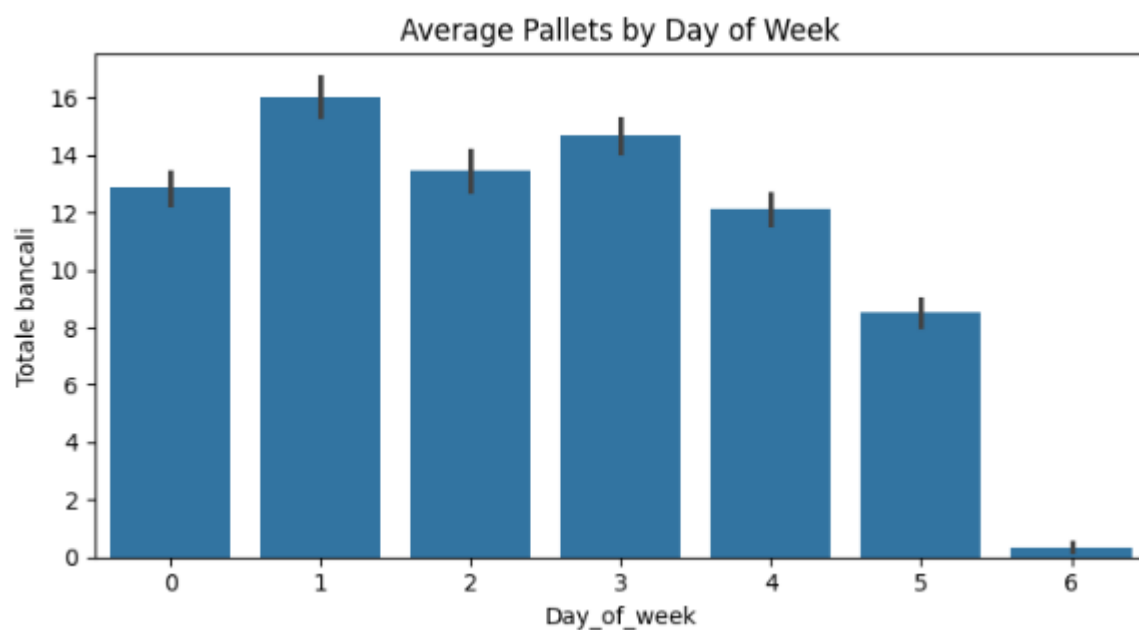


Figure 14. The average number of pallets delivered on each day of week (0 corresponds to Monday; 6 corresponds to Sunday).

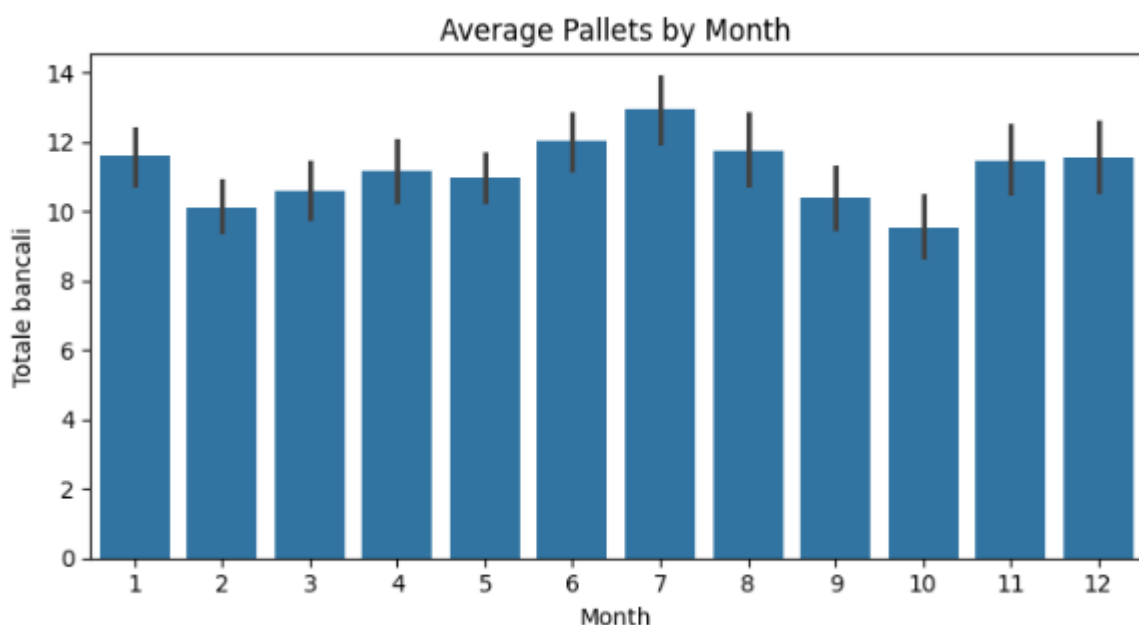


Figure 15. The average number of pallets delivered in each month.

3.3.1.2. Time series forecasting methods (ARIMA, ARIMAX and SARIMAX)

At the beginning of the forecasting procedure traditional statistical models have to be applied. Regarding time series, some of the most common forecasting methods are statistical models such as ARIMA, ARIMAX and SARIMAX. In the following, a short description of these three methods is

presented. Note that ARIMA, ARIMAX and SARIMAX are the traditional yet highly effective time series-based methods for forecasting that are described briefly as follows (Box et al., 2008):

ARIMA stands for:

- AR (Autoregressive): The model uses past values to predict future values.
- I (Integrated): Differencing is applied to make the time series stationary (removing trend or seasonality). Stationarity means the statistical properties (mean, variance, autocorrelation) of the series do not change over time. If a time series is non-stationary, we apply differencing (equation (3.64)):

$$y'_t = y_t - y_{t-1} \quad (3.64)$$

- MA (Moving Average): The model uses past error terms to improve predictions. The general formula of the ARIMA(p, d, q) is as the following (equation (3.65)):

$$\begin{aligned} &ARIMA(p, d, q): \\ \Delta^d_{y_t} &= c + \sum_{i=1}^p \phi_i \Delta^d_{y_{t-i}} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \end{aligned} \quad (3.65)$$

Where:

- $\Delta^d_{y_t}$: Represents the d -th order differenced series (to remove non-stationarity).
- $\sum_{i=1}^p \phi_i \Delta^d_{y_{t-i}}$: Autoregressive (AR) terms of the differenced series.
- $\sum_{j=1}^q \theta_j \varepsilon_{t-j}$: Moving average (MA) terms (past forecast errors).
- p : Number of autoregressive terms
- d : Number of differences to make the series stationary
- q : Number of moving average terms
- ε_t : White noise (random error)

- c : Optional constant

ARIMAX is an extension of ARIMA that includes the presence of exogenous (external) variables. The formula for ARIMAX is as the following (equation (3.66)):

$$\begin{aligned} &ARIMAX(p, d, q): \\ \Delta_{y_t}^d = &c + \sum_{i=1}^p \phi_i \Delta_{y_{t-i}}^d + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{k=1}^K \beta_k x_{k,t} + \varepsilon_t \end{aligned} \quad (3.66)$$

Where:

- $\sum_{k=1}^K \beta_k x_{k,t}$: Effect of K exogenous regressors at time t .
- $x(k, t)$: External variables at time t
- β_k : coefficient of the external variables

And lastly SARIMAX stands for Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors. It is a generalization of ARIMA that can handle both:

- Seasonal patterns (with seasonal autoregressive, seasonal differencing, and seasonal moving-average components), and
- Exogenous input variables ("external regressors") that may help explain the dynamics of the time series.

SARIMAX includes both seasonality *and* exogenous variables (Alharbi & Csala, 2022), making it more flexible for many real-world time series that show regular seasonal behavior and are influenced by external factors.

Using lag-operator notation, one standard form for a SARIMAX model for a univariate time series y_t with exogenous variables $x_t^{(i)} = 1, \dots, n$ seasonality period s , is (equation (3.67)):

$SARIMAX(p, d, q)$:

$$\Theta(L)^p \theta(L^s)^p (1-L)^d (1-L^s)^D y_t = \Phi(L)^q \phi(L^s)^Q (1-L)^d (1-L^s)^D \varepsilon_t + \sum_{k=1}^K \beta_k x_{k,t} \quad (3.67)$$

where:

- L is the lag operator ($Ly_t = y_{t-1}$)
- P , D and Q are the seasonal AR, seasonal differencing, and seasonal MA orders.
- s is the seasonal period.
- $\Theta(L)^p$ is the non-seasonal AR polynomial of order P .
- $\theta(L)^p$ is the seasonal AR polynomial in L^s .
- $\Phi(L)^q$ is the non-seasonal MA polynomial.
- $\phi(L)^Q$ is the seasonal MA polynomial in L^s .
- ε_t is a white-noise error term.

In shorthand, we can write:

$$SARIMAX(p, d, q)(P, D, Q)_s + X_t \quad (3.68)$$

where X_t indicates the exogenous variables.

Steps to build ARIMA, ARIMAX or SARIMAX model:

After cleaning and preprocessing the data, the following steps are required to proceed with forecasting using the two selected methods:

- a. Check for stationarity.
- b. Differencing if necessary.
- c. Choose p and q .
- d. Choose the day in which the forecasting will be performed.
- e. Fit the ARIMA or ARIMAX model (i.e., train the model) using previous historical data.
- f. Forecast the required number of time steps

- g. Evaluate model (MAE, RMSE, MAPE)
- h. If there are more days to predict, go to the step d) and repeat for the next day, until all the days of the testing experiment are forecasted and evaluated
- i. Finally, calculate the global evaluation metric for all the forecasted days, if the objective is to globally evaluate the performance of the models over the tested period

To apply the forecasting methods to the case study, five stores in the Piedmont region were selected. After testing for stationarity of the demand data for all stores in this category, the results indicated that the time series were stationary. Therefore, no differencing was required. Stationarity was examined by evaluating the p-values of the historical demand data for the stores using the Augmented Dickey–Fuller (ADF) test. In the ADF test, if the p-value is greater than 0.05, the series is considered likely non-stationary, and differencing is required to achieve stationarity. For the datasets used in our forecasting, all store demand series were found to be within the stationary range. The forecasting test was carried out under the following conditions:

- The 2.5 years of historical data were used. At the start, 1 years were used to fit the first ARIMA model, after which forecasts were generated for the subsequent 14 days. The remaining 1.5 year were successively used for testing the forecasting (comparing the obtained forecasts with the real values of that period).
- A part of data was used to fit the ARIMA model. After using that data for fitting ARIMA, forecasts were generated day by day for the following 14 days, after which the forecasting were evaluated. This rolling forecasting approach enabled evaluation over a longer time horizon.
- The forecasting was conducted for two separate targets: the number of pallets and the number of items.

3.3.1.3. Machine learning model

Other practical models for forecasting are Machine Learning (ML) models that, nowadays, play a key role for forecasting and predicting. Machine learning is a subfield of artificial intelligence that focuses on developing algorithms capable of learning patterns from data and improving their performance on specific tasks without being explicitly programmed. Through statistical and computational methods, ML systems automatically build predictive or descriptive models based on empirical data, enabling applications such as classification, regression, clustering, and anomaly detection. The adaptability of these models allows them to generalize from training data to unseen instances, making ML an essential component of modern data-driven research and decision-making systems (Janiesch et al., 2021).

Random Forest (RF) is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and control overfitting. Each tree in the forest is trained on a bootstrap sample of the data, and at each split, a random subset of features is considered, which introduces diversity among the trees. The final prediction is obtained by aggregating the outputs of individual trees, typically through majority voting for classification or averaging for regression. This structure allows RF to achieve high accuracy, robustness to noise, and effectiveness across a wide range of datasets and domains (Breiman, 2001). Figure 16 shows the random forest decision trees and result obtaining.

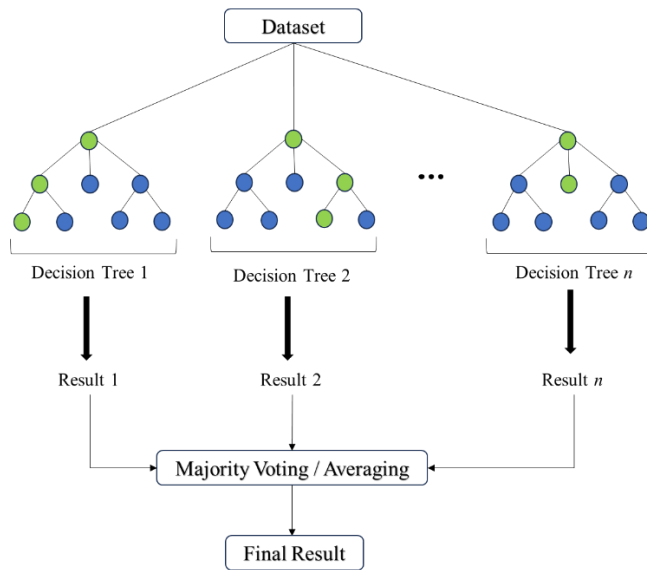


Figure 16. Random Forest structure

3.3.1.4. Rolling forecast

This section of the thesis describes the methodology used for the analysis of the forecasting models. A rolling forecast will be conducted using two different targets: total pallets and total items. The rolling forecast will be structured by designating one time period as the training set (initially, one year of data) and the subsequent period as the test set. Once the training period has ended, ARIMA models (with different hyperparameters) and machine learning models, such as Random Forest and XGBoost, will be fitted. The next period will then be initiated, and a daily forecast will be generated for the following 14 days. This process will be repeated day by day until the end of the test period (one year in total). For each forecast, errors will be calculated, and the forecasted amounts will be compared with the actual values. Figure 17 demonstrates the scheme of a day-by-day rolling forecast, showing the training and testing of each forecast.

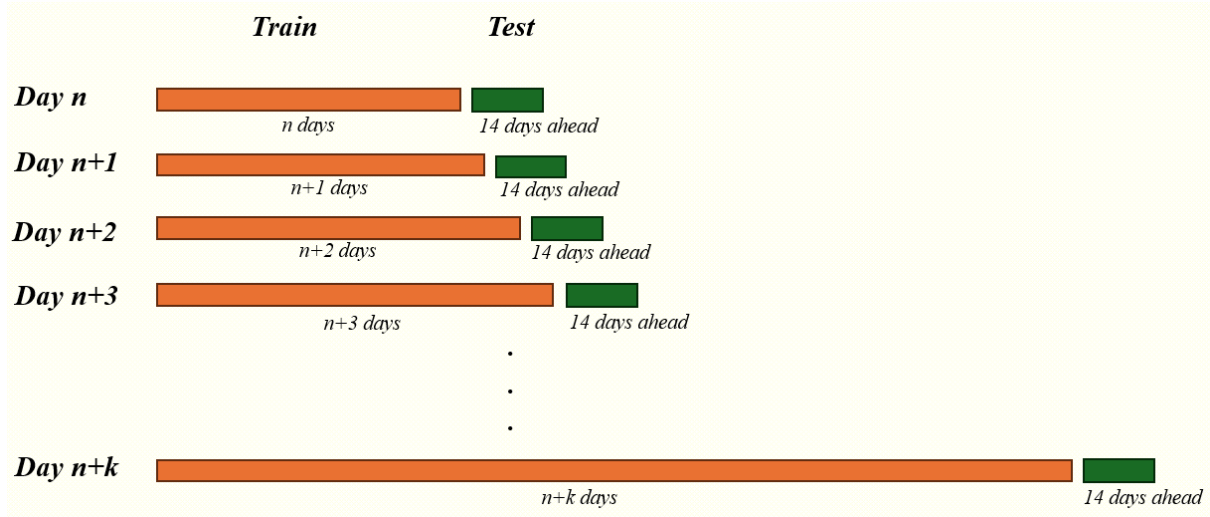


Figure 17. Day-by-day rolling forecast of the forecasting models

3.4. Bi-objective and multi-period mathematical model

In the last sections, a mixed-fleet mathematical model is presented for the distribution of products from the warehouse to a number of stores. The objective of the model was to minimize the total cost, which includes transportation cost and emission trade cost, in a single objective. Then, a set of forecasting methods was investigated to help us better understand future demand and enable decision-making over a longer horizon.

In this section, to improve emissions effectiveness, we decompose the objective into two sub-objects: total cost and total emissions. In classical literature, these two objectives are often in conflict with each other. On the other hand, with forecasted demand, decisions can be made over a longer horizon. With these two features, we now develop a bi-objective periodic mathematical model for the distribution of pallets from the warehouse to the stores, considering all assumptions of section 3.1.1., and the only assumption that has been changed is to have multi period decision making instead of day-by-day. All notations are the same as in Table 3.2, and only the sets, parameters, and variables that have been newly defined or modified are shown in Table 3.4. In the next section, the mathematical model and the multi-objective solution approach to deal with the model are presented.

Table 3.4. Sets and parameters for bi-objective multi-period model

Notation	Definition
<i>Sets</i>	
N	The set of all nodes (DC and Stores), $\forall i, j \in N$
$DC \subseteq N$	A subset of N that includes only DC nodes $\forall i, j \in DC$
$J \subseteq N$	A subset of N that includes only store nodes $\forall i, j \in J$
$V = V^{DV's} \cup V^{EV's} \cup V^{HV's}$	The set of all trucks with different characteristics and capacities $\forall v \in V$
$V^{DV's} / V^{EV's} / V^{HV's}$	A subset of V that includes only DVs/ EVs/ HVs
$3 T = \{1, \dots, \tau\}$	The set of all days for decision making horizon $\forall \tau \in T$
<i>Parameters</i>	
$d_{j\tau}$	Aggregate demand of the customer j , on day τ , $\forall j \in J, \forall \tau \in T$
$a_{j\tau}$	Earliest possible arrival time at the node j , on day τ , $\forall j \in J, \forall \tau \in T$
$b_{j\tau}$	Latest possible arrival time at the node j , on day τ , $\forall j \in J, \forall \tau \in T$
<i>Decision Variables</i>	
$x_{ijv\tau}$	Binary variable equal to 1 if truck v includes link (i, j) , on day τ , 0 otherwise, $\forall i, j \in N, v \in V, \forall \tau \in T$
$z_{ijv\tau}$	Load of truck v transferred between link (i, j) , on day τ , $\forall i, j \in N, v \in V, \forall \tau \in T$
$w_{jv\tau}$	Arrival time at the node j by truck v , on day τ , $\forall i, j \in N, v \in V, \forall \tau \in T$
$y_{ijv\tau}$	Auxiliary decision variable for the linearization, on day τ , $\forall i, j \in N, v \in V, \forall \tau \in T$
$\lambda_{jvl\tau}$	Binary variable equal to 1 if truck v arrives at node j before truck l , on day τ , 0 otherwise, $\forall j \in N, v, l \in V, \forall \tau \in T$

3.4.1. Torabi-Hassini method

To solve multi-objective optimization problems, the conflict between the objectives should first be examined using a payoff matrix. After confirming the existence of conflict between the objectives, the proposed model should be solved using a multi-objective optimization approach. Various methods have been proposed to solve multi-objective optimization problems. In this thesis, the Torabi and Hassini (TH) method (Torabi & Hassini, 2008) is used. The results of the TH method can be illustrated using a Pareto front by varying the weights. However, this method is typically used when a single aggregated solution is preferred rather than a set of Pareto-optimal solutions (Sadati-Keneti et al., 2023).

In the current problem, the demand of each store must be served on the exact day the order is forecasted. In a future extension of this work, where early or delayed deliveries are permitted, the model could be modified to optimize total routing costs and truck load utilization over a longer planning horizon. For example, if a truck is scheduled to depart on a given route and its load is below capacity, part or all of the demand for the following day could be delivered in advance to improve vehicle utilization. Conversely, if multiple trucks are assigned to the same route and the load of the last truck falls below a

predefined threshold, a portion of the demand could be postponed and consolidated with the next delivery.

To apply the TH method, Z_1 and Z_2 are defined as the total transportation cost (Euro) and total emissions (kg CO₂), and are shown in equations (3.69) and (3.70) respectively.

$$\begin{aligned}
Z_1 = & \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} \sum_{\tau \in T} \left[\left(P^{DVs, fuel} \left(\frac{l_{ij} (\alpha_{ijv}^{DVs} + \beta_{ijv}^{DVs} m_v^{\circ})}{\eta^{DVs} LHV^{DVs}} \right) + P^{DVs, dep} l_{ij} + P^{DVs, ma} l_{ij} + P^{DVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv\tau} + P^{DVs, fuel} \frac{\beta_{ijv}^{DVs} l_{ij} \omega}{\eta_{DVs} LHV^{DVs}} y_{ijv\tau} \right] + \\
& \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} \sum_{\tau \in T} \left[\left(P^{Electricity} \left(t_{ij} (\alpha_{ijv}^{EVs} + \beta_{ijv}^{EVs} m_v^{\circ}) \right) + P^{EVs, dep} l_{ij} + P^{EVs, ma} l_{ij} + P^{EVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv\tau} + P^{Electricity} \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv\tau} \right] + \\
& \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} \sum_{\tau \in T} \left[\left(P^{HVs} \left(\frac{t_{ij} (\alpha_{ijv}^{HVs} + \beta_{ijv}^{HVs} m_v^{\circ})}{\eta^{HVs} LHV^{HVs}} \right) + P^{HVs, dep} l_{ij} + P^{HVs, ma} l_{ij} + P^{HVs, drive} (t_{ij} + S_{jv}) \right) x_{ijv\tau} + P^{HVs} \frac{\beta_{ijv}^{HVs} t_{ij} \omega}{\eta^{H2} LHV^{H2}} y_{ijv\tau} \right] +
\end{aligned} \tag{3.69}$$

$$\begin{aligned}
Z_2 = & F^{DVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{DVs}} \sum_{\tau \in T} \left[(\alpha_{ijv}^{DVs} + \beta_{ijv}^{DVs} m_v^{\circ}) l_{ij} x_{ijv\tau} + \beta_{ijv}^{DVs} l_{ij} \omega y_{ijv\tau} \right] + \\
& F^{EVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{EVs}} \sum_{\tau \in T} \left[(\alpha_{ijv}^{EVs} + \beta_{ijv}^{EVs} m_v^{\circ}) t_{ij} x_{ijv\tau} + \beta_{ijv}^{EVs} t_{ij} \omega y_{ijv\tau} \right] + \\
& F^{HVs, CO_2} \sum_{i \in N} \sum_{j \in N} \sum_{v \in V^{HVs}} \sum_{\tau \in T} \left[(\alpha_{ijv}^{HVs} + \beta_{ijv}^{HVs} m_v^{\circ}) t_{ij} x_{ijv\tau} + \beta_{ijv}^{HVs} t_{ij} \omega y_{ijv\tau} \right]
\end{aligned} \tag{3.70}$$

Then, the following steps should be followed:

Step 1:

Solve the model once considering only transportation cost and once the total CO₂ emissions to obtain the optimal values of these two objectives separately as Z_1^* and Z_2^* .

Step 2:

Calculate the range for each objective using the equations (3.71) and (3.72) as are shown in the following:

$$R_1 = Z_1^{\max} - Z_1^* \tag{3.71}$$

$$R_2 = Z_2^{\max} - Z_2^* \tag{3.72}$$

Step 3:

Normalize each objective based on its optimal value and range utilizing the equations (3.73) and (3.74) in which N_1 is the normalized value for the cost and N_2 is the normalized value for CO2 emissions.:

$$N_1 = \frac{Z_1 - Z_1^*}{R_1} \quad (3.73)$$

$$N_2 = \frac{Z_2 - Z_2^*}{R_2} \quad (3.74)$$

Step 4:

Utilizing the TH method the objective function of the bi-objective multi-period MILP model is presented in equation (3.75), where:

Minimizing $(N_1 + N_2)$ is the compensatory (1-norm) method, which minimizes the sum of undesirability, and W_1 is the weight of the 1-norm.

And minimizing the maximum of (N_1, N_2) is the non-compensatory (infinity-norm) method, which minimizes the highest undesirability, and W_2 is the weight of infinity-norm.

$$\text{Min } Z = W_1(N_1 + N_2) + W_2 \max(N_1, N_2) \quad (3.75)$$

All the constraints of this version of the model are the same as those in the section 3.2.5, the constraints (3.45) - (3.63). The only change is to consider all the constraints $\forall \tau \in T$. Since each customer, if it has demand, must be served every day, all constraints must therefore be enforced for each.

Chapter 4: Cases and Results

4.1. Application to Decathlon case studies

In this chapter, a set of real cases from Decathlon (the main partner of this thesis) are examined to address different versions of the routing problem, as well as demand forecasting and the multi-objective model. Most of the cases are based on Decathlon Italy, while one case concerns Decathlon France. The following sections first present the results of the regression analysis used for cost estimation. Subsequently, the results of the first version of the Capacitated Vehicle Routing Problem (CVRP) model are discussed, followed by those of the hybrid fleet model. Finally, the outcomes of the demand forecasting analysis and the multi-objective, multi-period model are presented.

4.1.1. Regression results for cost estimation

The results of the estimation procedure presented in Section 3.1.2 are shown in Table 4.1. The regression model is applied under three different conditions and for three types of trucks: first, considering only distance as the coefficient in the regression; second, considering only travel time; and third, considering both distance and travel time as coefficients in a multiple regression model. The results indicate that the best-performing model includes distance and travel time, as the coefficient along with fixed costs. The minimization problem described in Equation (3.2) in section 3.1.2 is a straightforward optimization problem that determines the regression coefficients by minimizing the sum of squared errors.

Table 4.1. Results of the linear regression for the cost function for three different vehicle types.

Considered criteria	<i>K1</i>	<i>K2</i>	<i>K3</i>
	Vehicle Type 1		
Distance, Time and Fixed cost	2.4	67.6	23
Distance and Fixed cost	3.4	-	24
Time and Fixed cost	-	230.1	23
Vehicle Type 2			
Distance, Time and Fixed cost	1.8	44.6	0
Distance and Fixed cost	2.5	-	0
Time and Fixed cost	-	165.6	0
Vehicle Type 3			
Distance, Time and Fixed cost	1.7	12.5	0
Distance and Fixed cost	1.9	-	0
Time and Fixed cost	-	129.6	0

4.1.2. Routing result in Italy

This section examines a real-world case of distributing industrial goods from a central warehouse to multiple retail stores. The case study involves a total of 20 nodes, where the first node represents the warehouse and the remaining nodes correspond to stores located in different cities. There are 16 available trucks, each with a capacity ranging from 12 to 33 pallets. The unloading time at each store is assumed to be one hour for all trucks. After implementing the model in Python and executing the test case using the Gurobi Optimizer (version 10.0.2), the results for the one-day distribution scenario were obtained. Figure 18 illustrates the optimal routes obtained after solving the model, while Table 4.2 presents details of a subset of the optimal results, including the optimal values of the decision variables. The optimality gap is less than 4%, and the computation time reached 8,000 seconds, corresponding to the maximum time limit set for the solver.

The results indicate that the demand for certain stores is split and fulfilled by multiple trucks. This split delivery is managed by scheduling the arrival times of the trucks so that they arrive sequentially, immediately after the loading process. As shown in Table 4.2, some stores, such as Store 11 and Store 3, receive their deliveries from more than one truck. For instance, in the case of Store 11, the delivery is divided between Truck 2 and Truck 11, with Truck 2 arriving before Truck 11. The time gap between their arrivals is one hour, corresponding to the unloading time of the first truck. Similarly, for Store 3, the optimal solution involves distributing the orders among three different vehicles, as illustrated in Table 4.2. The scheduling of arrival times is particularly notable for this store: Vehicle 16 arrives first at 08:00, followed by Truck 6 at 09:00, and finally Truck 10 at 10:00.

The objective function value indicates that the total economic and emission cost amounts to €3,742. This demonstrates that the optimal procedure achieves approximately a 20% reduction in total cost compared to the actual distribution center's procedure for the same day, as implemented in the case of this part of the thesis. In terms of distance, the total distance traveled by all vehicles in the experiment was 1,453 km, whereas in the real-world scenario, the vehicles covered approximately 1,900 km, representing a 23% improvement.

The study involved a heterogeneous fleet of 10 vehicles, comprising 2 large trucks, 6 medium-sized trucks, and 2 small trucks. In contrast, the real-world operation utilized 16 trucks, including 5 large trucks, 9 medium-sized trucks, and 2 small trucks. This represents a reduction of approximately 60% in the number of large trucks and 33% in the number of medium-sized trucks compared to the real-world

case. In the optimized scenario, split deliveries were implemented for two stores, whereas in the real-world operation, the company applied split delivery for only one store.

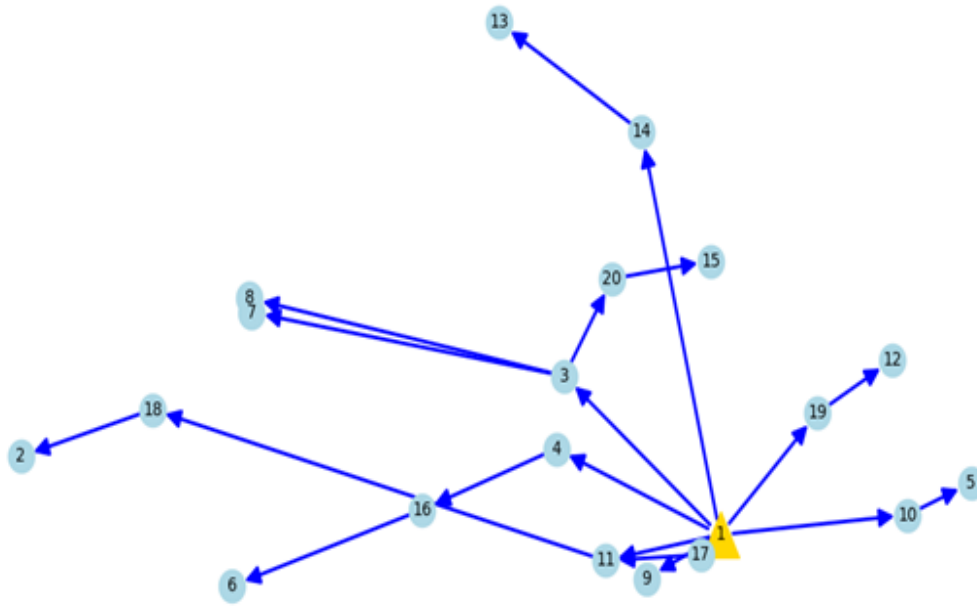


Figure 18. Optimal routes after solving the MILP model

Table 4.2. Optimal results and parameter ranges

Optimal Results				
Vehicle 2				
Optimal Path (x_{ijv})	1	→	11	→ 18 → 2
Load of Truck (z_{ijv})	-		33	23 11
Arrival Time (w_{jv})	-		8:00	10:00 12:00
Vehicle 6				
Optimal Path (x_{ijv})	1	→	3	→ 7
Load of Truck (z_{ijv})	-		17	9
Arrival Time (w_{jv})	-		9:00	11:00
Vehicle 10				
Optimal Path (x_{ijv})	1	→	3	→ 20 → 15
Load of Truck (z_{ijv})	-		18	14 6
Arrival Time (w_{jv})	-		10:00	11:00 13:00
Vehicle 11				

Optimal Path (x_{ijv})	1	→	17	→	11
Load of Truck (z_{ijv})	-		17		13
Arrival Time (w_{jv})	-		8:00		9:00
Vehicle 16					
Optimal Path (x_{ijv})	1	→	3	→	8
Load of Truck (z_{ijv})	-		12		10
Arrival Time (w_{jv})	-		8:00		10:00

4.1.3. Cost and CO2 Emissions Comparison

As the analysis over the first version of the mathematical model (section 3.1.4), the same sample of section 4.1.2 is considered and the model was applied with two distinct objectives: minimizing emission cost and minimizing economic cost. A comparative assessment of the routing result under these two scenarios was performed. Figure 19 presents the outcome when focusing on emission cost, revealing an improvement of approximately 5%. However, this gain was accompanied by higher resource utilization, with 11 vehicles employed, including one large truck. In contrast, when both objectives were considered simultaneously, only 10 trucks were required, two of which were large. Figure 19 also illustrates substantial modifications in the routing patterns and their sequences.

Conversely, when economic cost was the only optimization objective, just a single route has been changed, leading to a modest enhancement in economic efficiency (Figure 20). Interestingly, the number and types of trucks used in this case were identical to those in the bi-objective scenario. This observation suggests that the economic cost has more effect on the final route configurations compared to the emission cost.

Overall, the findings indicate that economic considerations exert a dominant influence over social emission costs. The routes derived from the bi-objective optimization closely resembled those optimized for economic efficiency alone, whereas the emission-focused scenario produced substantial route variations. This contrast underscores that economic efficiency (at least in the case of the first version of the mathematical model) plays a more decisive role than emission costs in shaping optimal logistics routing strategies.

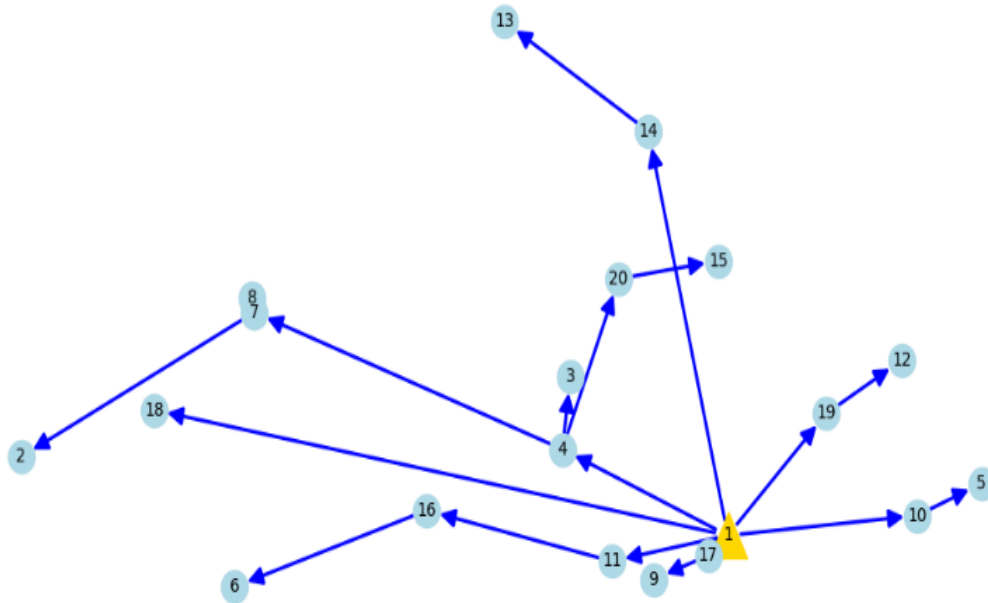


Figure 19. Optimal routes considering emission cost as the objective

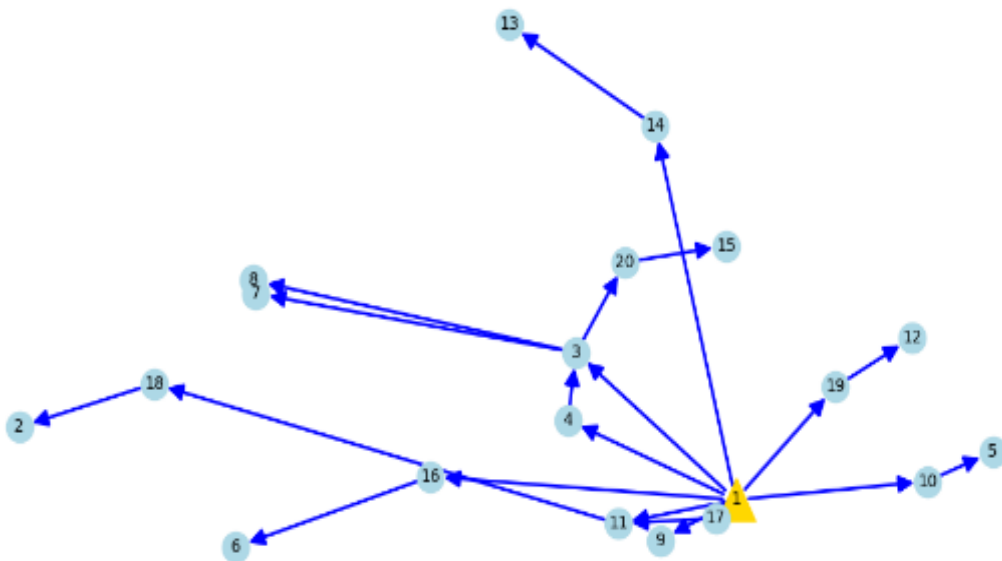


Figure 20. Optimal routes considering economic cost as the objective

4.2. Result the distribution in a web app demo

In this section, an interface of a proposed web application is presented as part of the future implementation of the model. As shown in Figure 21, the user can select the distribution date and specify the distribution starting point, including the country, city, and warehouse name. After selecting the warehouse, all stores supplied by that warehouse are displayed, along with their demand, delivery time windows, and unloading times.


Last Mile Delivery Planning from CAR to Stores

1. Choose Date

2. Choose Country

3. Choose Warehouse

4. Choose Stores and Set Details

Store	Demand (pallets)	Earliest Arrival Time	Latest Departure Time	Unloading Time (minutes)
ABBEVILLE	0	09:00	19:30	30
AMIENS	23	09:30	20:00	30
ARRAS	0	09:00	20:00	30

Figure 21. Primary routing information displayed in the Web App

Additional parameters can be defined based on daily updated data, as illustrated in Figure 22. These parameters include the number of available trucks, the maximum number of visits permitted per route and per truck, the objective function of the model, and the acceptable optimality gap specified for the solution method.

5. Truck Availability

Big Trucks (33 pallets):

Medium Trucks (18 pallets):

Small Trucks (12 pallets):

Max Number of Deliveries per Route: stops

Departure Time from the Warehouse: 🕒

Max Runtime: seconds

Max Estimated Gap: %

6. Choose Objective

7. Choose the tool

Start Routing

Figure 22. Defining the available trucks, objective function, and constraints for the solution method

Figure 23 and Figure 24 illustrate the outcomes of the mathematical model, including the optimized routing plan, the number of pallets assigned to each truck for transport between nodes along the selected routes, and the corresponding arrival times at each node. Furthermore, the Figure 25 presents the computed value of the objective function and additional performance indicators that facilitate a more comprehensive understanding of the decision-making process.



Results and Analysis

Optimal Load of Trucks

Vehicle	Route	Load (pallets)
Vehicle 1	DC_LOMPRET → GODAULT → FOUQUIERES	33, 20
Vehicle 2	DC_LOMPRET → BAILLEUL → LONGUENESSE → OPALE	32, 29, 17
Vehicle 3	DC_LOMPRET → ENGLOS	15
Vehicle 6	DC_LOMPRET → BAILLEUL → CALAIS	33, 20
Vehicle 7	DC_LOMPRET → AULNOY → HAUMONT	33, 19
Vehicle 8	DC_LOMPRET → GODAULT → AMIENS	33, 23
Vehicle 10	DC_LOMPRET → PETITE FORÊT → AULNOY	29, 6
Vehicle 11	DC_LOMPRET → NEUVILLE EN FERRAIN	17

Figure 23. Routing result of the mathematical model

Optimal Arrival Times

Vehicle	Route	Arrival Times
Vehicle 1	DC_LOMPRET → GODAULT → FOUQUIERES	10:00, 12:00
Vehicle 2	DC_LOMPRET → BAILLEUL → LONGUENESSE → OPALE	9:00, 11:00, 12:00
Vehicle 3	DC_LOMPRET → ENGLOS	9:00
Vehicle 6	DC_LOMPRET → BAILLEUL → CALAIS	10:00, 12:00
Vehicle 7	DC_LOMPRET → AULNOY → HAUMONT	9:00, 10:00
Vehicle 8	DC_LOMPRET → GODAULT → AMIENS	09:00, 11:00
Vehicle 10	DC_LOMPRET → PETITE FORÊT → AULNOY	9:00, 10:00
Vehicle 11	DC_LOMPRET → NEUVILLE EN FERRAIN	9:00

Figure 24. Arrival time result at each store

Additional Information

Total Estimated Cost: ... Euro

Total Distance to Travel: 636 km

Total CO2 Emission: 427104 gr

Total Traveling Time: 7.95 Hours

Filing Rate of Truck: 90 %

Fuel Consumption: 164 Liter

Truck Type	Number of used
Big Trucks	7
Medium Trucks	1
Small Trucks	0

[Back to Home](#)

[Show on Map](#)

Figure 25. Additional information of the mathematical model results

4.3. Hybrid fleet routing results

This section presents a case study for the hybrid fleet mathematical model, which contains three distinct fleet types (ICEs, EVs, and HVs) described vastly and in detail in Section 3.2. The case study focuses on the delivery of products by Decathlon from a distribution center (DC) to 19 stores located in northern Italy. The stores are located in the Piedmont, Liguria, and Lombardy regions, each pre-assigned one warehouse to receive shipments from the mentioned DC.

The stores have data on daily demand volumes, permitted delivery time windows, and constraints related to road accessibility, specifying the types of trucks allowed to access and unload to each store. The DC includes additional information, like truck availability, the maximum number of visits permitted per route by each truck, and other parameters necessary to construct the decision model effectively. Key data inputs required to run the model are summarized in Table 4.3.

It should be noted that all inputs and parameters are based on real-world data, with only minor modifications applied where necessary. The model considers three fleet types differentiated by their

powertrain configurations, enabling a comprehensive evaluation of its applicability and performance across a range of potential fleet characteristics.

Table 4.3. The real case data and input (Basma et al., n.d.; Dulău, 2023; Ennassiri et al., 2023; IVECO to Produce and Market Its Heavy-Duty Battery Electric Vehicle and Heavy-Duty Fuel Cell Electric Vehicle under Its Own Brand | Iveco, 2023; Jafari et al., 2025).

Parameter	Diesel Truck	Electric Truck	Hydrogen Truck
CO ₂ Emission Factor (F^{*,CO_2})	2.68 kg/L	~0.69 kg/kWh	~0.3 kg/kWh
Drag Coefficient (C_v^d)	0.5-0.8	0.5-0.8	0.5-0.8
Rolling Resistance Coefficient (C_v^r)	~0.005	~0.005	~0.005
Frontal Surface Area (A_v)	~10 m ²	~10 m ²	~10 m ²
Air Density (ρ)	~1.225 kg/m ³	~1.225 kg/m ³	~1.225 kg/m ³
Transmission Efficiency (η_v^{te})	-	~95%	~90%
Motor Efficiency (η_v^e)	-	~90%	~90%
Power Converter Efficiency (η_v^{in})	-	~95%	~90%
Internal Power Consumption (P_v^{acc})	2 kW	6 kW	6 kW
Lower Heating Value (LHV*)	~11.8 kWh/kg (diesel)	-	~33.33 kWh/kg (H ₂)
Operating Efficiency (η^*)	~40%	-	~55%
Regenerative Braking (K_v)	N/A	~20-30%	~20-30%
Truck Capacity (Q_v)	33 pallet	33 pallet	33 pallet
Empty Truck Weight (m_v^o)	~13,000 kg	~18,000 kg	~15,000 kg
Max Battery/Tank Capacity ($u_v^{*,cap}$)	N/A	~738 kWh	~70 kg H ₂
Fuel Prices	2.04 €/kg	0.15 €/kWh	~10-12 €/kg
Maintenance Cost ($P_v^{*,ma}$)	0.15 €/km	0.10 €/km	0.12 €/km
Driver Cost ($P_v^{*,drive}$)	~25 €/h	~25 €/h	~25 €/h
CO ₂ Market Price (P^{CO_2})	Varies (~70 €/ton)	Varies (~70 €/ton)	Varies (~70 €/ton)
Number of available trucks	7	7	7
Distance (l_{ij})	Varies 20-400 km		
Travel Time (t_{ij})	Varies 0.5-5 h		
Aggregate Demand (d_j)	Varies 1 – 50 pallet		
Time window	Varies between (8:00 – 19:00)		
Max. Number of visits (UV)	3		

The input data for the considered instance of the optimization model are presented in Table 4.3. The problem was implemented in Python and solved using the Gurobi Optimizer (version 11.0.3) on a PC equipped with a 13th Gen Intel Core i9-13900H processor (2.60 GHz) and 16 GB of RAM. The results for the CVRPTW problem over a single day indicate that, for the given instance size, the total runtime required to obtain the optimal solution ranged between 2 and 10 minutes. In contrast, achieving a solution with a maximum optimality gap below 3% typically required less than one minute.

Table 4.4 summarizes the main results, including the energy consumption of different truck types, arrival times, truck loads after departing each node, and the split deliveries occurring at three locations (Grugliasco, Asti, and Alessandria). These split deliveries were necessary to satisfy the respective store demands. To better visualize the optimal routes, Figure 26 provides a graphical representation of the routing solution.

For this specific case, the total cost amounted to €4,800, with an overall distance traveled of 1,347 km. The total energy consumption of all trucks was 5,567 kWh, while the total CO₂ emissions amounted to 1,392 kg. A total of 21 trucks were available in the fleet, comprising 7 diesel vehicles (DVs), 7 electric vehicles (EVs), and 7 hydrogen vehicles (HVs). The results indicate that the model prioritized the use of DVs. Once all available DVs were allocated, the model assigned EVs for deliveries to the stores, while HVs were not utilized. The reasons for this allocation pattern are analyzed in detail in the section 4.3.1 and section 4.3.2.

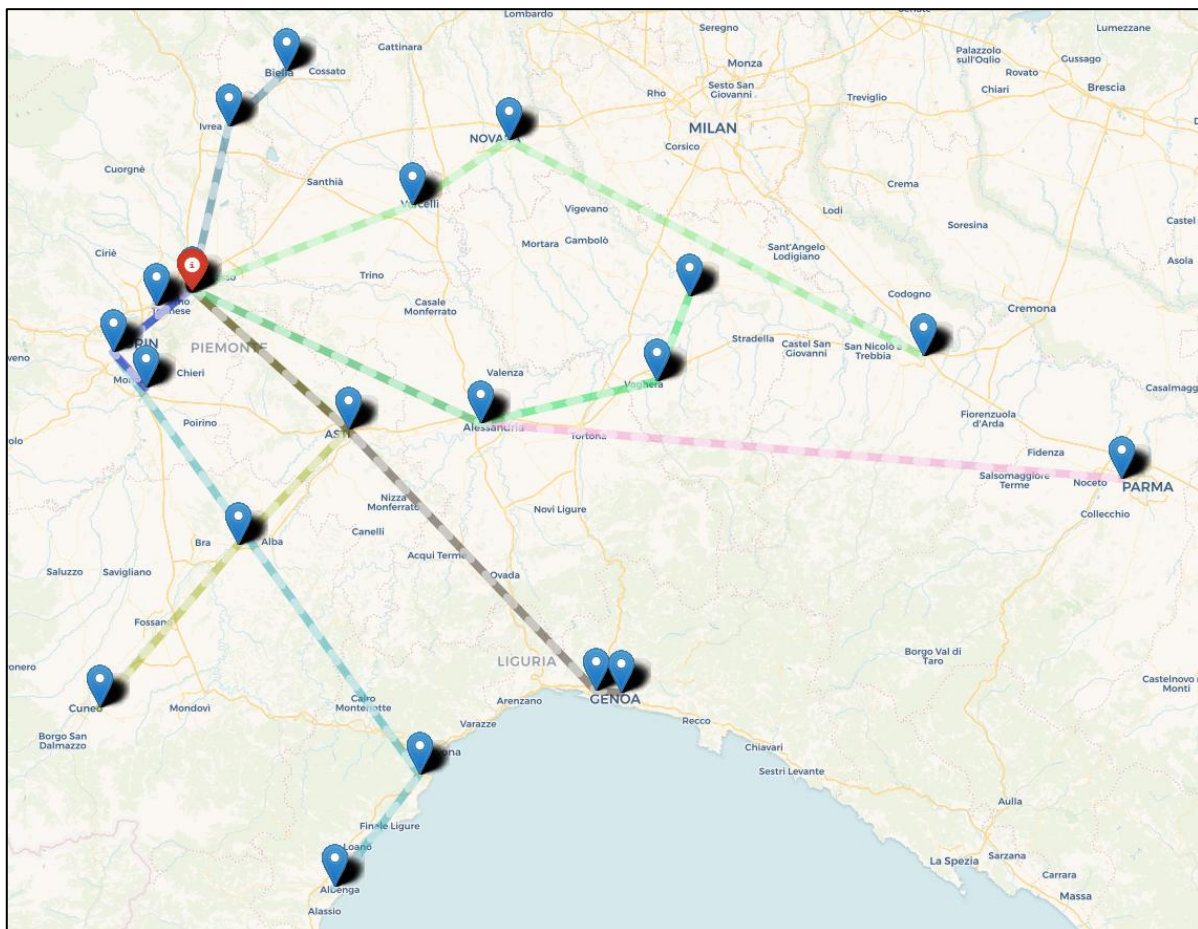


Figure 26. The optimal route of the one day for a real case (northern Italy).

Table 4.4. The result of the Hybrid fleet mathematical model.

Routes No.	Vehicle No.	Vehicle Type	Optimal Path				LT**
1	1	DVs	AT*	09:00	12:00	19:00	33, 28, 16
Depot → Grugliasco → Vado Ligure → Albenga							
2	2	DVs	AT*	09:30	11:06	16:00	33, 27, 15
Depot → Asti → Santa Vittoria d'Alba → Cuneo							
3	3	DVs	AT*	16:00	19:00		33, 19
Depot → Alessandria → Parma							
4	4	DVs	AT*	08:00	09:33	19:00	29, 24, 16
Depot → Vercelli → Novara → Piacenza							
5	5	DVs	AT*	08:00			15
Depot → Settimo Torinese							
6	6	DVs	AT*	10:30	13:02	14:24	32, 27, 12
Depot → Asti → Genova Campi → Genova Marassi							
7	7	DVs	AT*	08:00	09:38	11:08	32, 26, 14
Depot → Alessandria → Voghera → San Martino Siccomario							
8	8	EVs	AT*	08:00	19:00		33, 15
Depot → Grugliasco → Moncalieri							
9	9	EVs	AT*	08:00	19:00		10, 5
Depot → Ivrea → Biella							

(*) Arrival time at each node (AT), (**) Load of truck (Pallets) after departure of each nodes (LT).

4.3.1. Fuel, Energy and Hydrogen Cost Analysis

As shown in Table 4.4 in section 4.3, the prioritization of fleet usage follows a clear order: diesel vehicles (DVs) are utilized first, followed by electric vehicles (EVs), while hydrogen vehicles (HVs) have the lowest priority. This prioritization suggests that HVs are associated with the highest operating costs, followed by EVs and then DVs.

To further investigate the cost structure of different truck types, the model was solved under two alternative scenarios: one in which the entire fleet consisted solely of EVs, and another where all vehicles were HVs. The resulting optimal costs were €5,440 for EVs and €14,137 for HVs. The substantially higher costs associated with these two fleet types can be attributed to several factors, including energy and fuel prices, the advanced technology required for vehicle production (which leads to higher purchase and depreciation costs), and variations in motor efficiency, among others.

This section specifically examines the impact of fuel prices to first observe the sensitivity of the objective function over the fuel cost and then to determine the extent to which reductions in energy costs could enable EVs and HVs to compete with DVs. To this end, the fuel prices for both fleet types (hydrogen price and electricity price) were gradually decreased, and the model was re-solved after each reduction to determine the corresponding optimal costs. Figure 27 shows the relationship between

decreasing hydrogen and electricity prices and their respective intersections with the DVs cost in optimal mode. The intersection points occur when the total optimal routing cost equals €4,870, which corresponds to a hydrogen price of €2.20/kg and an electricity price of €0.12/kWh.

Further analysis (Figure 28) indicates that for EVs to become cost-competitive with DVs, the electricity price must decrease to approximately €0.115/kWh, whereas for HVs, the hydrogen price would need to fall to about €2.10/kg. Conversely, Figure 6 explores how changes in the price of diesel fuel affect the competitiveness of DVs relative to the other two fleet types. As shown in Figure 28, if the price of diesel increases slightly above €2.00/L, the total transportation cost of DVs would equal that of EVs. Furthermore, if the diesel price rises to approximately €9.00/L, the cost competitiveness of HVs would also be matched.

It is important to note that while hydrogen and electricity prices (and their associated infrastructure) play a crucial role in determining the competitiveness of different fleet types, they are not the only influencing factors. Nevertheless, the results clearly demonstrate that energy pricing remains a key determinant of fleet viability and the economic feasibility of transitioning to alternative powertrains.

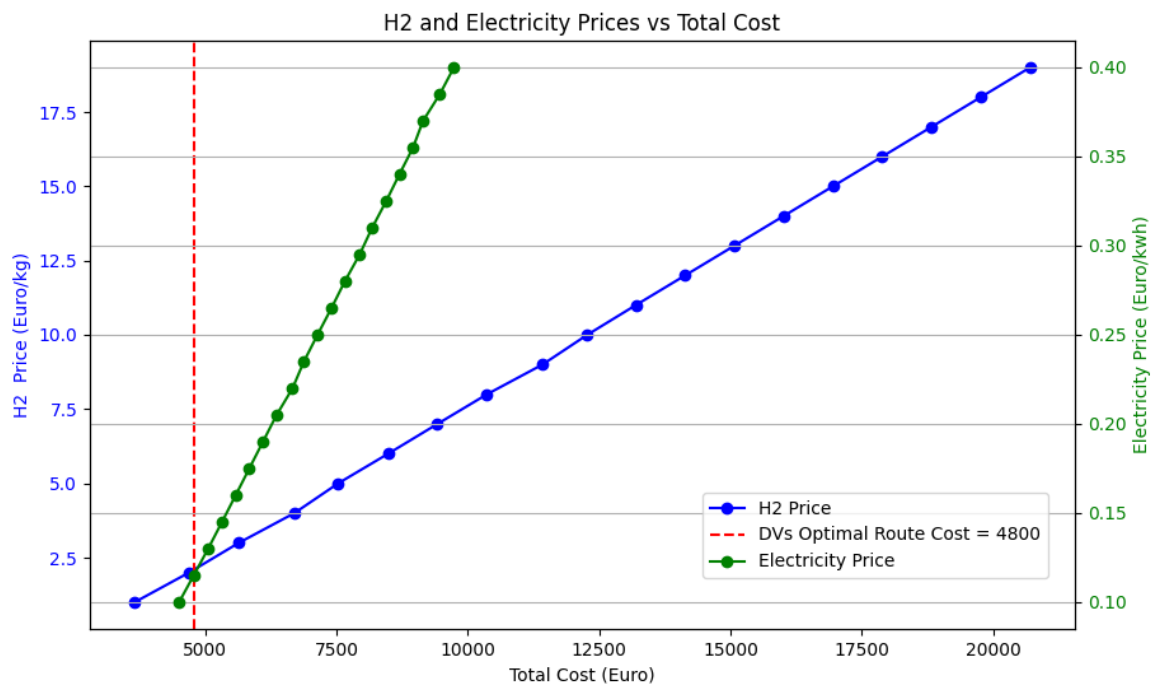


Figure 27. H2 and Electricity prices changes and their consequences transportation cost.

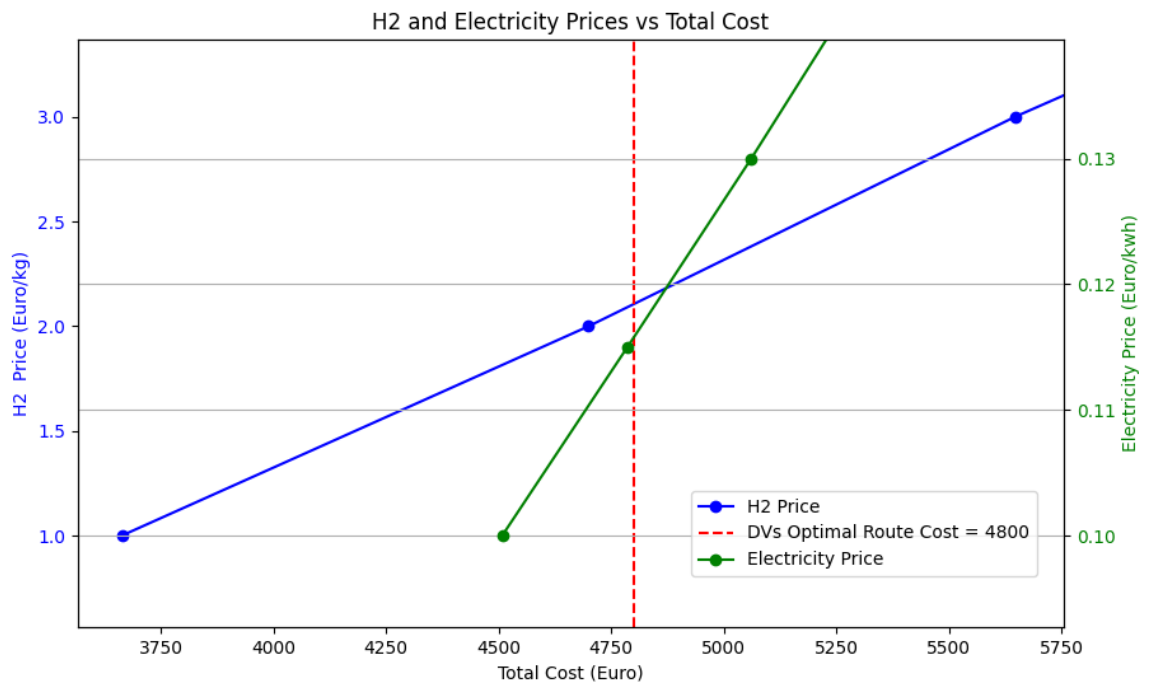


Figure 28. Intersection points of the Transportation cost and H2 and electricity prices.

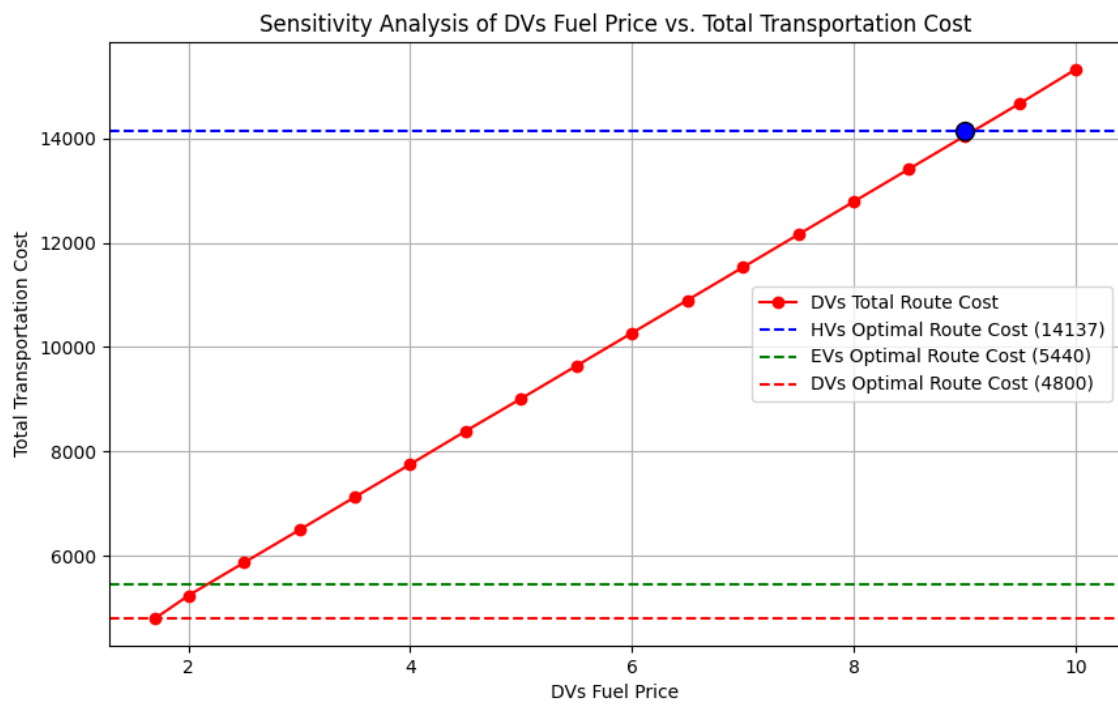


Figure 29. Intersection points of the Transportation cost after increasing the gasoil price.

4.3.2. Emissions of electric and hydrogen vehicles

In this section we are to evaluate the EVs and HVs environmental consequences. Although HVs and EVs are generally considered as environmentally friendly (green) modes of transportation, their overall emissions (indirect emissions) depend on the energy sources used for both their production and operation. When evaluating the entire supply chain, it is essential to account for emissions generated by the power plants that produce electricity and the facilities that generate hydrogen.

In order that this section examines various hydrogen production methods, calculates their corresponding emissions, and compares them with the emissions associated with other fleet types to provide a comprehensive evaluation of their environmental impacts. The analysis begins with an overview of hydrogen production technologies and their emission characteristics, as summarized in Table 4.5, which presents several hydrogen generation methods and their associated CO₂ emissions across different production scales.

To quantify and compare emissions, the mathematical model was first solved for a real-world case study by DVs as the only available fleet, thereby establishing the baseline level of direct CO₂ emissions. The model was then re-solved using only HVs as the available fleet. As previously discussed, various hydrogen production pathways exist, each associated with a specific level of CO₂ emissions (Dulău, 2023). To capture this variability, the model was solved multiple times under different hydrogen production scenarios to evaluate total HV emissions and to compare the indirect CO₂ emissions from hydrogen use with the direct emissions resulting from DV operations.

The results (Shown in Figure 30) clearly demonstrate that, even under the least favorable hydrogen production scenario in terms of emissions, the total CO₂ emissions associated with HV operation remain significantly lower than those generated by DVs for equivalent routing solutions. It is important to note, however, that the emissions associated with the production of diesel fuel itself were not considered in this analysis. Furthermore, Figure 30 compares the emissions of HVs under different hydrogen production pathways with the average emission production of EVs, taking into account all general electricity generation sources. The results indicate that, depending on the production methods for electricity and hydrogen, HVs and EVs can exhibit comparable levels of CO₂ emissions.

Table 4.5. Hydrogen production methods and its relevant CO₂ emissions (Dulău, 2023; Howarth & Jacobson, 2021; Longden et al., 2022; Tenhumberg & B  ker, 2020).

Hydrogen Production Method	CO ₂ Emissions (kgCO ₂ /kgH ₂)	CO ₂ Emissions (kgCO ₂ /kwh) $\left(\frac{CO_2 \text{ emission}}{LHV^{H_2}}\right)$	CO ₂ Emissions of usable H ₂ (kgCO ₂ /kwh) $\left(\frac{CO_2 \text{ emission}}{LHV^{H_2} \times \eta^{H_2}}\right)$
Hydro-powered electrolysis	0.3	0.009	0.016
Nuclear-powered electrolysis	0.6	0.018	0.033
Wind-powered electrolysis	0.7	0.021	0.038
Solar-powered electrolysis	1.8	0.054	0.098
Biomass gasification	5	0.15	0.273
Steam reforming of natural gas	9	0.27	0.491
Grid-powered electrolysis	14	0.42	0.764
Gasification of coal	19	0.57	1.037

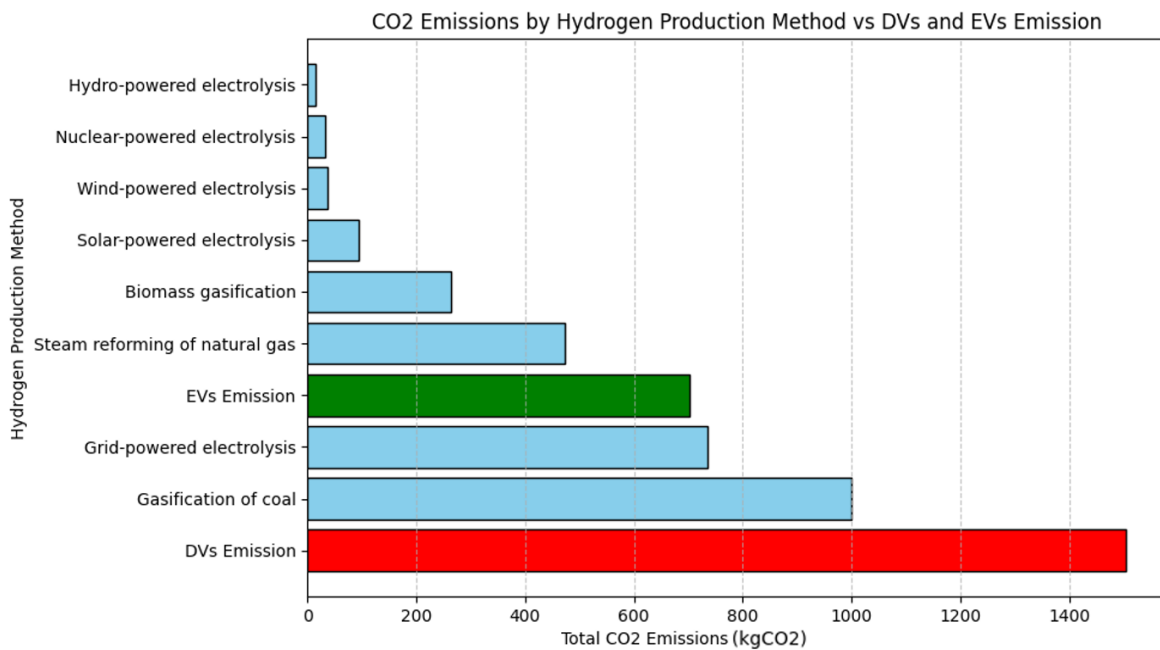


Figure 30. Different Hydrogen production methods and their emission for the optimal routing scenario of the case.

Continuing the previous analysis, this section investigates the emissions associated with different types of power plants. The emissions per kilowatt-hour (kWh) of energy generated by each production method are shown in Table 4.6. Considering these data of Table 4.6, the total emissions resulting from various electricity generation methods were calculated and are presented in Figure 31. This Figure 31 also compares the emissions produced by EVs under different electricity generation scenarios with the direct emission of DVs caused during vehicle usage and the general emissions associated with HVs.

The results shown in Figure 31 clearly indicate that EVs produce significantly lower emissions than DVs, confirming their environmental advantage under most electricity production conditions. It is important to note that, in this analysis, the emissions from gasoil production were not included and only the emission from burning gasoil is taken into account.

Furthermore, showing in Figure 32 a comparative assessment between HVs and EVs was analyzed to evaluate the relative efficiencies of electricity and hydrogen production. Considering all evaluated cases, the efficiency of electricity generation and its corresponding emissions (expressed in kgCO₂/kWh and total kgCO₂) were found to be better than the hydrogen production methods considering the current technologies. This finding holds for all hydrogen production methods considered in this study, with the exception of biomass gasification, which demonstrates comparable or better performance under certain conditions.

Table 4.6. Electricity production methods and its relevant CO₂ emissions (Dulău, 2023; Faria et al., 2012; Ramachandran & Stimming, 2015).

Power plant	CO ₂ Emissions (kgCO ₂ /kwh)
Wind	0.010
Hydro	0.012
Nuclear	0.012
Solar	0.050
Biomass	0.340
Gas	0.354
Coal	0.916

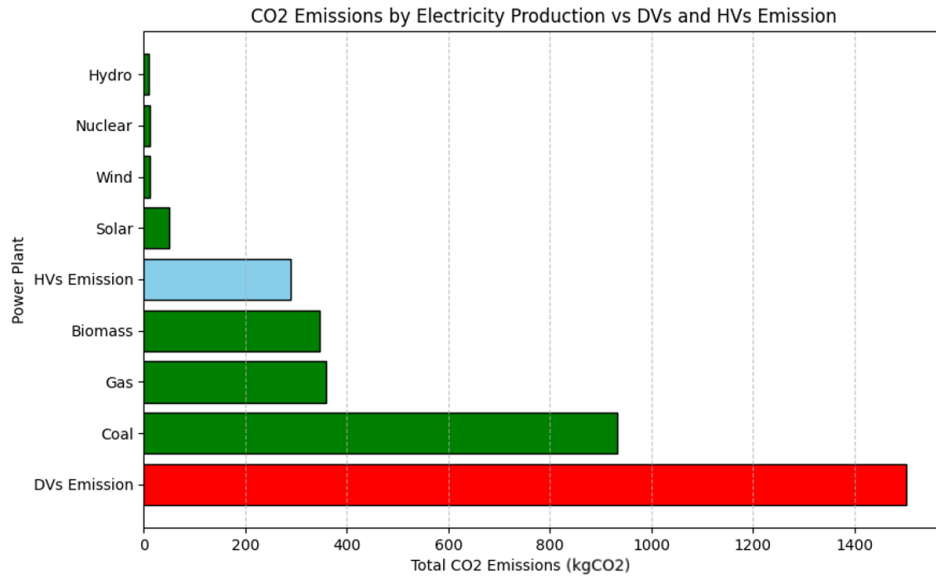


Figure 31. Different Electricity production methods and their emission for the optimal routing scenario of the case.

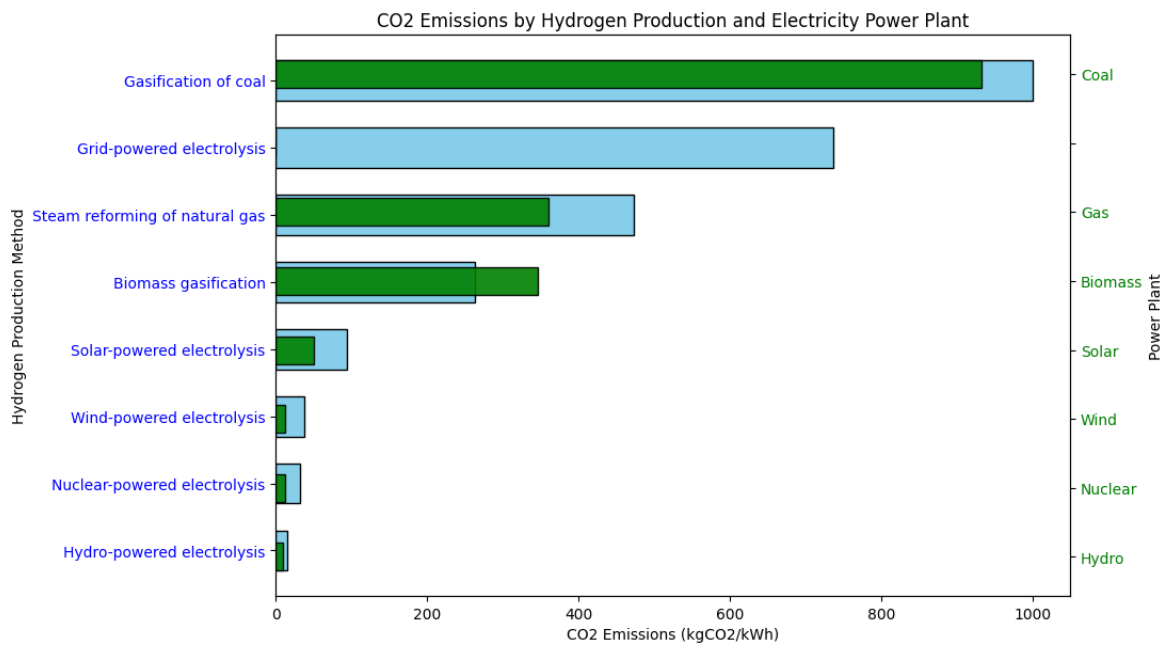


Figure 32. HVs and EVs emissions comparison.

4.4. Forecasting demand results

4.4.1. Rolling forecast for Pallets and Items

In this section, pallets are used as the forecasting target. Five Decathlon stores in the Piedmont region are analyzed as sample cases. The features and parameters used for forecasting these stores are summarized in Table 4.7. The forecasting results and corresponding errors for the test period are presented in Figure 33 to Figure 37. For clarity of visualization, the forecasting outcomes are illustrated

over a one-month horizon for each store compared with the actual demand of the company, while the error metrics are reported for the entire test period. For each day in the rolling forecast, the root mean square error (RMSE) and mean absolute error (MAE) are calculated to evaluate the forecasting model's performance.

4.4.1.1. Pallet Forecasting:

Table 4.7. Parameters for forecasting the number of pallets for five stores.

Store ID	Target of Forecasting	Forecasting Model	Forecasting Horizon	Initial train period data	Test period data
224	Number of Pallets	SARIMAX (7,0,7)	14 Days	01/01/2023-30/06/2024	01/07/2024-20/07/2025
314					
732					
1530					
2701					

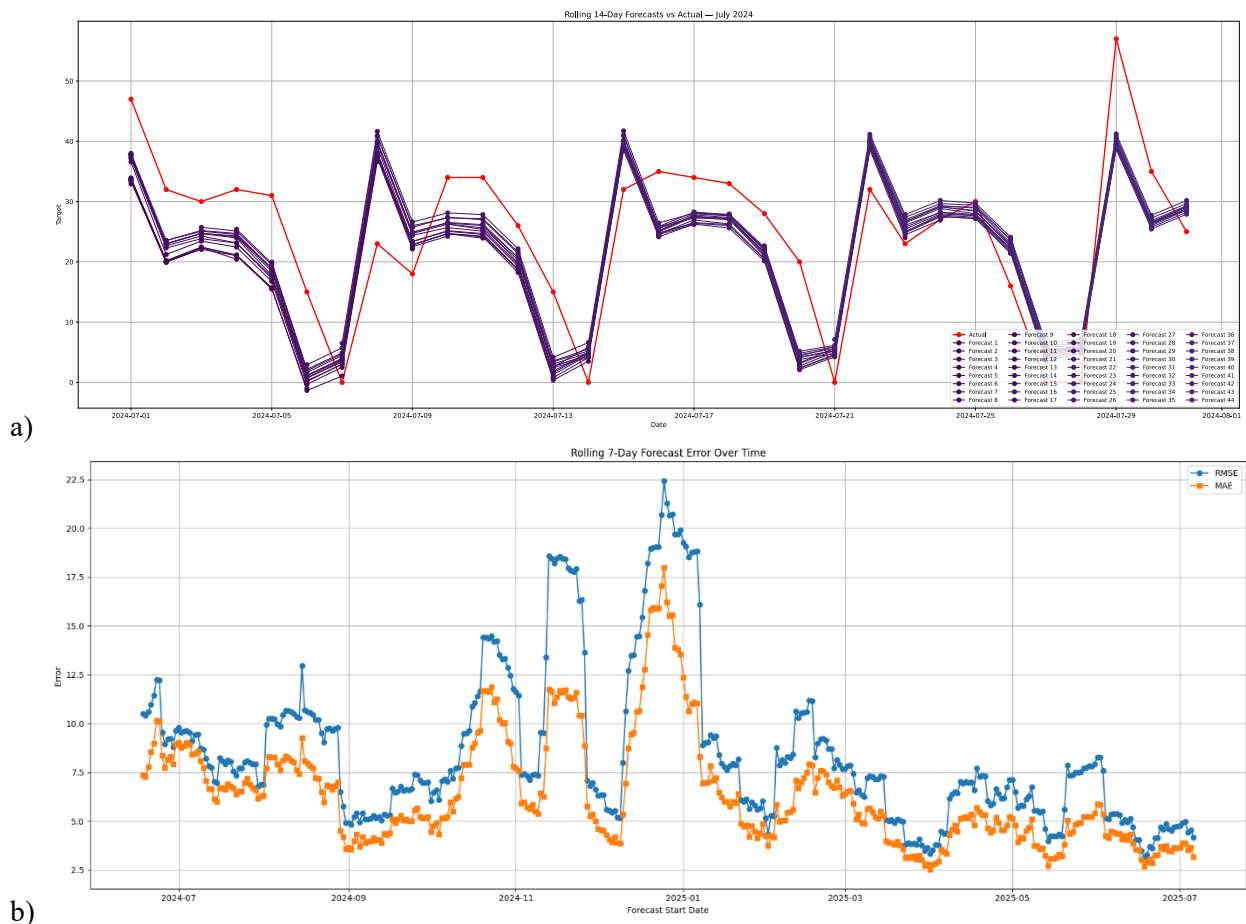
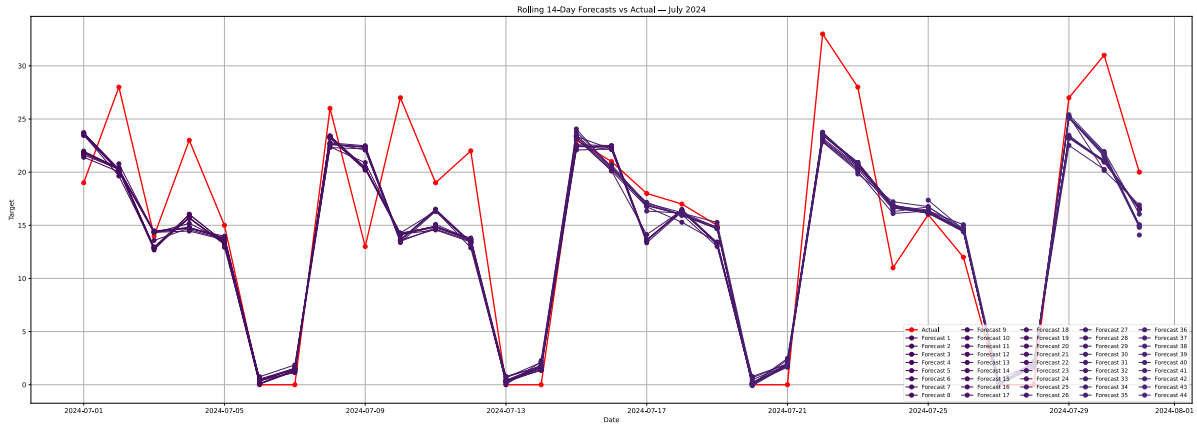
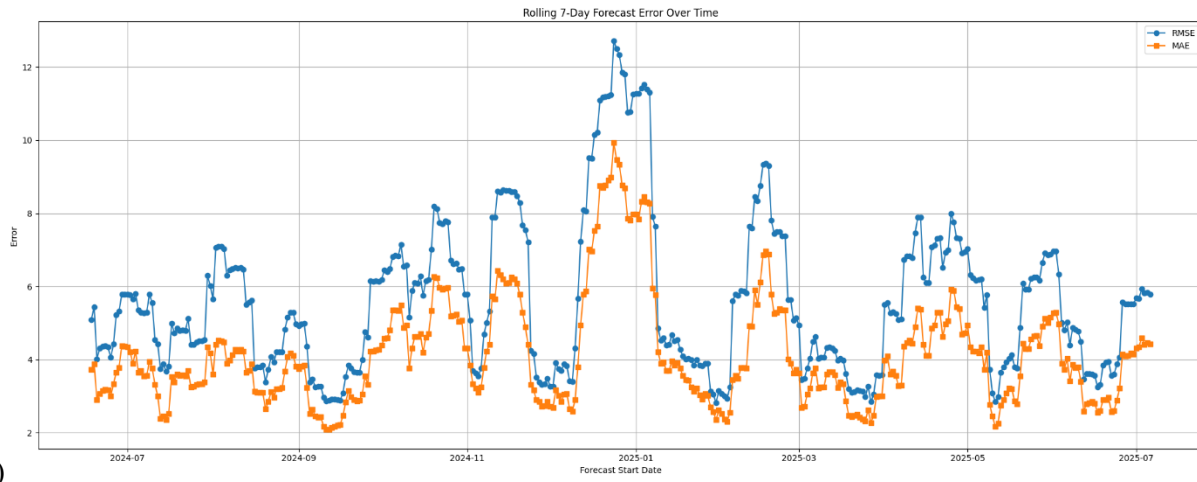


Figure 33. a) The pallet forecasting result of store 224 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 224 with ARIMA (7,0,7).

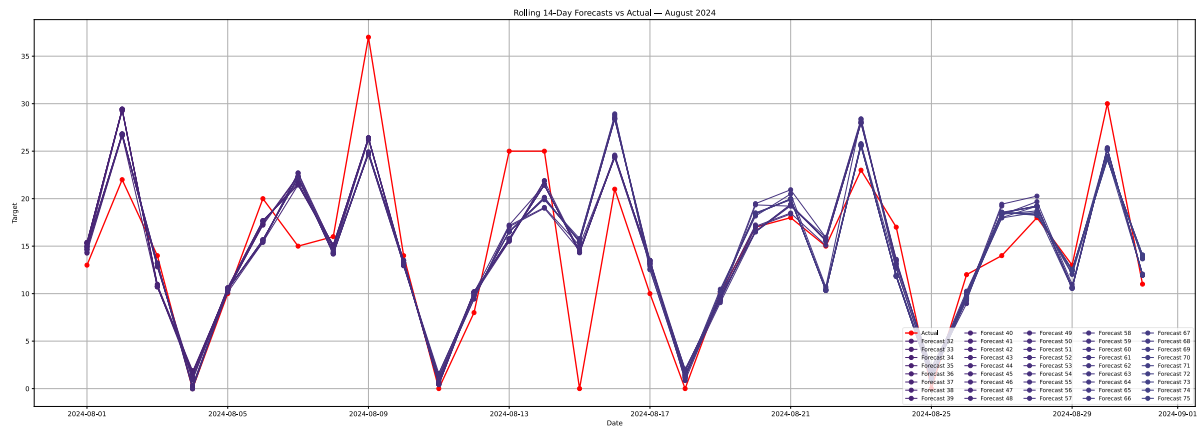


a)

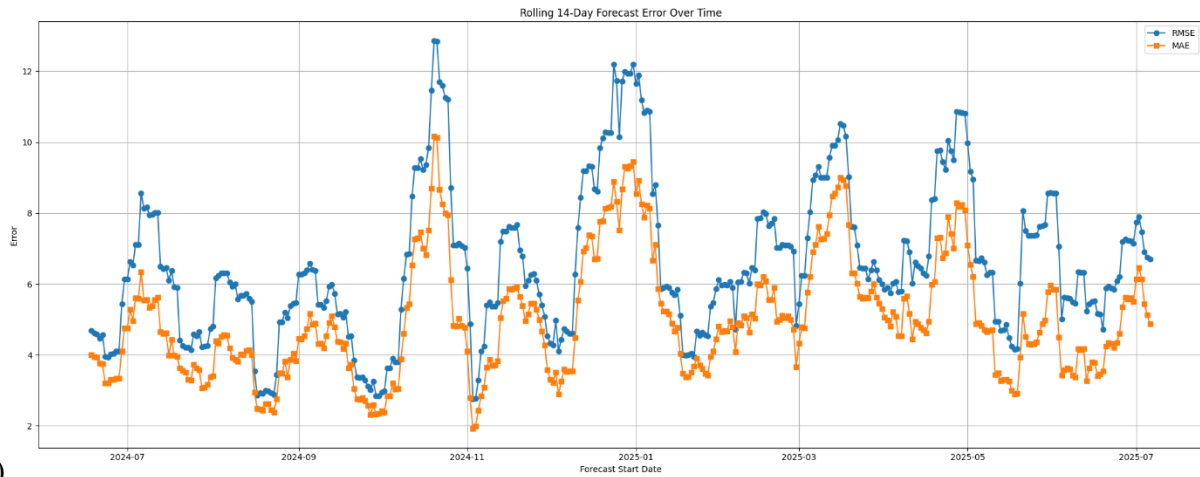


b)

Figure 34. a) The pallet forecasting result of store 341 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 341 with ARIMA (7,0,7).

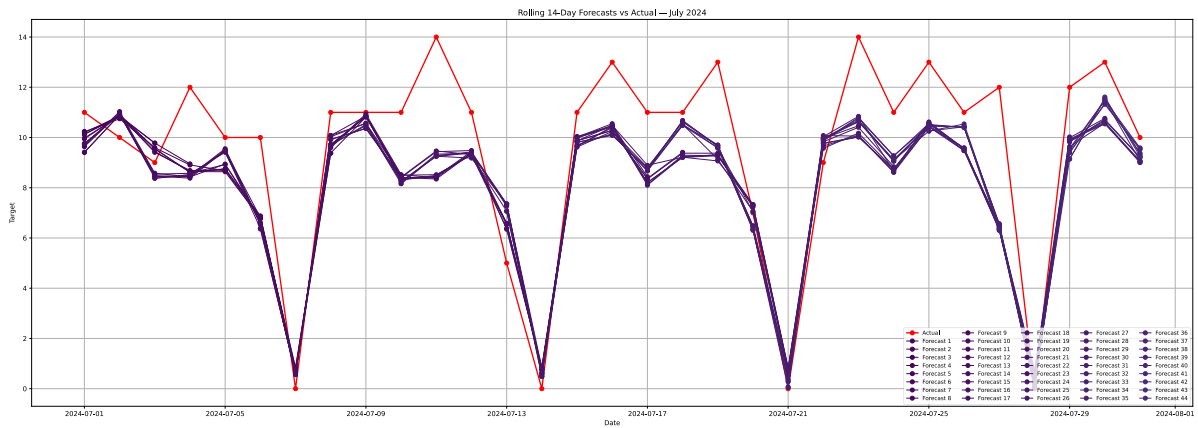


a)

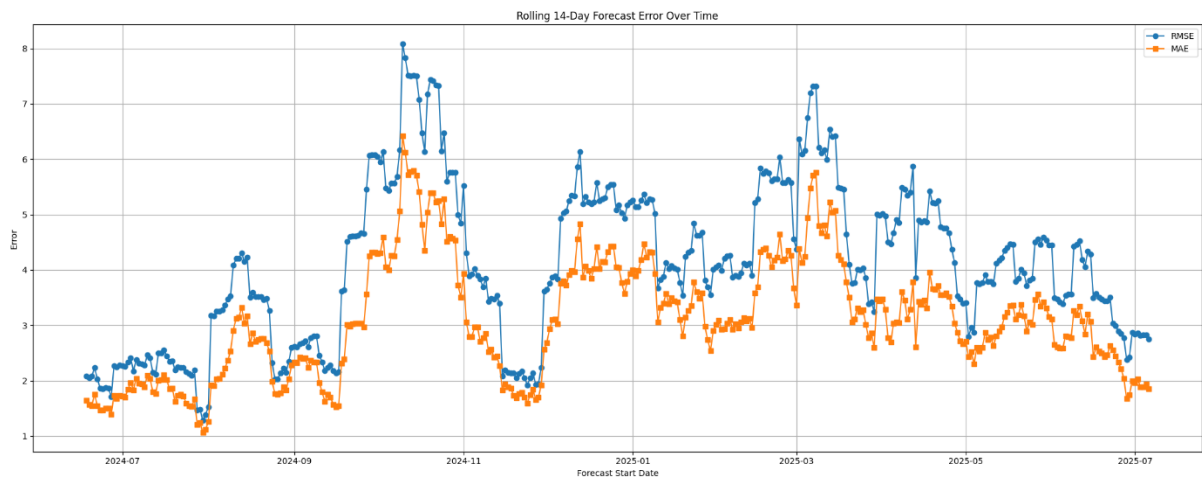


b)

Figure 35. a) The pallet forecasting result of store 732 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 732 with ARIMA (7,0,7).



a)



b)

Figure 36. a) The pallet forecasting result of store 1530 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 1530 with ARIMA (7,0,7).

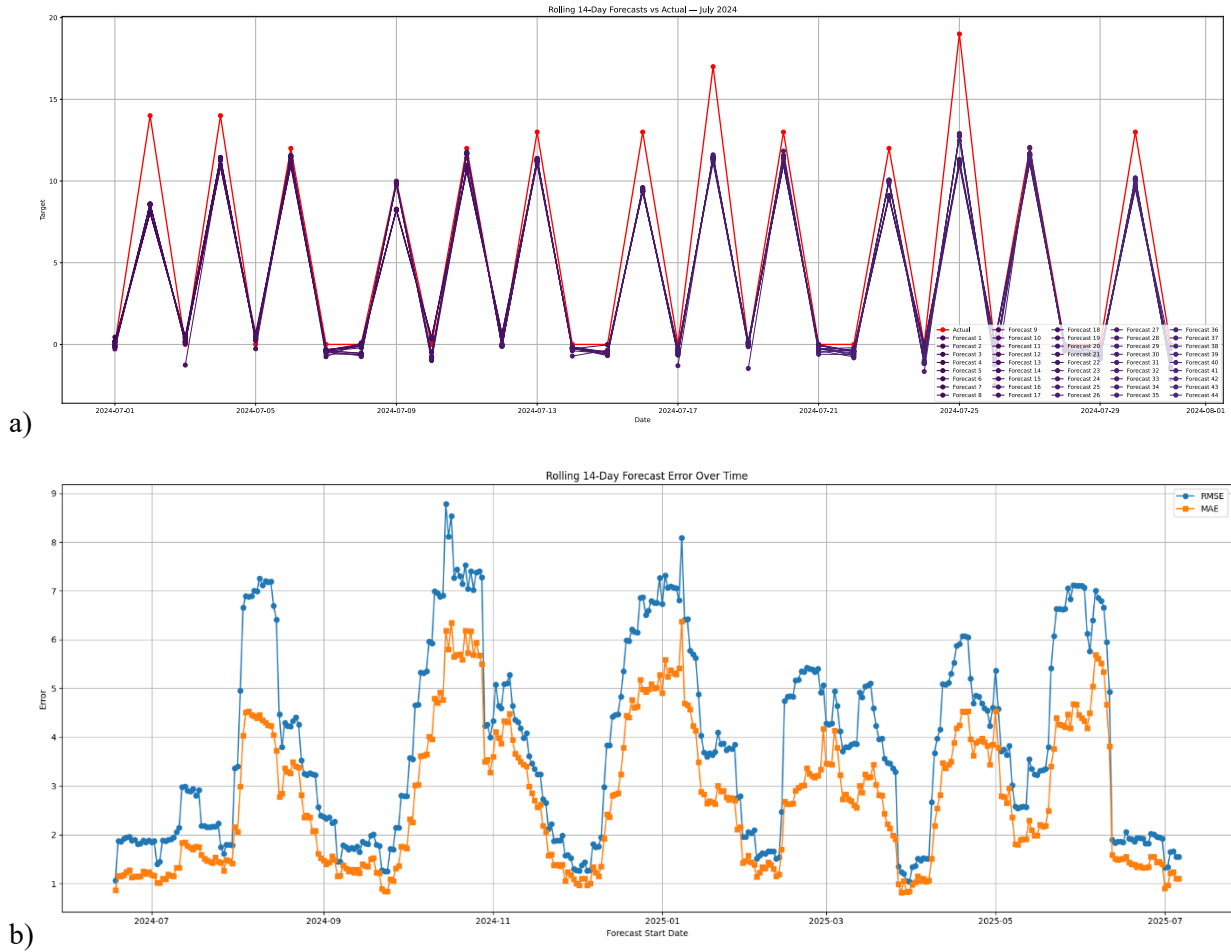


Figure 37. a) The pallet forecasting result of store 2701 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 2701 with ARIMA (7,0,7).

4.4.1.2. Item Forecasting:

In this section, forecasting is carried out with the number of items as the target. The same five stores as the previous section in the Piedmont region are selected as case studies. The features and parameters used in the forecasting process for these stores are listed in Table 4.8. The forecasting results, along with the errors for the test period, are presented in Figure 38 to Figure 42. To better illustrate the outcomes, the forecasts for each store are displayed over a one-month period, while the RMSE and MAE measures are reported for the entire test horizon.

Table 4.8. Parameters for forecasting the number of items for five Stores.

Store ID	Target of Forecasting	Forecasting Model	Forecasting Horizon	Initial train period data	Test period data
224	Number of Items	SARIMAX (7,0,7)	14 Days	01/01/2023-30/06/2024	01/07/2024-20/07/2025
314					
732					
1530					

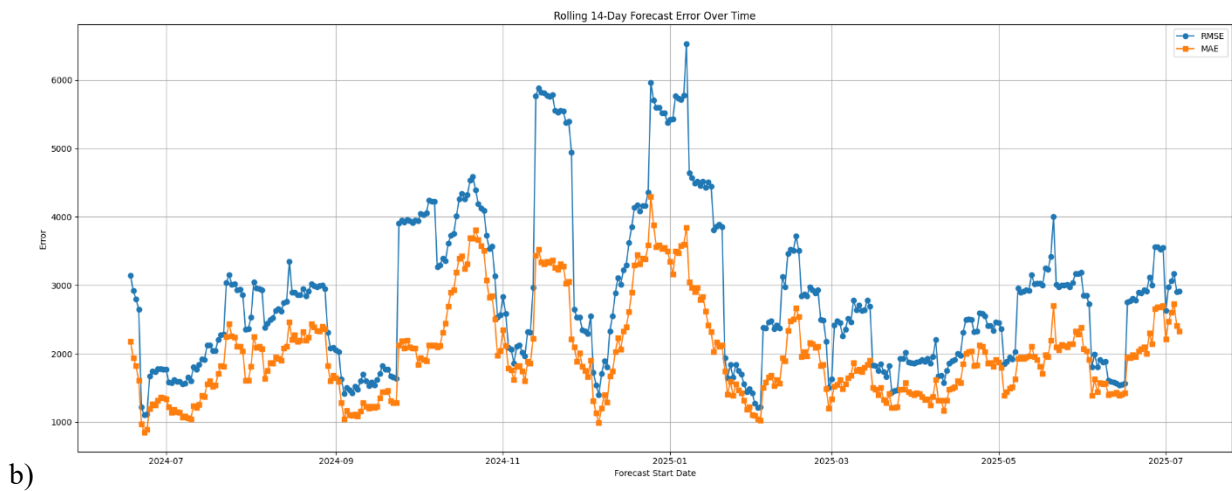
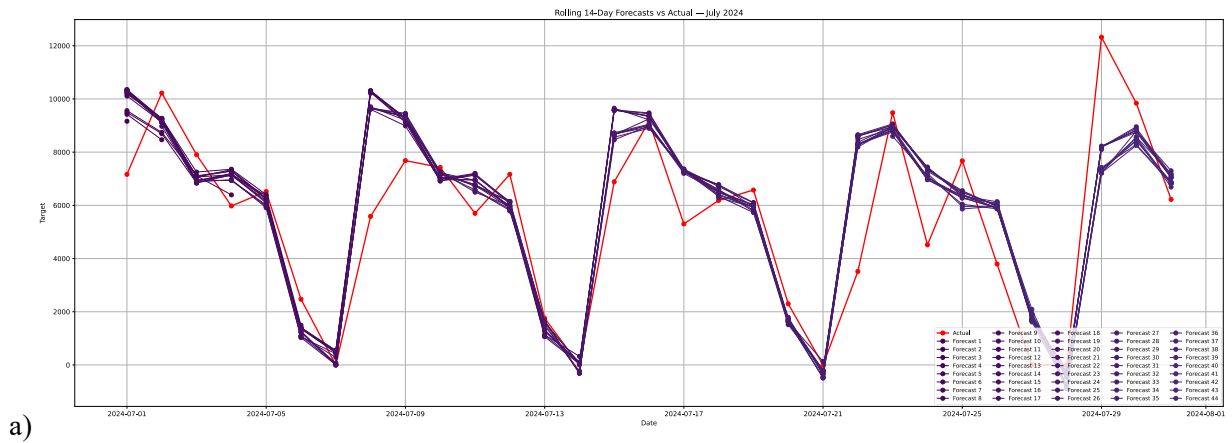
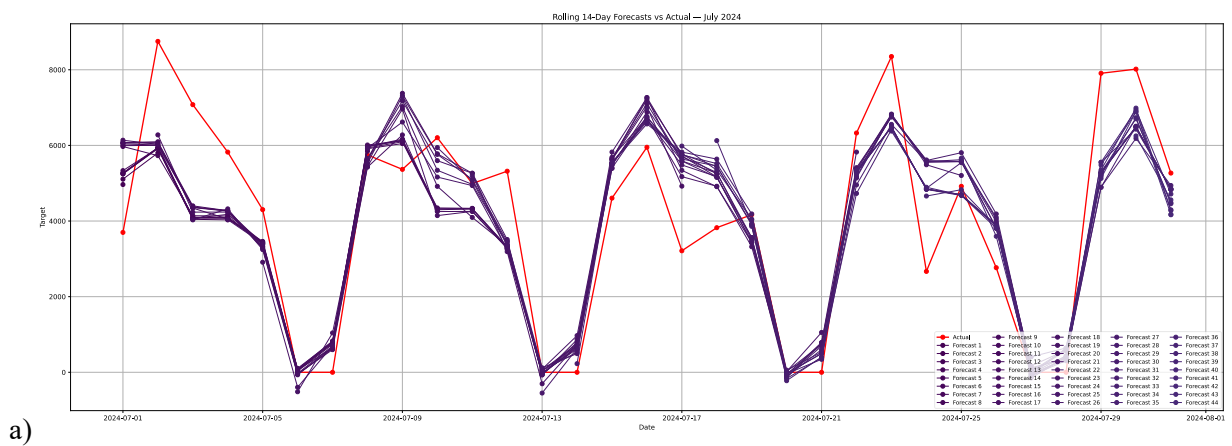
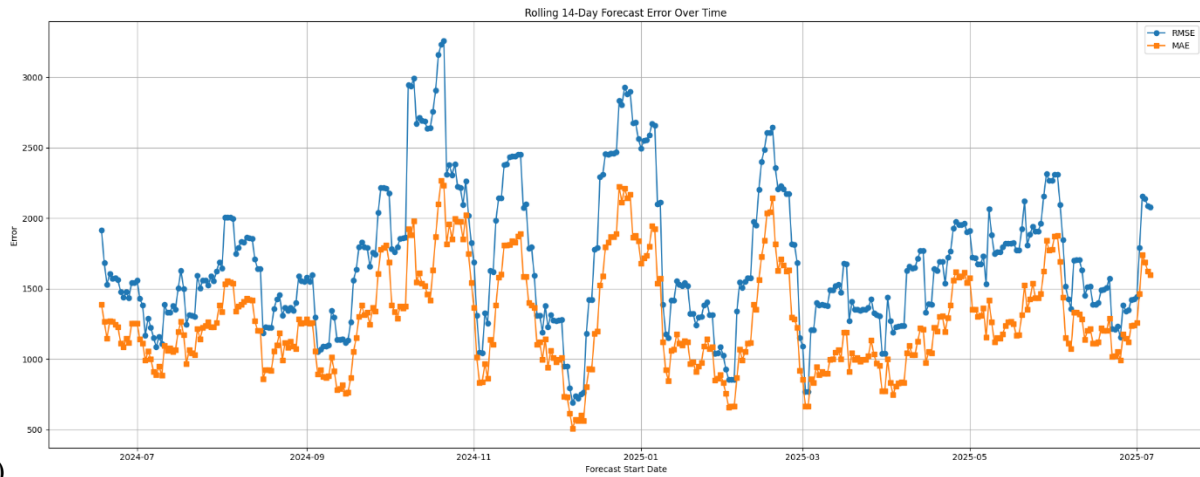


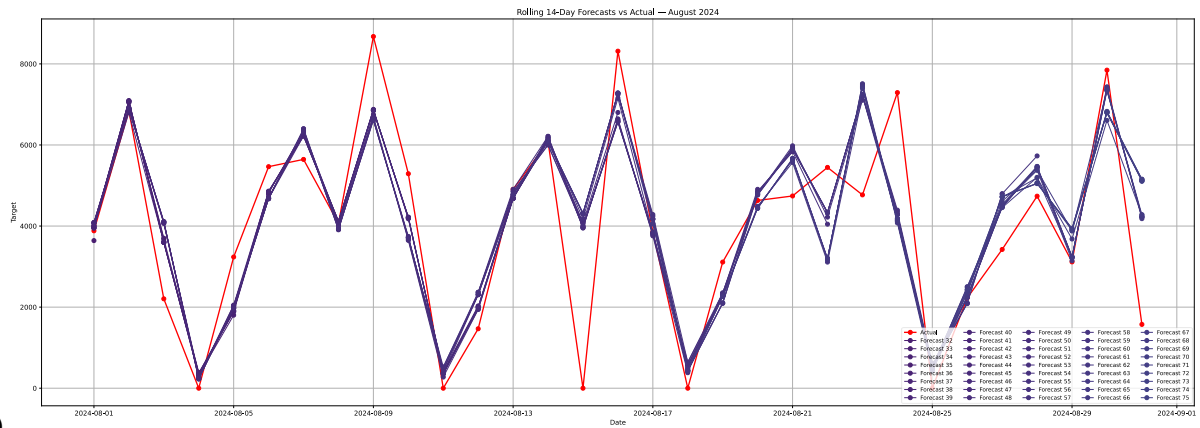
Figure 38. a) The item forecasting result of store 224 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 224 with ARIMA (7,0,7).



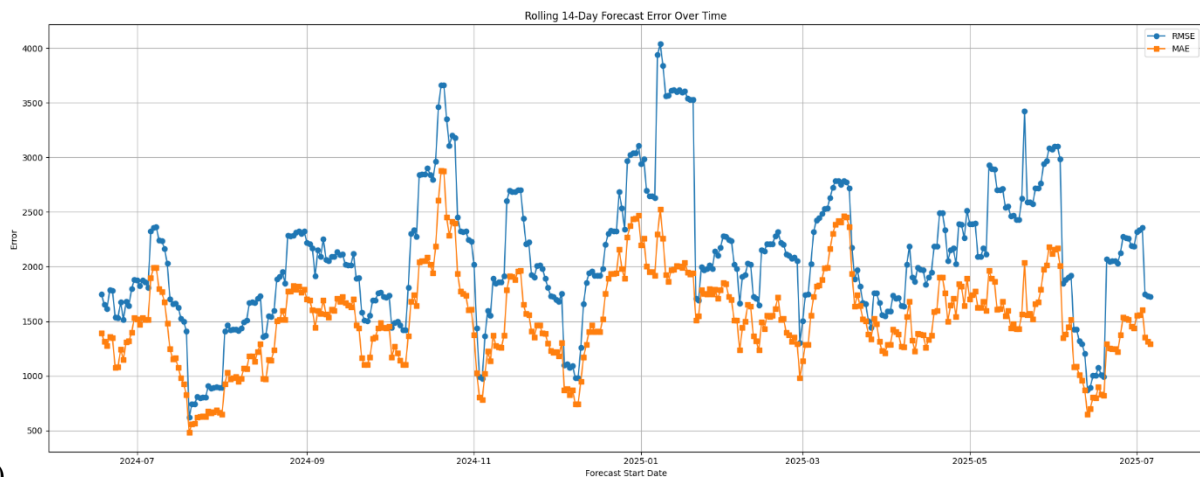


b)

Figure 39. a) The item forecasting result of store 341 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 341 with ARIMA (7,0,7).

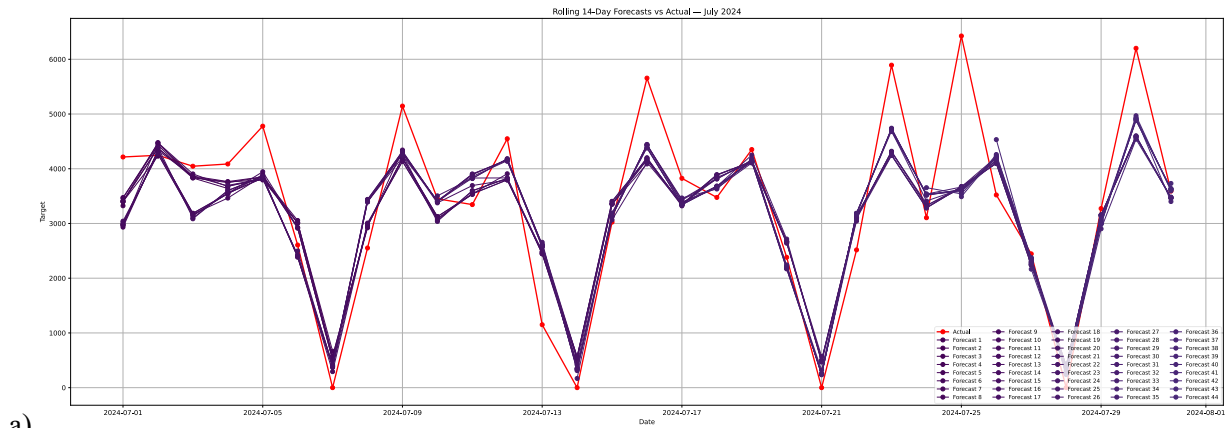


a)

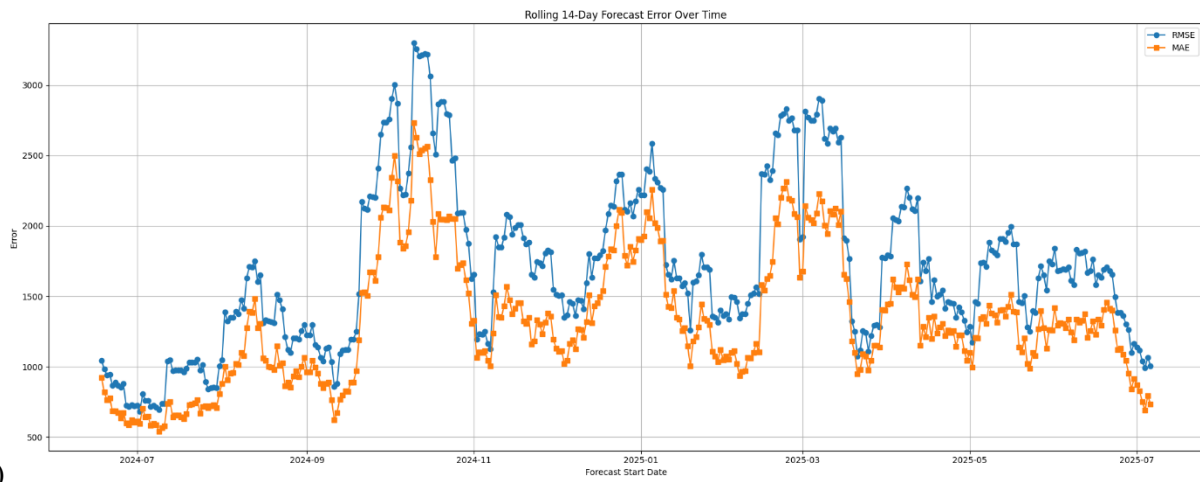


b)

Figure 40. a) The item forecasting result of store 732 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 732 with ARIMA (7,0,7).

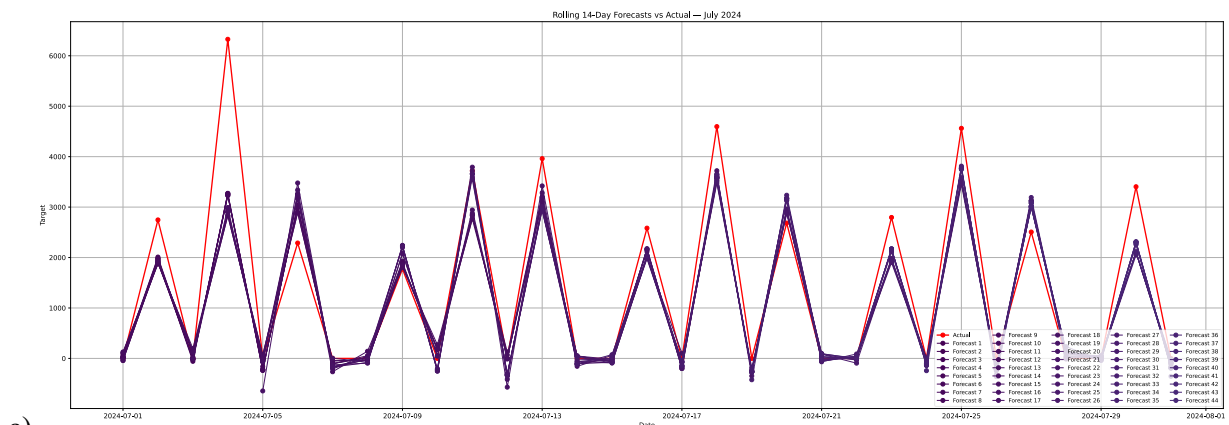


a)

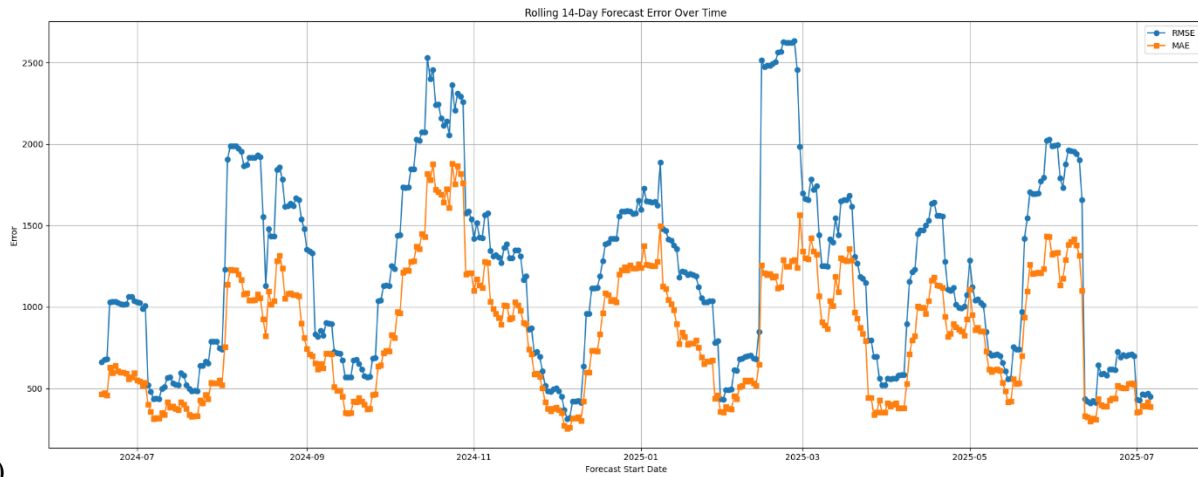


b)

Figure 41. a) The item forecasting result of store 1530 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 1530 with ARIMA (7,0,7).



a)



b)

Figure 42. a) The item forecasting result of store 2701 for one month vs actual values using ARIMA (7,0,7). b) RMSE and MAE of the rolling forecast of store 2701 with ARIMA (7,0,7).

4.4.2. Forecasting analysis

This section analyzes the forecasting results for both the number of pallets and the number of items ordered by the stores. Two error metrics, RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error), are calculated and examined. The outcomes of this analysis are presented in Table 4.9 for pallet forecasting and

Table 4.10 for item forecasting. In both tables, the average RMSEs and the average of MAEs over the entire test period are used as criteria to compare two ARIMA models: ARIMA (7,0,7) and ARIMA (14,0,14) as statistical time series models with random forest as a machine learning model. As illustrated in Table 4.9 and Table 4.10, the forecasting quality depends on the store data, meaning that certain models perform better for specific stores. However, overall, the Random Forest model provides more accurate forecasts.

Table 4.9. Analysis of the forecasting pallets with Average RMSE and MAE errors.

Pallets Forecasting Evaluation						
Stores ID	Average of all data	Average of test period	Error	ARIMA (7,0,7)	ARIMA (14,0,14)	Random Forest (100 trees)
224	23.9	22.10	RMSE (Average)	8.5	8.6	8.3
			MAE (Average)	6.4	6.5	6.0
341	18.1	16.4	RMSE (Average)	5.6	5.6	5.4
			MAE (Average)	4.1	4.1	3.8
732	17.5	17.1	RMSE (Average)	6.5	6.7	6.8
			MAE (Average)	4.9	5.1	5.1
1530	10.9	10.2	RMSE (Average)	4.0	4.1	4.0
			MAE (Average)	3.0	3.1	2.9
2701	12.1	11.7	RMSE (Average)	3.8	3.8	3.2
			MAE (Average)	2.7	2.7	2.0

Table 4.10. Analysis of the forecasting items with Average RMSE and MAE errors.

Items Forecasting Evaluation						
Stores ID	Average of all data	Average of test period	Error	ARIMA (7,0,7)	ARIMA (14,0,14)	Random Forest (100 trees)
224	6037	5968	RMSE (Average)	2824	2864	2769
			MAE (Average)	2000	2042	1913
341	4230	3957	RMSE (Average)	1693	1694	1738
			MAE (Average)	1269	1270	1260
732	4230	4426	RMSE (Average)	2079	2118	2075
			MAE (Average)	1525	1567	1500
1530	3265	3295	RMSE (Average)	1691	1713	1647
			MAE (Average)	1326	1343	1266
2701	2757	3030	RMSE (Average)	1209	1217	1074
			MAE (Average)	838	833	687

4.5. Bi objective multi-period problem results

In this section, a case study is provided for the multi-objective and multi-period model presented in section 3.4. All the data used in this case study are similar to those shown in Table 4.3, and the analysis is conducted over multiple days. The objectives of the model are to minimize total costs and total CO₂ emissions, and all other constraints and assumptions of the case are defined as described in section 3.2.3.

The case is solved using both the weighted sum method and the Torabi–Hassini method for multi-objective optimization. In the weighted sum method, after normalizing the objective functions, different weights are assigned to each objective in the model, and the corresponding results are obtained. By solving the model with varying weights, the results are presented as a Pareto front (Figure 43), where the y-axis represents total CO₂ emissions and the x-axis represents total costs. As shown in Figure 43, all the solutions are non-dominated, and improving one objective leads to the deterioration of the other. The Pareto front provides decision-makers with the flexibility to select an appropriate solution based on the relative priority of each objective or the current conditions of the organization.

The Torabi–Hassini (TH) method is typically used to obtain a single solution for multi-objective optimization problems. The model is also solved using the TH method considering 0.5 for each weight of 1-norm and infinity-norm, resulting in a total cost of €12446 and total CO₂ emissions of 1068[kg]. This solution is considered as a non-dominated solution.

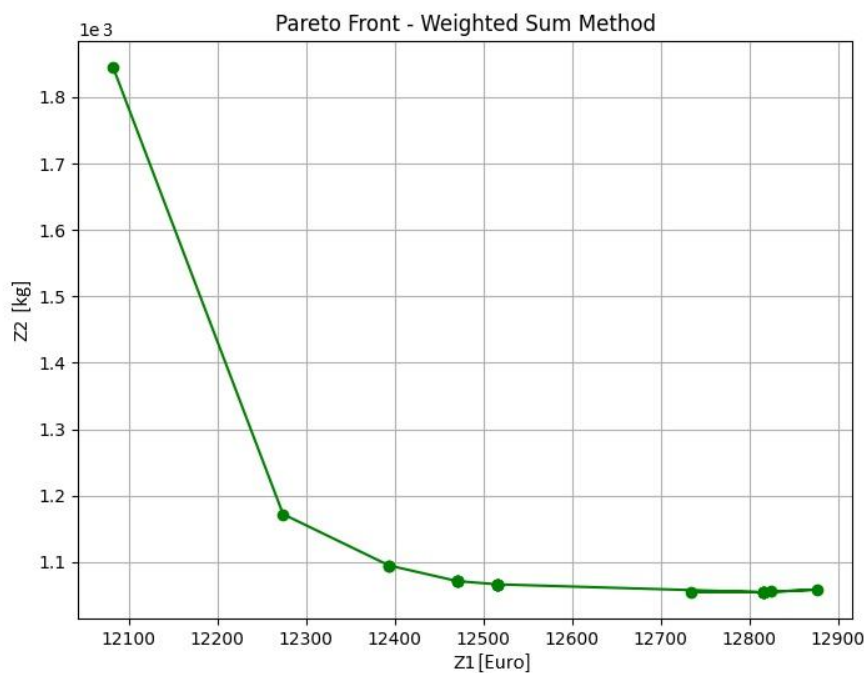


Figure 43. Pareto front derived from solving the model by weighted sum method.

Chapter 5: Conclusion and Future research

5.1. Conclusion

Over the last few decades, the Vehicle Routing Problem (VRP) has been an important research field for researchers, companies, and policymakers, especially as the need to control greenhouse gas emissions grows. This PhD project, carried out in collaboration between the University of Genova and Decathlon Italy, focused on improving the way products are delivered from distribution centers to stores in the final stages of the supply chain. The work aimed to reduce transportation costs and emissions while still satisfying store demand on time and respecting real operational limits such as delivery windows, the availability of trucks with different capacities, and all the other assumptions and constraints of the real case of the company.

To tackle these challenges, several optimization models based on the Capacitated Vehicle Routing Problem were developed. Each model represents a different scenario that Decathlon faces in practice. The first model combines total cost and emissions into a single objective and uses a regression model to estimate transportation costs. The second model introduces a mixed fleet of diesel, electric, and hydrogen vehicles and incorporates a carbon cap-and-trade mechanism by converting emissions into trade costs. The third model separates cost and emissions into two independent objectives, which makes it possible to study trade-offs more clearly. For this last model, long-term store demand was predicted using time-series and machine-learning forecasting methods.

All models were tested using real data from Decathlon Italy and France. The results show substantial improvements compared with the company's current procedures. Additional analyses were conducted to explore how the optimal solutions change when separating either cost or emissions. Then a set of sensitivity studies was performed for the hybrid fleet. These investigations show that, with current technology and prices, although diesel vehicles remain the most cost-effective, electric vehicles are becoming competitive by slightly reducing electricity prices or slightly increasing fuel prices. Emissions analyses also reveal that electric and hydrogen fleets behave differently depending on how electricity and hydrogen are produced. The results of the analysis showed that, in any case of electricity or hydrogen production methods, and considering their indirect emissions, they are far greener than DVs.

Several practical insights emerge from this research:

When both economic costs and emission-trading costs are considered, the most efficient order of fleet use is diesel first, followed by electric and then hydrogen vehicles.

When environmental impact alone is considered, hydrogen vehicles come first, followed by electric and then diesel, although current hydrogen production methods still produce relatively high upstream emissions.

Electric and hydrogen vehicles become cost-competitive with diesel if electricity prices fall to around 0.10–0.13 €/kWh and hydrogen prices to 2–2.5 €/kg, assuming vehicle purchase and maintenance costs stay the same.

Increases in diesel prices can quickly change the cost balance: a rise to 2.1 €/L would make diesel comparable to electric vehicles, and further increases up to 9 €/L would make it comparable to hydrogen vehicles.

These findings provide direct, real-world insights that can support Decathlon in making better decisions about fleet planning and sustainability strategies.

Future Research

Several directions are worth exploring in the future. Developing a software tool that can handle Decathlon's global-scale distribution network would help the company use these models in daily decision-making. Another valuable direction is the design of heuristic or metaheuristic algorithms to handle much larger problem sizes that exact optimization cannot solve efficiently. Since the company also deals with product returns, integrating reverse logistics into the distribution model (or treating it as a separate optimization problem) would offer an additional and meaningful extension of this work.

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