University of Twente

The Design of Fast-Moving Consumer Goods Distribution Networks, Considering the Trade-Off Between Costs and Sustainability

Industrial Engineering & Management

Author

N. van Weperen
Student No. 2106663

Supervisors

Dr. S.M. Meisel
Dr. D. Guericke
L.R.S. Eringfeld
A.M. Nugteren

1 September, 2024

Preface

I am excited to share that this thesis marks the end of my Master's in Industrial Engineering & Management at the University of Twente! I am truly grateful to everyone who helped me along the way. Writing my thesis at RHDHV has been a great experience. The team has shown great interest in my work and inspired me to explore several interesting aspects of the research topic. Particularly, I would like to acknowledge my supervisors at RHDHV, Lennart Eringfeld and Alex Nugteren. They have provided weekly guidance throughout the thesis process and spent time discussing their ideas on the study.

Furthermore, I would like to thank my first supervisor Stephan Meisel. Your encouraging feedback was highly appreciated. You challenged me to think critically about my thesis, while also providing me with positive feedback. I also want to thank Daniela Guericke, for being my second supervisor, and helping me out on topics in which she excels. And finally, I want to thank all my friends, fellow students and family who have been there for me every step of the way. You have been such a great support!

Nina van Weperen

Amsterdam, 1 September, 2024

Executive Summary

Introduction

The European Parliament has adopted the European Climate Law to address climate change, aiming for a 55% reduction in net greenhouse gas (GHG) emissions by 2030 and climate neutrality by 2050 (European Parliament, 2018b). Central to this effort is the European Emissions Trading System (ETS), a carbon cap-and-trade mechanism for regulating and pricing carbon dioxide (CO_2) emissions (European Parliament, 2018b, Harvard Business Review, 2015). With growing societal pressure for environmental responsibility, businesses are increasingly compelled to demonstrate their commitment to climate action (Yakavenka et al., 2019, Xu et al., 2016, Albitar et al., 2023).

Problem definition

The Fast-Moving Consumer Goods (FMCG) industry, known for its high sales volumes and frequent use of disposable products, has a significant impact on the environment. In response to CO_2 regulations and increasing consumer demand for greener products, FMCG companies are adopting strategies to reduce CO_2 emissions. While greener packaging is already a trend in the industry, the location of warehouses also has a direct impact on CO_2 emissions.

It is a common practice among companies in the FMCG industry to employ the use of a shared distribution network, whereby their transportation and warehousing activities are outsourced to logistics service providers. This allows for the optimisation of truck space and the reduction of costs. By pooling resources and sharing infrastructure, companies achieve economies of scale and adaptability to fluctuating demand patterns. This approach eliminates the need for individual dedicated facilities and allows for flexible expansion or contraction of operations as needed.

At Royal HaskoningDHV (RHDHV), they recognize a growing demand from clients for getting insight in the trade-off between CO_2 emissions and distribution costs in their distribution network. Therefore, the aim of our research is to visualize this trade-off, to gain insight into the impact of their logistics providers' warehouse locations and customer assignments on these two objectives. The resulting research question is formulated as follows:

How should FMCG companies design their distribution network, considering the trade-off between minimizing distribution costs and CO_2 emissions?

Model Development

We begin by introducing Facility Location Problems (FLP), particularly in the context of shared distribution networks, with the dual objective of minimizing distribution costs and CO_2 emissions. Through a literature review, we found that the model of Harris et al., 2009 is the most suitable model for our problem, since it addresses an Uncapacitated FLP (UFLP), with a discrete set of warehouses. We refined this model according to the FMCG industry characteristics, and a more extensive CO_2 emission calculation. According to the Greenhouse Gas Protocol, 2024, there are different methods for calculating CO_2 emissions from transportation and warehouses. We evaluated that the distance-based method and the site-specific method are the most suitable for our case.

Extensions to the model introduce a maximum distance constraint to ensure deliveries meet FMCG product delivery requirements. The Square Root Law (SRL) is applied to optimize warehouse utilization and manage inventory within a shared warehouse network. Enhanced CO_2 emission calculations integrate specific emission factors for transportation and warehouse operations, offering a detailed environmental impact assessment tailored to FMCG logistics.

Trade-off Distribution Costs and CO_2 Emissions

We employed the ϵ-constraint method to visualize the trade-off between the two objectives in a Pareto front (Figure 1). Our case study revealed significant impacts of the dual objective on warehouse configuration. Minimizing distribution costs led to fewer warehouses, while minimizing CO_2 emissions required more. The Pareto front showed that operating fewer warehouses reduce costs but increase emissions, and more warehouses have the opposite effect. Customer assignments remained stable when the same warehouses were selected. Optimal solutions derived from our analysis offered more effective ways to reduce both CO_2 emissions and distribution costs compared to the original configuration. The highest CO_2 reduction achieved, compared with the initial warehouse configuration, was 25.8%, with incremental costs of €380,654.71.

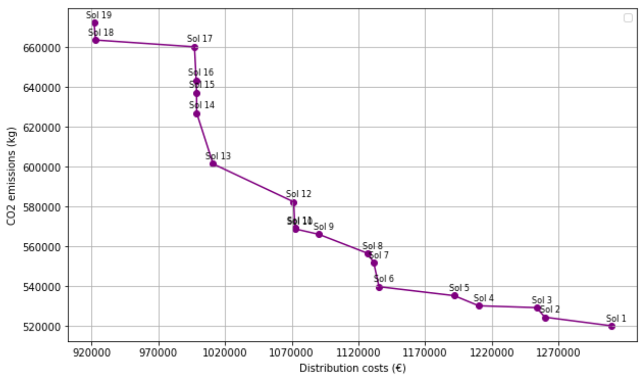


Figure 1: *Pareto front resulting from ϵ-constraint method.*

In comparing different temperature control logistics (TCL) scenarios, we found that chilled and heated scenarios increase both costs and emissions compared to frost-free scenarios. In the chilled scenario, higher warehouse emissions shifted the Pareto front, favoring fewer warehouses. In the heated scenario, while costs and emissions were slightly higher, the trade-off structure remained similar to frost-free scenarios. Our analysis of carbon pricing regulations (ETS2) concluded that the

trade-off remains largely unchanged unless transportation costs triple, which is unlikely. Therefore, carbon pricing has minimal impact on the trade-off unless costs increase significantly.

Keywords: FMCG industry, UFLP, shared distribution network, distribution costs, CO_2 emissions.

Contents

List of Figures

List of Tables

1

Introduction

In response to the urgent need to compete with climate change, the European Parliament acted by adopting the European Climate Law. This law raises the EU's target of reducing net greenhouse gas (GHG) emissions by at least 55% by 2030 and legally binds the EU to achieve climate neutrality by 2050 (European Parliament, 2018b). To support these ambitious goals, carbon dioxide (CO_2) emissions are increasingly examined, regulated, and priced (Harvard Business Review, 2015). This includes the implementation of the European Emissions Trading System (ETS), functioning as a carbon cap-and-trade mechanism (European Parliament, 2018b).

Alongside governmental initiatives, the societal pressure increases (Yakavenka et al., 2019), with a growing number of consumers expressing preferences for environmentally friendly products and favoring products from companies with positive reputation (Xu et al., 2016). Consequently, companies are compelled to demonstrate responsibility and commitment to addressing climate change (Albitar et al., 2023).

1.1 Problem Context

The Fast-Moving Consumer Goods (FMCG) industry, also known as the consumer-packaged goods sector, is one of the largest industries globally. However, its substantial size and scale also result in a significant environmental impact (Guo and Liu, 2023). FMCG products, which include items like household care, skincare, food and beverages, medicines, and affordable consumer electronics, are known for their low-profit margins but high sales volume to meet daily demands (Guo and Liu, 2023). Major FMCG companies such as Nestlé, Procter and Gamble, PepsiCo, Unilever, and Coca-Cola offer a diverse range of products within this sector (Team, 2023).

The environmental impact of the FMCG sector stems from various factors. The rapid turnover and short product life-cycles contribute significantly to their environmental impact, particularly in terms of emissions. The nature of FMCG products, which are quickly depleted from store shelves due to frequent usage, often results in a high volume of production and disposal. Additionally, many FMCG items are designed for single or limited use, leading to a significant amount of waste generated. The demand for fast delivery of FMCG products has grown rapidly, driven by evolving customer expectations for quick access to goods. As a result, short lead times have become increasingly important for FMCG companies aiming to stay competitive. However, shorter lead times can often result in more frequent and smaller shipments, which can contribute to higher transportation-related emissions.

Sales dynamics in the FMCG industry are influenced by factors such as store discounts, seasonal variations, and demand uncertainty, leading to price competition among retailers. Managing input costs becomes crucial, as even slight margin improvements can have a significant impact on the bottom line due to the large volumes involved (Rajalakshmi and Umadevi, 2020). Furthermore, to meet the high (uncertain) demand for FMCG products and to deliver in time, FMCG companies often need to maintain a high inventory level. This enables them to have sufficient stock on hand to quickly respond to customer needs and fluctuations in market demand.

To manage these complexities, FMCG companies often outsource their transportation and warehousing to logistics service providers, utilizing shared distribution networks. These networks consolidate FMCG products from multiple companies, enabling efficient distribution by optimizing truck space and reducing transportation costs.

Given the rising CO_2 price and the increasing preference of customers for companies that are committed to environmental responsibility, FMCG companies are compelled to reduce their footprint to maintain market share and brand loyalty. While greener packaging is already a trending subject in the FMCG sector, there is a growing recognition of the importance of designing sustainable logistics as well (Kellner and Igl, 2012). This underscores the need for FMCG companies to extend their sustainability efforts beyond packaging and encompass the entire supply chain, including transportation and warehouse logistics.

The locations of warehouses directly impact transport-related CO_2 emissions, with studies indicating that CO_2 pricing can influence facility relocation decisions (Gaigné et al., 2020). Location-allocation decisions, which encompass both the selection of warehouse locations (strategic decision) and the assignment of customers to these facilities (tactical decision), significantly influence both logistics costs and environmental factors (Afshari et al., 2014; Harris et al., 2014).

The FMCG sector's significant environmental impact, driven by factors such as high production volumes, short product life cycles and frequent transportation, requires the adoption of sustainable logistics practices and strategic decisions on warehouse locations to reduce CO_2 emissions, minimize distribution costs and meet customer demand for environmentally responsible solutions.

1.2 Problem Relevance

This research is conducted at Royal HaskoningDHV (RHDHV), an engineering and advisory firm established in the Netherlands and operating globally. RHDHV specializes in providing valuable services primarily tailored for clients and is driven by a shared passion for making a positive impact. RHDHV's expertise helps clients improve their businesses and they are committed to create a sustainable future. They notice a growing demand from clients seeking guidance on optimizing their networks, driven by the increasing importance of sustainability. This trend is demonstrated by recent inquiries from FMCG companies, whose perspective as shippers highlights a growing interest in achieving both cost-effectiveness and sustainability within distribution networks.

By providing a strategic framework aligned with both financial and environmental objectives, companies can make informed decisions that optimize their distribution networks. In assessing environmental sustainability, particularly GHG emissions, play a significant role (European Parliament, 2018a). This research focuses specifically on CO_2 emissions due to their substantial contribution to GHG emissions. The financial aspect of the research focuses on distribution costs, which includes warehouse costs and transportation costs.

The objective of this research is to give FMCG companies insight in the trade-off between distribution costs and CO_2 emissions, regarding the locations of their warehouses and the customer allocations. As we pursue two objectives, we perform multi-objective optimization to minimize distribution costs and CO_2 emissions within FMCG distribution networks. We employ multi-objective optimization techniques, exploring various scenarios to demonstrate the costs of varying degrees of CO_2 emission reduction. The goal of this research is to provide valuable insights into the placement of warehouses and customer allocation, illustrating the trade-off between cost minimization and CO_2 emission reduction.

This research addresses critical gaps not covered by existing studies. While previous research has examined the trade-off between cost minimization and CO_2 emission reduction, it typically lacks comprehensive calculations for CO_2 emissions. Additionally, the characteristics of shared distribution networks used by FMCG companies, such as inventory considerations, the need for timely delivery, and different temperature conditions for products, have not been investigated together. Furthermore, the impact of the CO_2 price (ETS2) in combination with locating warehouses has not been thoroughly investigated. Our study addresses these gaps by combining these elements, as further explained in Chapter 2. By doing so, the results of this research will support FMCG companies in their efforts to transition towards more sustainable operations, facilitating informed decision-making in network design.

1.3 Research Objectives

The SCQA (Situation Complication Question Answer) framework is a widely used method to structure problems (Minto, 1996). By dividing a problem into four components, this framework helps derive a conclusive answer. In formulating our primary research question, we focus on the initial three components of the SCQA framework, as outlined in Table 1.1. The final component, the answer, is covered in the conclusion.

Table 1.1: *Situation Complication Question*

Situation	Firms are transitioning to sustainability-driven models due to regulatory changes and consumer demand for green products.
Complication	FMCG companies recognize the importance of sustainability but face challenges to integrate to it into their supply chain while maintaining cost efficiency, particularly in redesigning logistics networks.
Question	How can FMCG companies effectively balance distribution cost minimization with CO_2 emission reduction in the design of distribution networks, considering regulatory requirements, consumer demands, and the need for sustainable business practices?

This framework leads to the formulation of the main research question:

How should FMCG companies design their distribution network, considering the trade-off between minimizing distribution costs and CO_2 emissions?

The research question can be translated into a theoretical objective and a practical objective:

- **Theoretical objective:** Contribute to the understanding of how distribution cost minimization and CO_2 emission reduction intersect in distribution network design.
- **Practical objective:** Provide insights for FMCG companies aiming to optimize their distribution networks in a way that balances cost minimization and CO_2 emission reduction effectively.

1.4 Research Questions

Given the complexity of the research question described in Section 1.3, we propose several sub-research questions.

1. *What is the most suitable model for selecting warehouse locations in a FMCG network to minimize distribution costs and CO_2 emissions, and how can it be modified for FMCG-specific characteristics?*

Considering the wide variation in FLPs (Facility Location Problem), influenced by factors such as echelon levels, time periods, capacity constraints, and other considerations, selecting the most suitable model for warehouse location in an FMCG network to minimize distribution costs and CO_2 emissions is crucial. We first classify our problem according to the type of FLP it represents. Following this classification, we conduct a literature review to identify the most suitable model for our research. Subsequently, we modify this model for FMCG characteristics.

2. *How does the dual objective of minimizing distribution costs and CO_2 emissions impact the selection for warehouses locations and customer assignments?*

This question directly addresses the optimization of warehouse locations and customer assignments, with the dual objective of minimizing distribution costs and CO_2 emissions. By using the selected model from the preceding research question, this question can be answered. The model will yield a set of optimal solutions, based on the two objectives of minimizing distribution costs and CO_2 emissions. Each optimal solution will present the optimal warehouse locations and corresponding customer assignments.

3. *What are the incremental costs associated with reducing CO_2 emissions in the FMCG distribution network, and how does this trade-off vary with changes in input parameters?*

This question directly contributes to informed decision-making by examining the trade-off between distribution costs and CO_2 minimization, aligning with the main research question. By evaluating incremental costs associated with CO_2 emission reduction initiatives, companies can gain valuable insights into the financial trade-offs involved in achieving their sustainability goals.

It is also important to understand the influence of regulatory changes regarding CO_2 emissions and the influence of diverse product types, on the cost-CO_2 trade-off. This analysis helps organizations understand and guide their decision-making process towards more effective and sustainable strategies. In the subsequent section we describe the methodology utilized in this study to answer each research question.

1.5 Research Design and Thesis Outline

In this section we discuss in more detail how we will answer the research questions outlined in Section 1.4, together with an overview of the thesis structure. In Chapter 1, we started with an introduction to the research topic. We formulated the research goal and several sub-questions.

1.5.1 Theoretical Framework

In order to identify the optimal locations for warehouses within an FMCG network, in Chapter 2 we begin by introducing FLPs. Following that, we conduct a literature review to categorize and evaluate existing models, and identify the research gap. Taking into account FMCG-specific characteristics, we select the most appropriate model for our research.

Building on this, in Chapter 3, we evaluate different calculation methods for quantifying CO_2 emissions in the model, for both transportation and warehouse emissions, contributing to research question 1.

1.5.2 Model Development

Subsequently, in Chapter 4, we design (parts of) the selected model from the literature review and refine it to align with the characteristics of FMCG networks and the requirements of a shared distribution network.

Next, we explain how we can demonstrate the trade-off between distribution costs and CO_2 emissions in a Pareto front. We implement a multi-objective optimization method to generate a diverse set of Pareto-optimal solutions. This approach guarantees that no solution is superior in both objectives when compared to another solution. This model will explore the trade-offs between minimizing distribution costs and reducing CO_2 emissions. This method aims to offer a set of different optimal solutions instead of one best solution, to facilitate a decision based on the trade-off between the two objectives, specifically addressing research question 2.

1.5.3 Case Study

To validate the model and obtain meaningful insights, in Chapter 5, we will apply a constructed case study. The dataset used is representative of a FMCG company, reflecting typical characteristics such as high turnover rates. With these results, we gain insights into the trade-off between the dual objective, addressing research questions 2 and 3.

1.5.4 Scenario Analysis

Through this case study, we will explore various scenarios in Chapter 7. A scenario refers to a specific set of conditions or circumstances that we will consider in our analysis. Each scenario represents a different situation or context that may impact the FMCG industry. To cope with the various types of products within the FMCG industry, we test the model for temperature conditions. Furthermore, we analyze the impact of CO_2 regulations on the trade-off. With a scenario analysis, we test the robustness of the model, offering insights into its performance under different conditions and highlighting the adaptability required to manage uncertainties and differences in the FMCG sector. This chapter addresses the second part of research question 3.

1.5.5 Evaluation

Finally, in Chapter 8, we present the conclusions of the thesis, provide limitations of the research, and explore potential paths for future research.

In the following section we will present an overview of the scope of the research, outlining the specific areas of focus included.

1.6 Scope

The scope (Figure 1.1) of this thesis centers on locating warehouses in a FMCG network, with a specific focus on shared distribution networks. In the FMCG industry, distribution networks typically feature shared logistics services due to the small size and high turnover of products, leading to frequent but less-than-full truckload deliveries. These networks facilitate the consolidation of FMCG products from multiple companies, thereby enabling efficient distribution through the optimization of truck space and the reduction of transportation costs. To illustrate, shared distribution networks can deliver a diverse range of FMCG products to supermarkets in a single truck, thereby reducing the time and resources required for transportation (Alikhani et al., 2023).

Figure 1.1: *Scope of the research, highlighted in green.*

Moreover, shared logistics operations provide the advantage of pooling resources and sharing warehouse and transportation infrastructure, eliminating the need for individual dedicated facilities for FMCG companies. This approach leverages economies of scale, resulting in cost savings. Additionally, shared distribution networks offer flexibility and scalability, allowing FMCG companies to adjust their warehousing and transportation capacities based on fluctuating demand patterns and seasonal variations. This adaptability enables companies to expand or contract their operations as needed without being constrained by dedicated infrastructure (Alikhani et al., 2023).

Considering shared distribution networks, we do not have knowledge of the other customers included in our routes. As a result, solving the Vehicle Routing Problem has limited academic relevance in this context.

In order to ensure the practicality and real-world applicability of our research, we adopt a discrete solution space without capacity constraints. This implies that we consider a limited set of potential warehouse locations, rather than an infinite or continuous range. The locations we consider for warehouses are determined by the availability of logistics service providers, meaning we only choose from locations where these providers already operate. Moreover, we assume that these warehouses have unlimited capacity. This assumption is justified by the fact that the focus of this research is on shared logistics networks, where capacity is typically flexible and can be adjusted based on demand.

In the FMCG industry, B2C logistics, which involve the delivery of products to customers through a network of retailers, are relatively limited. Therefore, our primary focus is on B2B logistics operations. We focus specifically on distribution warehouses (single echelon). This is particularly crucial in the FMCG sector, where the ability to deliver products on-time and in-full is a key factor in maintaining market share and building customer loyalty. In such a competitive landscape, the efficiency and reliability of warehouse operations can be crucial in a company's success. Although logistics involves multiple echelon levels, distribution costs make up a large part of the total logistics expenditure, particularly in the FMCG industry, where companies deliver small loads to a multitude of addresses. This supports our choice to focus on a single echelon, warehouse-centered perspective.

By focusing on these elements, this research contributes to the development of a generalized model that can be applied to a range of cases. In the next chapter, we begin by addressing the first research question.

2

Facility Location Problem

In FMCG distribution networks, the strategic placement of warehouses is crucial for optimizing operational efficiency and achieving sustainability goals. Our research aims to identify and modify the most appropriate FLP model for FMCG logistics. By drawing on insights from existing models and methodologies, our objective is to develop a model that shows the trade-off between distribution costs and CO_2 emissions considering FMCG characteristics. The solutions produced by the model will identify the optimal locations for warehouses and customer assignments.

In this chapter, we start with an introduction on FLPs and a classification of this problem (Section 2.1). Subsequently, we apply this classification to our specific problem. In Section 2.2, we conduct a literature review in order to obtain related articles. In Section 2.3, we identify the research gap and we determine the most appropriate model for our problem. The primary research question addressed in this chapter is:

What is the most suitable model for selecting warehouse locations in a FMCG network to minimize distribution costs and CO_2 emissions, and how can it be modified for FMCG-specific characteristics?

By delving into various types of FLPs and assessing their applicability within FMCG networks, we aim to contribute valuable insights to the field of logistics optimization and sustainability in FMCG distribution.

2.1 Introduction

The first study in the field of location theory, conducted by Weber, 1909, consists of determining optimal facility locations and customer allocations. Subsequently, a variety of FLPs have been developed, including the determination of the optimal number of emergency services (Toregas et al., 1971) and the implementation of charging infrastructure for electric vehicles (Sun et al., 2020). To address the diverse set of businesses, researchers have developed a comprehensive set of models. In this section, we will elaborate on various FLPs to identify the type of model suited for addressing our research problem.

2.1.1 Objectives

Farahani et al., 2010 provided a comprehensive classification of the objectives of FLPs in their study. In Figure 2.1, we present an overview of this classification. Real-world problems in the FMCG industry often present themselves as multi-objective problems. Typically, these objectives are conflicting, making it challenging to find a single optimal solution (Tadaros and Migdalas, 2022).

FMCG companies aim to balance various objectives, including minimizing transportation costs by reducing the expense of moving goods from production facilities to distribution centers and retailers, and reducing delivery times to ensure timely delivery, meet customer expectations, and maintain competitiveness. They also focus on optimizing inventory levels to maintain adequate stock and prevent stock outs while minimizing holding costs, and improving customer satisfaction by enhancing service levels and reliability to build customer loyalty. Additionally, since there is an increasing shift towards sustainability objectives, FMCG companies striving to reduce their environmental impact by optimizing routes and minimizing emissions.

The general formulation of a multi-objective minimization model is defined in equation 2.1, where k denotes the number of objectives.

$$\begin{aligned} &\min \left(f_1(\vec{x}), f_2(\vec{x}), \ldots, f_k(\vec{x})\right) \\ &\text{s.t. } \vec{x} \in X \end{aligned} \tag{2.1}$$

Multi-objective models can be categorized into two primary types: bi-objective models and k-objective models. Bi-objective models aim to optimize two distinct yet interrelated objectives simultaneously. These objectives may often be inversely correlated, posing a trade-off between the two objectives. Bi-objective models seek to find solutions that achieve a balance between these conflicting goals, offering decision-makers a range of Pareto optimal solutions that represent efficient trade-offs between the objectives.

Scenarios with more than two objectives, k-objective problems (Farahani et al., 2010), introduce further complexity. These objectives can span a wide range, including dealing costs, demand coverage, profit maximization, environmental concerns, equity-efficiency trade-offs, and more. The inclusion of multiple objectives adds layers of complexity to decision-making processes, as decision-makers must navigate trade-offs and compromises among a diverse set of goals.

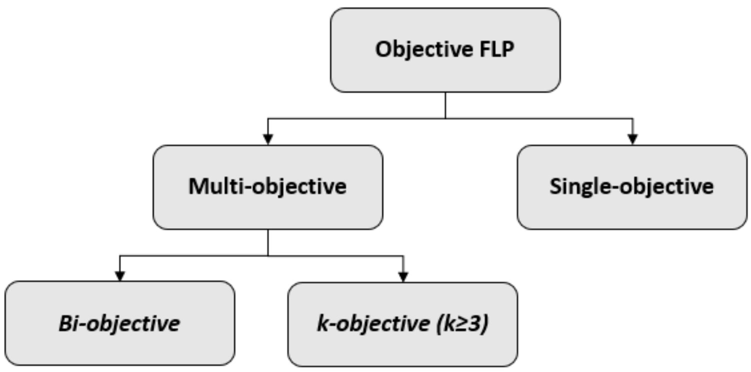


Figure 2.1: *Classification of multi-criteria Facility Location Problems.*

2.1.2 Discrete Multi-Facility Location Problem

The FLP presents two primary modeling approaches: continuous and discrete. Continuous models allow facility locations to be chosen from a continuous solution set, offering greater flexibility in decision-making. Despite this flexibility, continuous models are characterized by high computational time and often suffer from missing data on potential facility locations. Furthermore, practical constraints such as space availability and regulatory limitations may be overlooked, resulting in potentially sub-optimal facility placements, particularly in densely populated urban areas.

In contrast, discrete models involve the selection of facility locations from a predefined set of candidate solutions, offering simplicity in decision-making but may result in the exclusion of optimal locations that are not included in the predefined set (Melo et al., 2009). However, since we assume a shared distribution network, this approach aligns with our consideration of a limited set of potential warehouse locations, determined by the availability of logistics service providers. Consequently, our research focuses on a discrete set of warehouse locations determined by logistics service providers' existing operations. In this context, a solution comprises the selection of specific warehouse locations and the assignment of customers to these warehouses, ensuring that the solution satisfies the model constraints, illustrated in Figure 2.2.

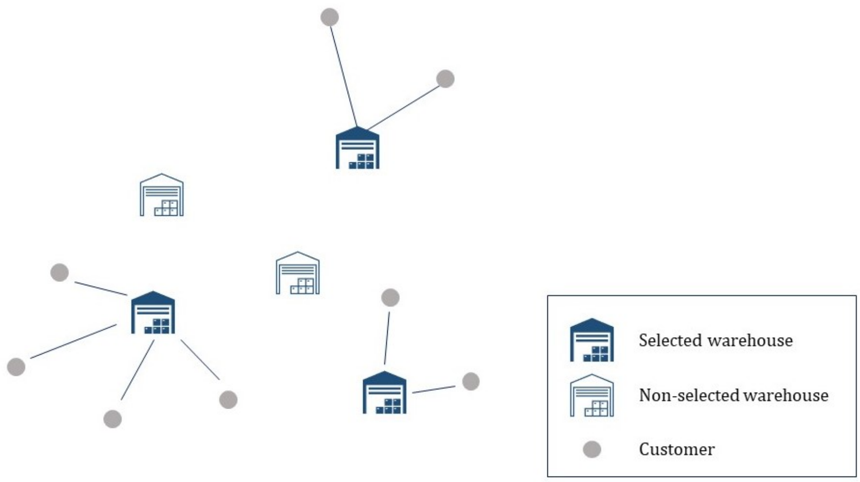


Figure 2.2: *Visual presentation of a discrete multi-FLP.*

In Figure 2.3 we provide five modifications of this problem. We explain each type of problem.

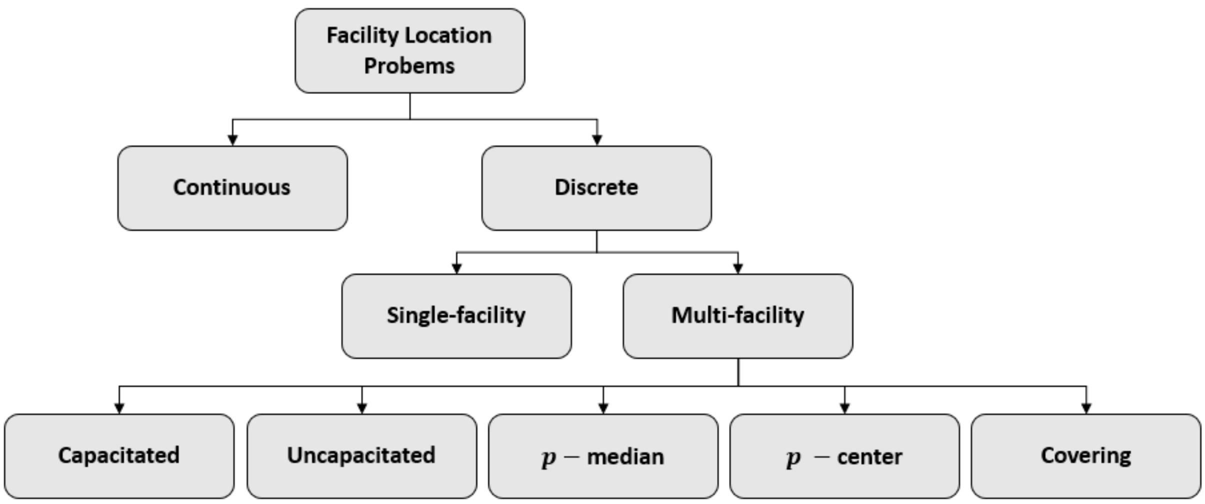


Figure 2.3: *A classification of discrete FLPs.*

1. **Uncapacitated (UFLP)**: Determines the optimal locations of an undetermined number of facilities

to minimize cost and meet customer demand. It is also known as the simple facility location problem, under which both potential facility locations and customers are discrete points in a network. The assumption of this problem is that potential facility locations are predetermined and customer demand is centered on specific points within each region (Verter, 2011).

2. **Capacitated (CFLP)**: The problem is similar to the UFLP, but here the facilities have capacity limits (Verter, 2011).
3. ***P*-median**: Determines the optimal locations of p facilities and their assigned customers in order to minimize the total distance or cost of transportation between customers and facilities (Dantrakul et al., 2013).
4. ***P*-center**: P-center is a special case of p-median, where problems have a specific objective function to minimize the distance between each customer and its assigned facility (Dantrakul et al., 2013).
5. **Covering**: The objective of covering problems is to find the minimum number of facilities to cover all customers or to maximize the number of customers covered by a given number of opened facilities (Dantrakul et al., 2013).

Maintaining a high service level and customer satisfaction is important in the FMCG industry to maintain customer loyalty. The p-center problem, which aims to minimize the distance between customers and facilities, contributes to this aspect. However, our problem differs in that we are not seeking to determine a specific number of facilities to open. Instead, our objective is to minimize distribution costs and CO_2 emissions by deciding on the number and location of facilities. Therefore, the p-median and p-center approaches are not representative for our research. In addition, covering problems focus on service objectives. Given that the FMCG industry prioritizes efficient and reliable service, it is essential to incorporate this consideration into the model. However, rather than treating service efficiency as an objective, our research addresses it as a constraint.

As outlined in the scope (1.1), we assume unlimited capacity, given that we are examining a shared distribution network. In light of this, the UFLP appears to be the most appropriate model for our problem. However, the CFLP can be seen as a more constrained version of the UFLP. Since we can easily adjust the CFLP to an UFLP, we will explore both in the literature.

In a shared distribution network, the costs associated with a warehouse are determined by the proportion of the total inventory space that a company occupies, rather than by the costs of operating individual warehouses. Therefore, our research problem considers a UFLP with two objectives, minimizing distribution costs and CO_2 emissions, while taking inventory into account for calculating warehouse costs and warehouse emissions, and having a service constraint to cope with customer expectations of fast delivery.

In the next section, we delve into related literature to investigate the research gap and explore existing models that can serve as a starting model.

2.2 Related Literature

In this section, we employ a systematic literature review, with the details of this approach included in Appendix A. We present an overview of relevant literature in Table 2.1. This table comprises articles on discrete FLPs, whether uncapacitated or capacitated, which address, at the least, one of the research objectives, namely, cost and the environment. Each column classifies the articles based on specific characteristics. The last row contains information about our research problem, facilitating comparison with other articles sharing similar attributes.

Table 2.1: *Overview of most related literature.*

Article	Objective			Capacity	Inventory	Service constraint	Solution method
	Cost	Service	Environment				
Harris et al., 2009	✓		✓	-	-	-	NSGA-II
Atta et al., 2019	✓	✓	-	-	-	-	NSGA-II, WSGA
Xifeng and Peng, 2013	✓	✓	✓	-	-	-	Hybrid Algorithm
Harris et al., 2014	✓	-	✓	✓	-	-	SEAMO2, NSGA-II
Caselli et al., 2022	-	-	✓	✓	-	-	MILP
Xi-Feng et al., 2020	✓	-	✓	✓	-	-	SEAMO2, NSGA-II
Das and Roy, 2019	✓	✓	✓	✓	-	-	Loc-Alloc heuristic
Wang et al., 2011	✓	-	✓	✓	-	-	Normalized constraint method
Yu and Solvang, 2016	✓	-	-	✓	-	-	ϵ-constraint method
Chandra et al., 2020	✓	✓	-	✓	-	-	ϵ-constraint method
Research Problem	✓	-	✓	-	✓	✓	ϵ-constraint method

Harris et al., 2009 propose an UFLP, to optimize cost and environmental impact simultaneously. They implement an evolutionary multi-objective algorithm, the non-dominated sorting genetic algorithm II (NSGA-II), to show a set of non-dominated solutions in a Pareto-front. The environmental impact is incorporated by the introduction of weighting factors, denoted by W_T and W_F. These factors derive the environmental impact from transportation and facilities, respectively, in relation to transportation costs and fixed facility costs. The results show that minimizing environmental impact often requires opening more facilities, which increases costs, highlighting the trade-off between cost efficiency and environmental sustainability.

Harris et al., 2014 extends the basic UFLP of Harris et al., 2009 with a maximum capacity. They propose a bi-objective CFLP to minimize the total costs and CO_2 emissions. Harris et al., 2014 combines an evolutionary algorithm (SEAMO2) and Lagrangian Relaxation technique. The results show that the lowest cost solution results in the highest CO_2 emissions with less facilities open and the higher number of open facilities produces lowest emissions at much higher cost.

Xifeng and Peng, 2013 conducted a study based on the UFLP, using a multi-objective optimization model. This model aimed to determine the trade-off among economic costs, service reliability, and environmental impact. Specifically, they incorporated environmental impact by calculating CO_2 emissions from transportation. The study used CO_2 emissions factors for fully loaded trucks on the outbound journey and empty trucks on the return trip, as well as considering distance and weight to quantify the environmental impact. The results of their study indicated that it might be beneficial to open more facilities than what is considered optimal from only a economic perspective. However, in shared distribution networks, trucks often carry products from multiple companies, reducing the number of completely empty trips and improving truck capacity utilization. Consequently, the distinction between full and empty truck trips is less pertinent to our research, as the shared nature of loads enhances overall efficiency.

Xi-Feng et al., 2020 builds upon there previous research. The NSGA-II and SEAMO2 algorithms are employed to solve the model. Three different allocation rules based on distance, cost, and emissions are applied. The results show that the allocation rules have nearly no influence on the solution quality, and the allocation rule based on the distance has an absolute advantage of computation time.

Atta et al., 2019 evaluated the NSGA-II and the weighted sum genetic algorithm (WSGA) to solve the the multi-objective of minimizing costs and maximizing the sum of preferences for all customers.

Caselli et al., 2022 developed a Mixed-Integer Linear Programming (MILP) model to minimize CO_2 emissions in a waste transfer facility location problem. The objective was to optimize the network of facilities for waste collection while considering environmental impacts. The model incorporated capacity constraints, binary variables for facility selection, and continuous variables for waste flow. CO_2 emissions were calculated by summing emissions from transportation, based on vehicle type, travel time, fuel consumption, and the number of trips between customers, intermediate, and final facilities, as well as from facility operations, divided into variable and fixed components depending on waste processed and energy use. The MILP model was solved exactly, yielding a single optimal solution that minimizes total CO_2 emissions across the waste transfer network.

Das and Roy, 2019 propose a hybrid approach to minimize transportation costs, time, and carbon emissions by locating p-facilities and allocating product flow. Their study considers variable carbon emissions under carbon tax or cap and trade regulations. The study also includes sensitivity analysis for supply and demand parameters.

Wang et al., 2011 propose a multi-objective model to minimize both total cost and environmental impact in a green supply chain network. The model incorporates CO_2 emissions by evaluating two main sources: emissions from facility operations and emissions from transportation. Facility emissions are influenced by the environmental protection level of each facility, affecting how much CO_2 is generated per unit of product handled. Transportation emissions arise from the movement of products between suppliers and facilities, with each arc in the network contributing to the total CO_2 emissions, based on the volume of goods transported. The sensitivity analysis demonstrates that increasing network capacity and supply can lower both CO_2 emissions and total cost, emphasizing the need to consider environmental impacts as demand levels rise.

Chandra et al., 2020 present a CFLP to minimize installation, transportation, treatment costs, and social costs using the ϵ-constraint method to generate Pareto optimal solutions.

Yu and Solvang, 2016 addresses hazardous waste location-routing problems using a multi-objective mixed integer programming model. The study uses the ϵ-constraint method to generate Pareto optimal solutions and explores trade-offs between cost and risk objectives.

As shown in Table 2.1, we identify a clear gap in the existing literature on this topic. In the following section, we will explore this gap in greater detail.

2.3 Literature Gap

In this section, we discuss the literature gap filled by this thesis. The previous section shows that a wide variety of (un)capacitated FLP is available. However, our research problem differs from the aforementioned articles in certain aspects.

The FMCG industry gives high priority on providing efficient and reliable service to customers. Therefore, it is crucial to consider service constraints when optimizing facility locations. While Harris et al., 2009 and Xifeng and Peng, 2013 studied an UFLP while simultaneously minimizing costs, CO_2 emissions, and maximizing service, our model does not address service as an objective but as a constraint.

Furthermore, the articles do not include inventory in their model, when deciding on the number of facilities to open. However, in our model the inclusion of inventory is critical because the decision to open additional facilities affects the total inventory and consequently impacts the associated facility costs. By incorporating inventory considerations, our research model provides a more comprehensive and realistic representation of the FMCG industry's facility location optimization problem.

While several models incorporate environmental factors, they often focus on different aspects. Xi-Feng et al., 2020 specifically addresses CO_2 emissions related to transportation but does not extend the analysis to broader environmental impacts within the context of facility location. Harris et al., 2009 assesses the environmental impact of both transportation and warehousing, yet this impact is considered in conjunction with financial factors rather than being isolated to CO_2 emissions alone. The study by Caselli et al., 2022 centers on waste management and CO_2 emissions related to waste, which falls outside the scope of our research objectives. Moreover, Wang et al., 2011 examines environmental protection levels rather than focusing specifically on CO_2 emissions, which does not align with our goal of integrating CO_2 emissions into the facility location model.

In addition, there is a lack of detailed analysis regarding the share of CO_2 emissions attributable to different companies using the same warehouse within a shared distribution network. Most studies that consider CO_2 emissions related to facilities usually calculate the total emissions for each facility. Our research aims to fill this gap by providing a more detailed analysis of the CO_2 emissions for a shared distribution network.

Another identified gap in the literature is the limited use of scenario analysis. Das and Roy, 2019 performed sensitivity analysis for supply and demand parameters, and Wang et al., 2011 conducted sensitivity analysis by increasing network capacity and supply. However, these studies do not consider changes in CO_2 regulations and different product types, and they both focus on CFLPs.

In conclusion, we address the identified literature gaps by incorporating both a service constraint and inventory considerations into the UFLP. We also conduct an extensive scenario analysis to account for the unpredictable future of CO_2 regulations and the diverse range of product categories within the FMCG industry. Furthermore, we perform comprehensive and precise calculations of CO_2 emissions associated with a shared distribution network.

To establish a baseline model, we utilize the model proposed by Harris et al., 2009, which balances cost minimization with environmental impact, accounting for both transportation and warehousing. In Chapter 4, we will adapt this model to align with our research problem. In the next chapter, we evaluate different methods for CO_2 calculation for warehouses and transportation.

3

Quantifying CO_2 Emissions

In this chapter, we describe the methodologies for calculating CO_2 emissions in the context of our problem. The focus of our analysis will be on two key sources of emissions: transportation and warehouses. We will not focus on waste and production-related emissions, as the location of warehouses does not directly influence those factors.

The first section of this chapter will provide an explanation of the GHG protocol, which serves as a recognized framework for measuring GHG emissions. Understanding this protocol is essential as it provides the foundation for calculating CO_2 emissions accurately. In the subsequent section, we will elaborate on the calculation of CO_2 emissions specifically related to transportation activities. Lastly, we will focus on calculating CO_2 emissions coming from warehouses. We evaluate these methodologies for calculating both transportation and warehouse emissions and identify the most suitable methods for our research problem.

3.1 Greenhouse Gas Protocol

The GHG protocol is a recognized framework for measuring and reporting GHG emissions (Greenhouse Gas Protocol, 2024). It was developed by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). The protocol provides a standardized method and guidelines for organizations to quantify and report their emissions accurately and transparently. By using this protocol, we can ensure meaningful comparisons across different studies and organizations. The GHG protocol provides guidelines on measuring emissions across different emission sources and activities. Greenhouse Gas Protocol, 2024 categorizes emissions into three scopes:

- **Scope 1:** This includes direct emissions from sources that are owned or controlled by the organization, such as on-site fuel combustion or in-house transportation emissions.
- **Scope 2:** This covers indirect emissions resulting from the generation of purchased electricity, heat, or steam consumed by the organization.
- **Scope 3:** These are indirect emissions that occur in the value chain of the organization, encompassing activities such as the extraction and production of purchased materials, transportation of purchased fuels, and the use of sold products and services.

The division of emissions into these scopes helps prevent double counting, ensuring accurate and comprehensive reporting of GHG emissions. In Figure 3.1, we provide an overview of the scopes mentioned above.

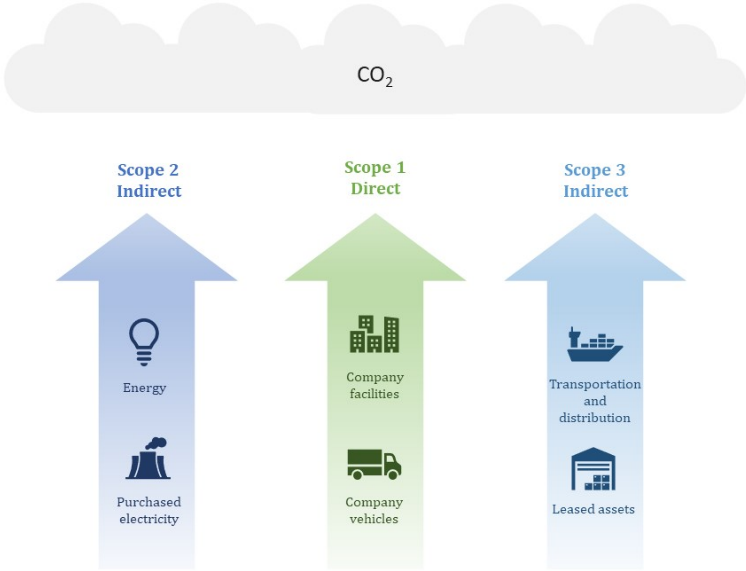


Figure 3.1: *Overview of GHG protocol scopes and CO_2 emissions.*

The quantity of CO_2 emitted by a vehicle is directly linked to its fuel consumption, which is influenced by speed, load, and traffic conditions (Demir et al., 2014). In this research, we consider FMCG that outsource their distribution to a logistic service provider. As a result, emissions from transportation and warehouses fall within scope 3 classification. This category includes third-party distribution services procured by the reporting company during the reporting year. According to Greenhouse Gas Protocol, 2024 transportation emissions from this class can be calculated by different methods:

- **Fuel-based method:** Determines the amount of fuel consumed and applying the appropriate emission factor for that fuel.
- **Distance-based method:** Determines the mass, distance, and mode of each shipment, and applies the appropriate mass-distance emission factor for the vehicle used.
- **Spend-based method:** Determines the amount of money spent on each mode of business travel transport and applying secondary (EEIO) emission factors.

According to Greenhouse Gas Protocol, 2024 we can use two different methods to calculate CO_2 emissions from distribution centers or warehouses in scope 3: the site-specific method and the average-data method.

- **The site-specific method:** determines the emissions based on the energy consumption of the warehouse facilities and allocates these emissions based on the actual usage of these warehouse facilities.
- **The average-data method:** Estimates emissions for each distribution activity based on average data. Emissions are estimated using average values, such as emissions per pallet or cubic meter stored per day.

In order to conduct our research, we must employ methods to calculate CO_2 emissions for both transportation and warehouse activities within a shared distribution network. In the following sections we explain and justify the specific methods we employ for the calculation of CO_2 emissions.

3.2 Transportation Emissions

We employ the distance-based method for transportation emissions due to the nature of our logistics operations. Since we outsource transportation to a logistics service provider, our goods are transported alongside other products. The distance-based method allows us to accurately account for emissions based on the mass, distance traveled, and transportation mode used. The alternative fuel-based method relies on detailed fuel consumption data, which may be limited in outsourced transportation scenarios. This detailed fuel consumption data is often more readily available when transportation is handled in-house because you can directly access information such as customer and delivery addresses from your own systems. On the other hand, the spend-based method could be useful when detailed mass and distance data are unavailable. However, in most cases, companies have access to data on the mass of their products, the distance traveled, and the transportation mode used. Thus, we focus on the distance-based method, which is addressed by the following equation:

$$\begin{aligned}\text{CO}_2 \text{ emissions from transportation} = \sum & (\text{mass (tonnes)}) \\ & \cdot \text{distance travelled (km)} \\ & \cdot \text{emission factor of transport mode type (kg CO}_2 \text{ / tonne-km)}\end{aligned} \tag{3.1}$$

3.3 Warehouse Emissions

In order to calculate emissions from warehouses, we employ the site-specific method, which is suitable for shared distribution networks. This method determines emissions based on the total energy consumption of the warehouse and allocates them according to the space in use of each company.

According to data from CBS, 2018, natural gas represents the primary energy source for warehouses, comprising 75% of total consumption, primarily for heating purposes. Approximately 15% of energy consumption is attributed to electricity, which is primarily used for lighting and operating equipment. However, this can vary greatly depending on the warehouse's specific requirements, such as whether it is heated, maintained frost-free, or chilled. In Chapter 7, we will examine the impact of these different requirements.

The site-specific method enables us to accurately calculate emissions using detailed data on gas and electricity consumption. This approach ensures precise emissions allocation based on actual usage in a shared distribution network. The site-specific method is defined by the following formula:

$$\begin{aligned}&\text{CO}_2 \text{ emissions from warehouses} = \\ &\quad \sum \left(\frac{\text{inventory}_{\text{company}}\,(\text{m}^2)}{\text{inventory}_{\text{warehouse}}\,(\text{m}^2)} \right) \cdot \Big[\big(\text{gas consumption}\,(\text{m}^3) \cdot \text{gas emission factor}\,(\text{kg CO}_2 \text{ per m}^3)\big) \\ &\qquad + \big(\text{electricity consumption}\,(\text{kWh}) \\ &\qquad \cdot \text{electricity emission factor}\,(\text{kg CO}_2 \text{ per kWh})\big) \Big]\end{aligned} \tag{3.2}$$

By applying Equation 3.2, we can calculate the total emissions allocated to a company by summing the emissions of each individual warehouse, based on the proportion of inventory the company occupies. This method ensures an accurate reflection of a company's portion of the emissions from shared warehouse operations. Furthermore, incorporating energy consumption allows for allocation of emissions based on different storage methods, including temperature-controlled and ambient storage.

3.4 Emission Factors

According to CO2 Emissiefactoren, 2022, there are three definitions of CO_2 emission factors:

1. **Well to Tank (WtT)**: This approach focuses on emissions in the upstream phase of the activity, encompassing fuel extraction and production.
2. **Tank to Wheel (TtW)**: This approach considers direct emissions from the activity, specifically fuel usage in vehicles.
3. **Well to Wheel (WtW)**: This comprehensive approach combines both the WtT and TtW approaches, accounting for emissions throughout the entire life-cycle, from upstream phases to direct emissions.

Given that we are outsourcing both storage and transportation within a shared distribution network, we determine our specific share of the CO_2 emissions. For this purpose, we employ TtW emission factors. TtW emission factors measure the direct emissions produced during the consumption of fuel or energy in operational activities. Specifically, for transport, TtW factors account for the CO_2 emissions generated by the vehicles while they are in use, directly reflecting the environmental impact of transporting goods from warehouses to customers. Similarly, for warehouse operations, TtW factors capture the emissions resulting from the consumption of electricity and natural gas for lighting, heating, cooling, and other warehouse activities.

Selecting appropriate emission factors is critical for accurately calculating the environmental impact of warehouse operations. Emission factors for transportation are typically measured in kilograms of CO_2 per tonne-kilometre and vary depending on the type of vehicle. In the context of warehouses, the emission factors are determined by the type of energy consumed and are expressed in kilograms of CO_2 per kilowatt-hour (kWh) for electricity and per cubic metre (m^3) for natural gas.

The selection of specific emission factors and the details of energy usage will be further specified in the accompanying case study. In the subsequent chapter, we integrate these CO_2 emission calculation methods in our mathematical model.

4

Mathematical Model

In this chapter, we begin by presenting the mathematical formulation of our baseline model. Subsequently, we introduce our own mathematical model, taking into consideration the characteristics of the FMCG industry.

4.1 Baseline Model: The Multi-Objective UFLP for Green Logistics

As we introduced in Section 2.3, the model by Harris et al., 2009 provides a starting point for the research model since it addresses the UFLP in a single echelon environment while minimizing costs and CO_2 emissions. It operates under the assumptions of unlimited warehouse capacity and the selection of warehouses from a predefined set. These assumptions are aligned with the requirements of our research problem, as explained in Subsection 2.1.2. In the following section (4.1.1), we provide a comprehensive formulation of the baseline model.

4.1.1 Model Formulation

- **Sets**

  $\tau = \{1, \ldots, N\}$ (set of potential depots)

  $\gamma = \{1, \ldots, K\}$ (set of customers)

- **Parameters**

  c_{ij} transportation cost of serving the demand from customer j using depot i (€)

  f_i fixed cost for opening depot i (€)

  W_T factor for the environmental impact from transport in relation to transportation costs

  W_F factor for the environmental impact from depots in relation to fixed costs

- **Decision Variables**

$$x_{ij} = \begin{cases} 1, & \text{if the demand of customer } j \text{ is fulfilled by depot } i \\ 0, & \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1, & \text{if depot } i \text{ is chosen to operate} \\ 0, & \text{otherwise} \end{cases}$$

- **Objectives**

Minimizing costs:
$$\min \left[\sum_{i \in \tau} \sum_{j \in \gamma} c_{ij} x_{ij} + \sum_{i \in \tau} f_i y_i \right] \tag{4.1}$$

Minimizing environmental impact:
$$\min \left[\sum_{i \in \tau} \sum_{j \in \gamma} c_{ij} \cdot W_T \cdot x_{ij} + \sum_{i \in \tau} f_i \cdot W_F \cdot y_i \right] \tag{4.2}$$

The objective contains the transportation costs of attending to customer demand by the open depots and the fixed facility costs of the open depots. The second objective has the same formulation as the cost objective except for the addition of weight factors W_T and W_F. The weight factors W_T and W_F represent the environmental impact of the transportation cost and fixed cost, respectively.

- **Constraints**

$$\sum_{i \in \tau} x_{ij} = 1, \qquad \forall j \in \gamma \tag{4.3}$$

$$x_{ij} \leq y_i, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.4}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.5}$$

$$y_i \in \{0, 1\}, \qquad \forall i \in \tau \tag{4.6}$$

Constraint 4.3 ensures that each customer is served by exactly one depot. Constraint 4.4 assigns the customers to only the open depots. Constraints 4.5 and 4.6 define the decision variables as binary.

4.2 The Multi-Objective UFLP for Green Logistics within the FMCG Industry

Our research model extends the baseline model proposed by Harris et al., 2009 in order to better align with the characteristics of the FMCG industry. In the following subsections, we explain the extensions we make to the baseline model in order to develop our own research model, together with an explanation of the resulting new assumptions.

4.2.1 Extensions

In Table 4.1 we present the extensions we make to the baseline model to address the key characteristics in the FMCG supply chain. We incorporate a maximum distance constraint to ensure timely deliveries. Inventory considerations are integrated to account for the share of a shared warehouse. Lastly, we enhance the CO_2 calculation to provide a detailed assessment of emissions from transportation and warehouse operations.

Table 4.1: *Extensions to the baseline model.*

#	Extension	Model implementation
1	Maximum distance constraint	$h_{ij} \leq h_{\max}$
2	Inventory inclusion	$k \cdot \sqrt{\sum_{i \in \tau} y_i}$
3	Extended CO_2 calculation	$(h_{ij} + h_{ji}) \cdot W_T \cdot x_{ij} \cdot d_j + (W_E \cdot E + W_G \cdot G)$

Extension I: Maximum distance constraint

The growing demand for fast delivery of FMCG products, driven by higher customer expectations, demands the incorporation of short lead times into the model. While it is possible to introduce an additional constraint specifying that deliveries must occur on the requested delivery day, our current model does not take specific days or times into account, as they are not directly relevant to our defined objectives. Our primary focus is on optimizing costs and emissions based on factors such as overall weight and distance traveled, rather than the frequency of trips to customer locations. As a result, we have incorporated a maximum distance constraint into the model to maintain the desired service level.

$$h_{ij} \leq h_{\max}$$

This constraint sets a limit on the distance that can be covered within a specified time frame.

Extension II: Inventory inclusion

The baseline model focuses on opening costs per depot. In a shared distribution network, however, the allocation of warehouse costs is based on the proportion of the total inventory space that each company occupies, rather than on the specific operational costs of individual warehouses. This approach allows for the determination of warehouse costs on a costs per m^2 basis, reflecting the shared usage of warehouse space.

Given that costs and CO_2 emissions can be expressed per m^2, we adopt the assumption that all warehouses have uniform characteristics. From a long-term perspective, fluctuations in performance, costs, and other factors are likely to average out, making the assumption of uniform characteristics across warehouses more reasonable for strategic planning. Furthermore, this assumption provides a clear baseline scenario, serving as a foundation for exploring more complex scenarios that incorporate variations in warehouse conditions, such as differing temperature requirements. This will be tested in Chapter 7.

The Square Root Law (SRL) is a commonly used formula to calculate inventory levels based on the number of operational warehouses (Fleischmann, 2016). The total inventory increases with the square root of the number of warehouses that are operational. The SRL formula (Equation 4.7) states that the future inventory level (X_2) is equal to the existing inventory level (X_1) multiplied by the square root of the ratio of the number of future facilities (n_2) to the number of existing facilities (n_1).

$$X_2 = X_1 \cdot \sqrt{\frac{n_2}{n_1}} \tag{4.7}$$

While the total inventory across the network increases with the addition of more warehouses, the average inventory per warehouse decreases due to risk pooling effects, enabling the network to better handle temporary fluctuations in demand. Additionally, more warehouses mean closer proximity to customers, which can reduce lead times and thus the need for safety stock.

In order to establish a theoretical basis for the practical application of the SRL in different logistical scenarios, we derive a generalized formula that determines inventory levels based on the number of open warehouses. This eliminates the need for a comparative analysis of the current inventory and the future inventory each time. By determining a baseline scenario, where the inventory for one open warehouse, denoted as $n_1 = 1$, is known as X_0, we formulated the following equation:

$$I = X_0 \cdot \sqrt{\frac{n}{1}} = X_0 \cdot \sqrt{n}$$

Here, I represents the inventory requirement for n facilities, and X_0 is the baseline inventory for one facility. Introducing a constant factor k to represent the baseline inventory, we can further simplify the relationship as:

$$I = k \cdot \sqrt{n}$$

Here, n represents the number of open warehouses, which is equal to the sum of y_i for all i in the set τ. To calculate the total warehouse costs and warehouse CO_2 emissions, we can incorporate the inventory formula into the objective function of our optimization problem. By using the following expression:

$$k \cdot \sqrt{\sum_{i \in \tau} y_i}$$

This formulation allows us to optimize the number of open warehouses while considering the associated distribution costs and CO_2 emissions, as stated in the objective function of our model.

By assuming equal characteristics for all warehouses, we can apply the SRL consistently across the entire set of potential warehouses. Since we consider costs per m^2, we only need to know the total inventory to determine the total costs. Consequently, the distribution of inventory across different warehouses does not impact our objective values.

Accordingly, our model incorporates two additional assumptions relative to the baseline model: 1) that all warehouses exhibit uniform characteristics, and 2) that inventory is distributed uniformly across all warehouses.

Extension III: Extended CO_2 calculation

The baseline model calculates the environmental impact through weighted cost factors, assuming a direct correlation between costs and emissions. Transportation costs are scaled by a weight factor W_T, suggesting that the environmental impact of transporting goods is proportional to the cost. Similarly, facility operations are evaluated using a weight factor W_F, applied to the operational costs of each warehouse. In order to improve this calculation, we integrate more detailed CO_2 calculations from the GHG Protocol for both transportation and warehousing, as detailed in Equations 3.1 and 3.2 in Chapter 3. As stated in the calculation method in Equation 3.1, we calculate transportation emissions by considering the distances traveled between warehouses and customers. The distance is multiplied by the appropriate emission factor and scaled by the demand in weight (d_j). This methodology directly measures transport emissions based on the volume of goods transported and the distance traveled.

The calculation of warehouse emissions according to Equation 3.2 involves two key components: fuel consumption and electricity consumption. Each component's emissions are quantified by multiplying the respective consumption levels by their emission factors (W_E for electricity and W_G for gas).

Since we assume equal characteristics across all warehouses, all warehouses are equal in size, temperature condition, costs, and energy consumption rates. Consequently, the energy usage per m^2 are consistent across all warehouses.

By multiplying the fuel and electricity usage per m^2 by the total inventory (m^2) of the reporting company, we can calculate the share of the company's emissions. This method focuses on our proportional share of inventory and energy usage, thereby avoiding the need to consider the total inventory of each warehouse.

We quantify the emissions using specific emission factors (W_E for electricity and W_G for gas), applied to the energy consumed per m^2 of facility space. This energy consumption is then scaled by a function of the number of facilities $k\sqrt{\sum_{i\in\tau} y_i}$. This results in the following formula:

$$(h_{ij} + h_{ji}) \cdot W_T \cdot x_{ij} \cdot d_j + \sum_{i\in\tau} (W_E \cdot E + W_G \cdot G) \cdot k\sqrt{\sum_{i\in\tau} y_i}$$

This approach allows us to account for variations in emissions resulting from differences in energy consumption rates and operational efficiencies. We analyze these variations in greater detail in the scenario analysis (Chapter 7) of our thesis.

We incorporate the extensions mentioned above in our mathematical model, as presented in the following subsection.

4.2.2 Model Formulation

In this section, we present our mathematical model for the multi-objective discrete UFLP.

- **Sets**

  $\tau = \{1, \dots, N\}$ (set of potential warehouses)

  $\gamma = \{1, \dots, K\}$ (set of customers)

- **Parameters**

c	transportation costs (€/km)
k	baseline inventory (m^2)
d_j	demand of customer j (tonnes)
h_{ij}	distance from warehouse i to customer j (km)
h_{ji}	distance from customer j to warehouse i (km)
W_T	emission factor for transportation (kg CO_2/tonne-kilometre)
W_E	emission factor for electricity (kg CO_2/kWh)
W_G	emission factor for gas (kg CO_2/m^3)
$h_{\max}$	maximum distance allowed (km)
f	warehouse costs (€/m^2)
E	electricity consumption (kWh/m^2)
G	gas consumption (m^3/m^2)

- **Decision variables**

$$x_{ij} = \begin{cases} 1, & \text{if the demand of customer } j \text{ is fulfilled by warehouse } i \\ 0, & \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1, & \text{if warehouse } i \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

- **Objectives**

  Minimizing distribution costs:

$$\min \left[\sum_{i\in\tau} \sum_{j\in\gamma} \left((h_{ij} + h_{ji}) \cdot c \cdot x_{ij} \right) + f \cdot k \sqrt{\sum_{i\in\tau} y_i} \right]$$

  Minimizing CO_2 emissions:

$$\min \left[\sum_{i\in\tau} \sum_{j\in\gamma} \left((h_{ij} + h_{ji}) \cdot W_T \cdot x_{ij} \cdot d_j \right) + \sum_{i\in\tau} (W_E \cdot E + W_G \cdot G) \cdot k \sqrt{\sum_{i\in\tau} y_i} \right]$$

- **Constraints**

$$\sum_{i\in\tau} x_{ij} = 1, \qquad \forall j \in \gamma \tag{4.8}$$

$$x_{ij} \le y_i, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.9}$$

$$h_{ij} \le h_{\max}, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.10}$$

$$x_{ij} \in \{0,1\}, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.11}$$

$$y_i \in \{0,1\}, \qquad \forall i \in \tau \tag{4.12}$$

Constraint 4.8 ensures that every customer is served by one warehouse. Constraint 4.9 specifies that customers should only be assigned to operating warehouses. Constraint 4.10 sets a maximum allowed distance between the warehouse and the customer. This constraint limits the distance between a warehouse and its assigned customer, ensuring that the customer is within a specific range from the warehouse. And constraints 4.11, 4.12 define the decision variables as binary.

In conclusion, we have extended the baseline model proposed by Harris et al., 2009 to better align with the specific characteristics of the FMCG industry. Our extensions include inventory considerations and the incorporation of a maximum distance constraint to ensure timely deliveries. Furthermore, we have extended the CO_2 calculations to provide a more detailed assessment of emissions from both transportation and warehouse operations.

However, it is important to note that the formulated model represents a non-linear function as a result of the incorporation of the square root within the objective functions. In optimization problems, especially those formulated using linear programming, non-linear functions such as the square root pose significant challenges. Gurobi and similar optimization tools are designed to handle linear constraints and objectives efficiently but cannot directly process non-linear functions. In the next subsection, we explain how we address this non-linear function.

4.2.3 Piecewise Linear Approximation of the Square Root Function

In order to address the non-linear function, we incorporate a piecewise linear approximation of the square root function into the model. This allows us to maintain linearity in the model while still incorporating the inventory level based on the number of open warehouses. The piecewise linear approximation involves defining several constraints that represent linear segments approximating the square root function (D'Ambrosio et al., 2010). Each segment is tailored to approximate the square root curve within a specific interval of the number of warehouses. By dividing the function into these linear segments, we effectively simplify the original non-linear problem into a series of linear constraints.

Let z represent the approximation of the square root of the total number of open warehouses:

$$z \approx \sqrt{\sum_{i \in \tau} y_i}$$

We introduce breakpoints and binary decision variables to linearize the square root function. The breakpoints are selected in advance to divide the range of possible inputs into intervals. For each interval, we use a linear function to approximate the square root.

Parameters

- Breakpoints: $\{0, 1, 2, \ldots, m\}$, where m is the maximum number of open warehouses.
- Sqrt values: $\{\sqrt{0}, \sqrt{1}, \sqrt{2}, \ldots, \sqrt{m}\}$, the actual square root values at the breakpoints.

Variables

- z: Continuous variable representing the approximated value of the square root.
- β_k: Binary variables to indicate which interval (or segment) the total number of open warehouses falls into.

Constraints

We introduce binary variables β_k and a set of constraints to enforce that only one segment is active at a time. The constraints are written as:

$$\sum_{k=1}^{m-1} \beta_k = 1$$

For each segment k, we enforce the following constraints to approximate the square root function:

$$z \geq \text{sqrt\_values}[k] + \frac{\text{sqrt\_values}[k+1] - \text{sqrt\_values}[k]}{\text{breakpoints}[k+1] - \text{breakpoints}[k]} \cdot \left(\sum_{i \in \tau} y_i - \text{breakpoints}[k] \right) - M(1 - \beta_k)$$

$$z \leq \text{sqrt\_values}[k] + \frac{\text{sqrt\_values}[k+1] - \text{sqrt\_values}[k]}{\text{breakpoints}[k+1] - \text{breakpoints}[k]} \cdot \left(\sum_{i \in \tau} y_i - \text{breakpoints}[k] \right) + M(1 - \beta_k)$$

where M is a large constant used to deactivate the constraints for segments that are not selected.

Objectives

The approximation z is then used in the objective functions to minimize costs and CO_2 emissions.

$$\min \left[\sum_{i \in \tau} \sum_{j \in \gamma} \left((h_{ij} + h_{ji}) \cdot c \cdot x_{ij} \right) + f \cdot k \cdot z \right]$$

$$\min \left[\sum_{i \in \tau} \sum_{j \in \gamma} \left((h_{ij} + h_{ji}) \cdot W_T \cdot x_{ij} \cdot d_j \right) + (W_E \cdot E + W_G \cdot G) \cdot k \cdot z \right]$$

The result of the linear approximation used is shown in Figure 4.1. We observed that the linear approximation accurately approximates the square root.

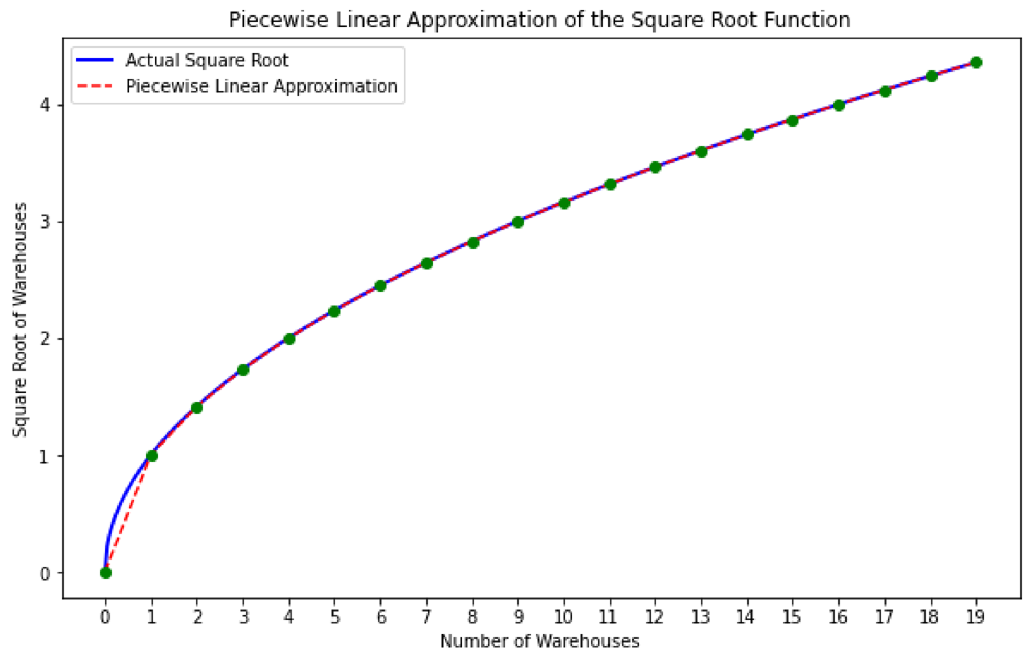


Figure 4.1: *Piecewise linear approximation of the square root function for the number of open warehouses.*

In order to obtain a set of optimal solutions and demonstrate the trade-off between distribution costs and CO_2 emissions, we require a multi-objective optimization. In the following section we will elaborate on the method employed for the multi-objective optimization and present the adjusted mathematical model, including the linear approximation of the square root.

4.3 Multi-objective Optimization

In this section, we discuss our approach to solving the multi-objective optimization problem using a Pareto front. A Pareto front represents a set of efficient solutions where any improvement in one objective results in the degradation of another (Ahmadi et al., 2016).

The ϵ-constraint method provides exact solutions to multi-objective optimization problems by systematically varying ϵ values to generate the entire Pareto front. This precision is crucial for strategic decisions, such as warehouse placement, where accuracy directly impacts long-term efficiency and cost.

In contrast, heuristic algorithms, such as the NSGA-II, use evolutionary algorithms to find multiple Pareto optimal solutions, and it excels in handling larger, more complex problems. However, these solutions are approximations and may not capture the optimal set as comprehensively as exact methods. Given the strategic nature of our research, where long-term, high-impact decisions are necessary, we employ the ϵ-constraint method.

4.3.1 Introduction Epsilon-Constraint Method

The ϵ-constraint method is a widely used approach for solving Multi-Objective Mixed Integer Linear Programming (MOMPP) problems (Mavrotas, 2009). Consider the general formulation of a multi-objective minimization problem:

$$\begin{aligned} \min \quad & (f_1(x), f_2(x), \ldots, f_p(x)) && (4.13)\\ \text{s.t.} \quad & x \in S, && (4.14) \end{aligned}$$

where x is the vector of decision variables, $f_1(x), \ldots, f_p(x)$ are the p objective functions, and S is the feasible region. In the ϵ-constraint method, we optimize one of the objective functions while treating the other objective functions as constraints. These objectives are incorporated into the constraint part of the model with specified threshold values (ϵ-values). This transformation allows us to handle the original multi-objective problem as a single-objective problem, formulated as follows (Haimes et al., 1971):

$$\begin{aligned} \min \quad & f_1(x) && (4.15)\\ \text{s.t.} \quad & f_2(x) \leq \epsilon_2, \\ & f_3(x) \leq \epsilon_3, \\ & \vdots \\ & f_p(x) \leq \epsilon_p, \\ & x \in S. \end{aligned}$$

Th ϵ-values range from the minimum and maximum value of the objective that is written as a constraint. The step size by which the ϵ-value increases can be obtained by:

$$\text{Step size} = \frac{f_2^{max} - f_2^{min}}{\text{number of steps}}$$

The range of ϵ-values will then be from the minimum ϵ-value to the maximum ϵ-value with the appropriate step size. Using these ϵ-values, we generate a series of single-objective optimization problems. Each problem minimizes the primary objective while ensuring that the second objective does not exceed a specific ϵ-value. This approach yields a set of Pareto optimal solutions, illustrating the trade-off between the the two different objectives. In Figure 4.2 we present the steps of this model in a flowchart.

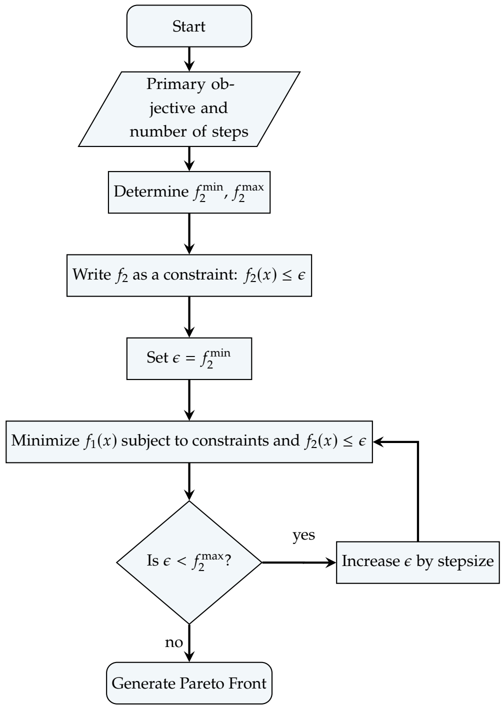


Figure 4.2: *Flowchart of the ϵ-constraint method.*

In our research, we select distribution costs as the primary objective in examining the trade-off between these costs and CO_2 emissions. This decision enables us to gain insights into the expenses associated with achieving various target levels of CO_2 emissions, which can be viewed as the ϵ-constraint values. By doing so, we can analyze the incremental costs linked to different levels of CO_2 emissions.

Subsequently, in the following subsection, we reformulate our mathematical model to include both the linear approximation and the ϵ-constraint method.

4.3.2 Epsilon Constraint Model Formulation including Piecewise Linear Approximation

In this section, we present our epsilon constraint model. In this model, the objective is to minimize distribution costs, while a constraint is imposed on CO_2 emissions.

- **Sets**

$\tau = \{1, \dots, N\},$ (set of potential warehouses)

$\gamma = \{1, \dots, K\},$ (set of customers)

$\mathcal{B} = \{1, \dots, m\},$ (set of breakpoints for piecewise linear approximation)

- **Parameters**

c	transportation costs (€/km)
k	baseline inventory (m^2)
d_j	demand of customer j (tonnes)
h_{ij}	distance from warehouse i to customer j (km)
h_{ji}	distance from customer j to warehouse i (km)
W_T	emission factor for transportation (kg CO_2/tonne-kilometre)
W_E	emission factor for electricity (kg CO_2/kWh)
W_G	emission factor for gas (kg CO_2/m^3)
$h_{\max}$	maximum distance allowed (km)
f	warehouse costs (€/m^2)
E	electricity consumption (kWh/m^2)
G	gas consumption (m^3/m^2)
breakpoints_b	breakpoint values for piecewise linear approximation, $b \in \mathcal{B}$
sqrt_values_b	square root values at each breakpoint, $b \in \mathcal{B}$
M	large constant

- **Decision variables**

$$x_{ij} = \begin{cases} 1, & \text{if the demand of customer } j \text{ is fulfilled by warehouse } i \\ 0, & \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1, & \text{if warehouse } i \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

$z \in \mathbb{R}_+$, continuous variable representing the square root approximation

$$\beta_k = \begin{cases} 1, & \text{if the } k\text{-th segment of the piecewise linear approximation is used} \\ 0, & \text{otherwise} \end{cases} \quad \forall k \in \mathcal{B}$$

- **Objective**

Minimize distribution costs:

$$\min \left[\sum_{i \in \tau} \sum_{j \in \gamma} \left((h_{ij} + h_{ji}) \cdot c \cdot x_{ij} \right) + f \cdot k \cdot z \right]$$

- **Constraints**

$$\sum_{i\in\tau} x_{ij} = 1, \qquad \forall j \in \gamma \tag{4.16}$$

$$x_{ij} \leq y_i, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.17}$$

$$h_{ij} \leq h_{\max}, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.18}$$

$$\sum_{k=1}^{m-1} \beta_k = 1, \tag{4.19}$$

$$z \geq \text{sqrt\_values}_k + \frac{\text{sqrt\_values}_{k+1} - \text{sqrt\_values}_k}{\text{breakpoints}_{k+1} - \text{breakpoints}_k} \cdot \left(\sum_{i\in\tau} y_i - \text{breakpoints}_k\right) - M(1-\beta_k), \quad \forall k \in \mathcal{B} \tag{4.20}$$

$$z \leq \text{sqrt\_values}_k + \frac{\text{sqrt\_values}_{k+1} - \text{sqrt\_values}_k}{\text{breakpoints}_{k+1} - \text{breakpoints}_k} \cdot \left(\sum_{i\in\tau} y_i - \text{breakpoints}_k\right) + M(1-\beta_k), \quad \forall k \in \mathcal{B} \tag{4.21}$$

$$\sum_{i\in\tau}\sum_{j\in\gamma} \big((h_{ij} + h_{ji}) \cdot W_T \cdot x_{ij} \cdot d_j\big) + \sum_{i\in\tau} (W_E \cdot E + W_G \cdot G) \cdot k \cdot z \leq \epsilon, \tag{4.22}$$

$$x_{ij} \in \{0,1\}, \qquad \forall j \in \gamma, \forall i \in \tau \tag{4.23}$$

$$y_i \in \{0,1\}, \qquad \forall i \in \tau \tag{4.24}$$

In the next chapter, we will apply this model to our case study in order to obtain and analyse the results.

5

Case Study

In this chapter, we introduce the case study. In Section 5.1, we provide a general overview of the case. In the following sections, we will explore the dataset in more detail.

5.1 Introduction Case

The case study data set has been constructed based on actual data from a FMCG company. The initial dataset included detailed information on customers (country and zip code), current warehouse locations (country and zip code), and outbound orders (shipment ID, order line ID, weight, and volume). The initial dataset has been modified to guarantee anonymity and confidentiality. The modifications made guarantee that the overall characteristics remain realistic. Inventory levels, order quantities, and product weights are maintained within comparable ranges to those observed in the original dataset, ensuring a representative FMCG dataset.

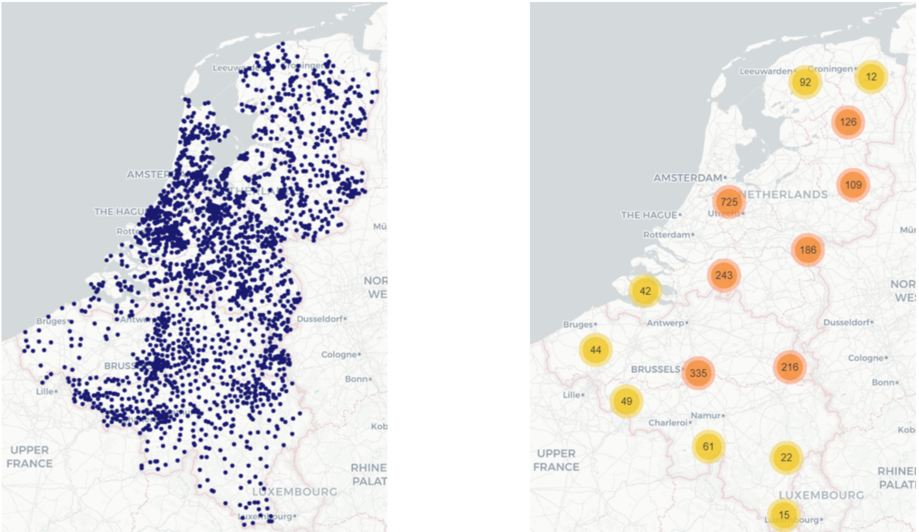
The dataset reflects the characteristics of FMCG distribution, where products have relatively short shelf lives and high demand, coupled with high turnover rates. This necessitates the implementation of efficient distribution networks and frequent replenishment. It captures a variety of shipment destinations, including supermarkets, convenience stores, and major online platforms, reflecting a geographically dispersed and dense customer base concentrated in populated areas.

Despite the wide range of FMCG products, the diversity within this dataset remains relatively consistent across borders, thereby facilitating the consolidation of inventories. Furthermore, certain FMCG products require storage in a conditioned or temperature-controlled environment due to food safety regulations. However, this particular case does not involve such requirements. The impact of different temperature conditions on the results will be analysed in 7.

While seasonality is an inherent characteristic of the FMCG industry, it is not directly addressed in our analysis. Although the dataset includes seasonal variations, these variations do not influence the objective values of our study.

5.2 Customers and Demand

The constructed data set comprised 11,578 customers in the Netherlands (NL) and in Belgium (BE). From this dataset, we removed the orders with a total weight of less than 50 kg, as these are to be distributed by a parcel service. Subsequently, we aggregated the customers based on a four-digit zip code. Furthermore, we removed the zip codes associated with customers on the Wadden Islands from the dataset, as our study only considers truck transport, not boat. This yielded a set of 2,277 zip codes, which are illustrated in Figure 5.1a. Figure 5.1b illustrates the number of customers in each area. We calculated the demand for each zip code over a one-year period.



(a) *Map of all customers.* **(b)** *Customers clustered per area.*

Figure 5.1: *Visual representation of customer distribution.*

5.3 Set of Warehouses

In this case study, we utilize two existing warehouses operated by logistic service providers, located in Tiel (NL) and Waterloo (BE).

The set of candidate warehouses includes these warehouse locations, as well as potential locations provided by logistic service providers. In Figure 5.2, we present a map of all candidate warehouse locations considered in this case, comprising a total of 19 locations. These locations are based on actual logistic service provider sites, which are typically situated on the outer edges of urban areas rather than in city centres.

The selection process also considered geographical relevance and strategic positioning within the supply chain network. Specifically, we did not identify logical locations in regions such as Drenthe, Groningen, or the Ardennes, as these areas are far from the central logistics hub and do not align with the strategic focus on locations near the population and industry centers.

We assume that all candidate warehouses are available in every period. However, it is important to recognize that real-world warehouse availability can vary. It is possible that logistics service providers who own these warehouses may not always have the capacity to accommodate additional clients.

Figure 5.2: *Candidate locations for warehouses.*

5.4 Inventory

In order to incorporate the inventory into the model, we need to determine the baseline inventory, as outlined in Subsection 4.2.1. The inventory level at the warehouses in Tiel and Waterloo are 4,100 m^2 and 3,902 m^2, respectively. This yields a total inventory of 8,002 m^2 (I = 8002) for two warehouses (n = 2). This number and the following formula determine the baseline inventory.

$$I = k * \sqrt{n}$$

$$8,002 = k * \sqrt{2}$$

$$k = 5,658.268463 \approx 5,658$$

By applying the aforementioned formula and employing the known value of k, we can calculate the inventory for any number of open warehouses (Appendix C). Since we assume that the warehouse have equal characteristics, all warehouses have identical costs per m^2 (€70) (Industrial Real Estate Partners, 2020). In Figure 5.3, we present how the warehouse costs increase with the number of open warehouses.

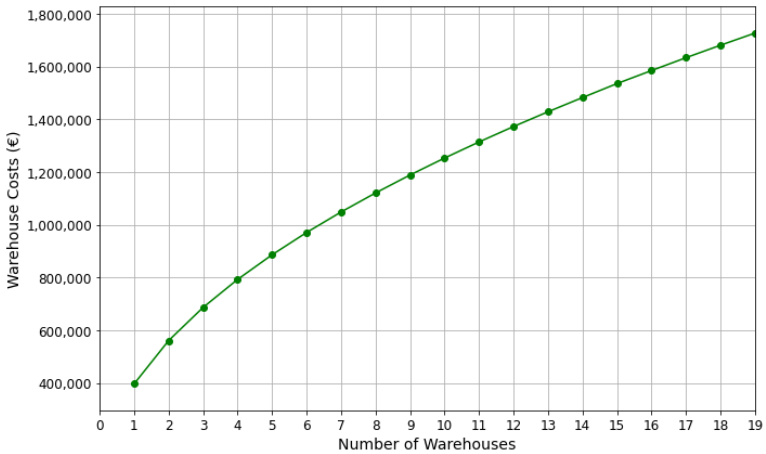


Figure 5.3: *Warehouse costs (€/m^2/year) with increasing number of open warehouses.*

The graph demonstrates that as we open more warehouses, the costs do not develop as quickly as the number of operational warehouses. This highlights the effectiveness of the SRL in managing and optimizing warehouse operations, as explained in Section 4.2.

5.5 Maximum Distance

The maximum distance allowed between a warehouse and a customer is determined by the company's desired delivery time. In the initial dataset, no information was given about the required delivery time. Therefore, we determine the maximum distance allowed based on the current warehouse locations in the dataset. The analysis involves examining the distances between all customers and the warehouses in Tiel and Waterloo. Each customer is assumed to be served by the nearest warehouse. Consequently, the highest distance between a warehouse and assigned customer represents the maximum distance. In this case, the maximum distance between a warehouse and a customer is found to be 175.42 km.

5.6 Emissions Factors

In this case study, we have chosen to use emission factors specific to NL, for both warehouse and transportation emissions. As a significant portion of the demand and the majority of kilometers traveled occur within NL, we employ Dutch emission factors for our calculations.

While it might initially seem reasonable to consider different emission factors for warehouses located in NL and BE, doing so would introduce inconsistencies when combined with transportation emissions. The ability of trucks to refuel in both NL and BE makes it impractical to assign a single country's emission factor to all transportation activities.

Using different emission factors for warehouses in NL and BE, while applying a single emission factor for transportation from NL, would result in inconsistent and potentially inaccurate calculations. Therefore, to maintain a straightforward and consistent methodology, we will standardize the emission factors to those of NL for both warehouses and transportation. This approach avoids the complexities of cross-border refueling. In Table 5.1 we present the emission factors we employ. For transportation we employ the emission factor of a Diesel truck of 10-20 tonne.

Additionally, the transportation cost per kilometer comprises a range of variables cost, such as driver expenses, toll charges, insurance costs and fuel expenditures. These transportation costs vary based on factors such as the type of vehicle, the fuel type, and the country of operation. We will use a transportation cost of €1.18 per kilometer, as this provides a good indication based on data from the RHDHV logistic service provider tariffs database.

Table 5.1: *Emission factors per energy type (CO2 Emissiefactoren, 2024).*

Category	Energy Type	Unit	Emission Factors TtW (kg CO_2/unit)
Warehouse	Electricity	kWh	0.27
	Gas	m^3	1.779
Transportation	Diesel	tkm	0.194

5.7 Energy Consumption for Warehouses

In order to calculate the CO_2 emissions of a warehouse, we need to consider the energy usage per m^2. Table 5.2 provides key figures for gas and electricity usage per m^2 for different surface classes and temperature conditions, as reported by CBS, 2019.

Table 5.2: *Energy consumption per surface class (CBS, 2019).*

Energy type	Surface class (m^2)	Temperature condition		
		Frost-free	Heated	Chilled
Electricity (kWh/m^2)	4,000 - 10,000	27.5	32.2	139.4
	10,000 - 25,000	28.4	38.8	125.1
	25,000 - 50,000	31.9	30.9	78.7
	50,000 - 100,000	29.5	59.1	-
Gas (m^3/m^2)	4,000 - 10,000	3.1	3.8	3.4
	10,000 - 25,000	2.7	3.7	2.2
	25,000 - 50,000	2.4	4.9	3.9
	50,000 - 100,000	1.9	1.7	-

The data presented in the table indicates that the highest electricity consumption occurs in chilled conditions across the surface classes. This observation is consistent with the high electricity usage of cooling systems. Conversely, gas consumption is higher for heated conditions in comparison to frost-free and chilled conditions. This is due to the fact that heating is frequently conducted using gas. The variations in energy consumption across different surface classes indicate that the efficiency of a warehouse can have a significant impact on its overall energy usage. Larger warehouses might be more energy-efficient due to economies of scale, whereas smaller ones may consume more energy per square meter due to less efficient space utilization. However, this is dependent on the specific warehouse in question, and therefore, there is some variation in these figures.

In our model, we assume equal characteristics across all warehouses. Consequently, we consider warehouses with a surface area between 4,000 and 10,000 m^2, maintaining a single temperature condition of frost-free. In a frost-free environment, the warehouse temperature is kept above the freezing point to prevent stored goods from freezing, without maintaining a specific temperature above freezing. Given the typical temperatures in NL and BE are above zero, and the absence of data regarding the energy usage of ambient warehouses, we will use the frost-free figures for energy usage in our calculations.

In Table 5.3 we present an overview of the aforementioned parameter values for this case. We will utilize the figures as inputs for our model. In the following chapter, we will present the results obtained.

Table 5.3: *Parameter settings of the case study.*

Description	**Parameter**	**Value**
Transportation costs (€/km)	c	1.18
Baseline inventory (m^2)	k	5,658
Emission factor for transportation (kg CO_2/tonne-kilometre)	W_T	0.194
Emission factor electricity (kg CO_2/kWh)	W_E	0.27
Emission factor gas (kg CO_2/m^3)	W_G	1.779
Maximum distance allowed (km)	$h_{\max}$	175.42
Facility costs (€/m^2)	f	70
Electricity consumption (kWh/m^2)	E	27.5
Gas consumption (m^3/m^2)	G	3.1

6

Results

In this chapter, we apply the theory of previous chapters to obtain results. In Section 6.1, we present the results of optimizing the individual objectives. In Section 6.2 we present the results of the multi-objective optimization. We address the second research question and the first part of the last research question:

How does the dual objective of minimizing distribution costs and CO_2 emissions impact the selection for warehouses locations and customer assignments?

What are the incremental costs associated with reducing CO_2 emissions in the FMCG distribution network?

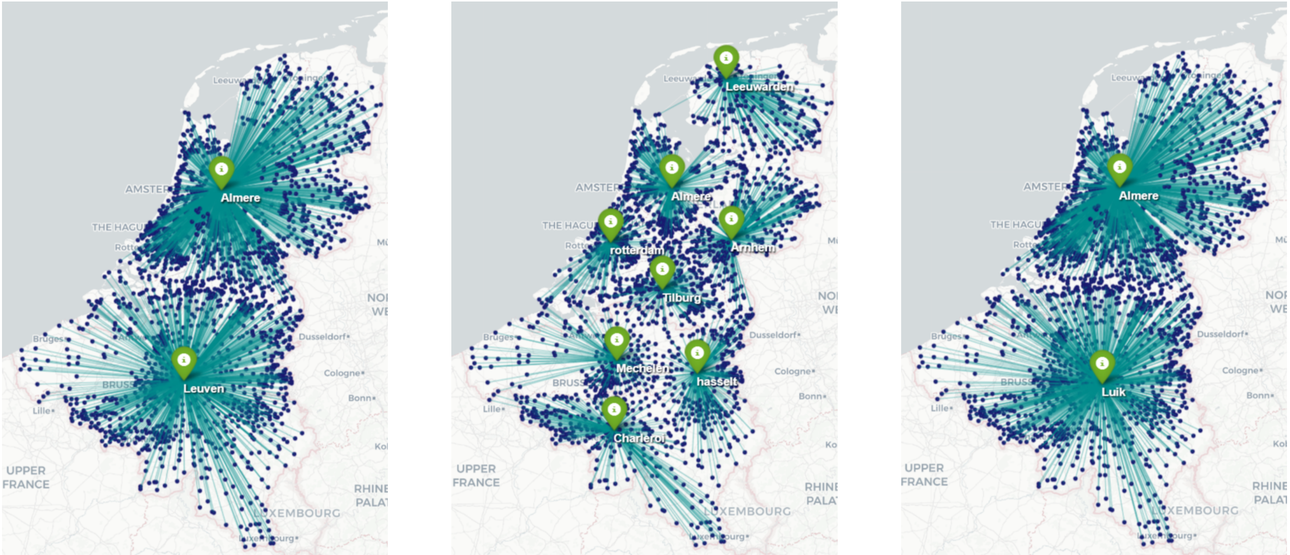
6.1 Optimization Results for Individual Objectives

In this section, we present the results of optimizing the individual objectives: minimizing distribution costs, minimizing CO_2 emissions, and minimizing both by combining the two objective values. The model is solved using Gurobi solver (11.0.1) in Python (3.11.8).

Figure 6.1 illustrates the warehouse locations and customer assignments for each objective. When the objective is to minimize costs only, the optimization model prioritizes warehouses that minimize the sum of transportation distances and the associated costs. For our dataset, this approach leads to the selection of warehouses in Leuven and Almere (Figure 6.1a). The maximum distance constraint contributes to the selection of two warehouses instead of one; without this constraint, only one warehouse is selected (Tilburg).

In contrast, optimizing for CO_2 emissions increases the number of warehouses from two to eight (Figure 6.1b). This approach reduces the distance goods need to travel, thereby minimizing CO_2 emissions from transportation, despite increasing the total number of warehouses. This indicates that transportation emissions outweigh warehouse emissions, leading to a preference for more warehouse locations when optimizing for CO_2 emissions. Conversely, lower transportation costs compared to warehouse costs lead to a preference for fewer warehouses when optimizing for distribution costs.

When both objectives are optimized by adding up their values, the model once again selects two warehouses, as was the case with cost minimization alone. However, in this case, Luik is chosen instead of Leuven (Figure 6.1c). This results in slightly higher distribution costs but slightly lower CO_2 emissions compared to focusing solely on minimizing distribution costs. This difference can be explained by the specific factors considered in each objective. For cost minimization, only the distance and transportation costs are taken into account. On the other hand, CO_2 emission calculations



(a) *Minimizing distribution costs.* **(b)** *Minimizing CO_2 emissions.* **(c)** *Minimizing both objectives.*

Figure 6.1: *Optimal warehouse locations and customer allocations for each objective.*

incorporate the total weight of goods per customer, the distance, and the emission factor. Luik, while less centrally located than Leuven, is closer to a subset of high-demand customers (Figure 6.2). This proximity is crucial for reducing total CO_2 emissions. The reduced distance to these high-demand customers means that the emissions, which are influenced by the weight of goods transported over a given distance, are lower even if the transportation costs might be higher due to the overall distance. Therefore, although the distribution costs increase slightly with the selection of Luik, the overall CO_2 emissions decrease, making it a preferable choice when balancing both objectives.

However, the results may not be entirely accurate due to the scale differences between distribution costs and CO_2 emissions. When combining objectives with different scales, the larger-scale term can disproportionately influence the optimization outcome. In this case, distribution costs have a significantly larger numerical value compared to CO_2 emissions. As a result, the optimization model places more emphasis on minimizing distribution costs, leading to suboptimal consideration of CO_2 emissions.

This imbalance occurs because a small change in distribution costs has a more substantial impact on the overall objective function than a relatively larger change in CO_2 emissions. Consequently, the model's choice of Luik, while beneficial in reducing CO_2 emissions, may not fully reflect the optimal trade-off between cost and environmental impact due to this scale difference. In order to achieve more balanced results, it may be necessary to normalize the objectives. However, since we employ the ϵ-constraint method, whereby one objective is minimized and the other is set as a constraint, this is not a necessary step.

In Table 6.1 we present the results, where MC represents minimizing costs and ME represents minimizing CO_2 emissions. The comparison shows how different objectives impact the optimal number and location of warehouses, balancing transportation costs and emissions. In the next section, we will use these results as an input for the multi-objective optimization.

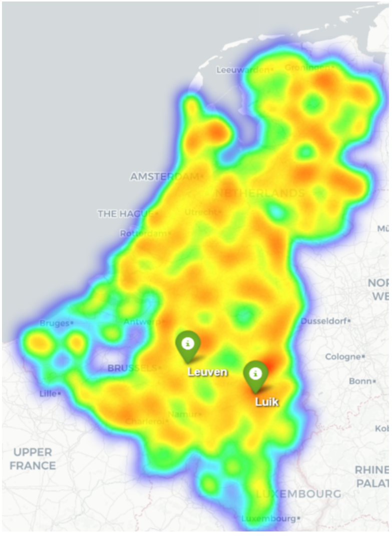


Figure 6.2: *Heat map illustrating customer demand around Leuven and Luik (red indicates higher demand).*

Table 6.1: *A comparison of the results of separate and combined objectives.*

Objective	Number of warehouses	Distribution costs (€)	CO_2 emissions (kg)	Total Objective Value
MC	2	922,036.52	672,159.25	1,594,195.77
ME	8	1,309,461.50	520,076.28	1,829,537.78
MC + ME	2	923,117.23	663,586.37	1,586,703.60

6.2 Optimization Results Epsilon-Constraint Method

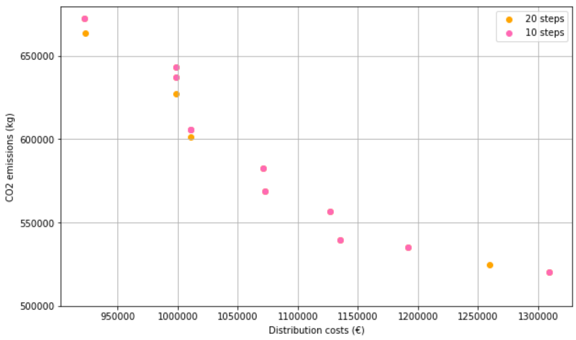
In this section, we first establish an appropriate step size. We then present our results and proceed to compare the solutions on the Pareto front with the initial warehouse configuration.

6.2.1 Determining the Step Size

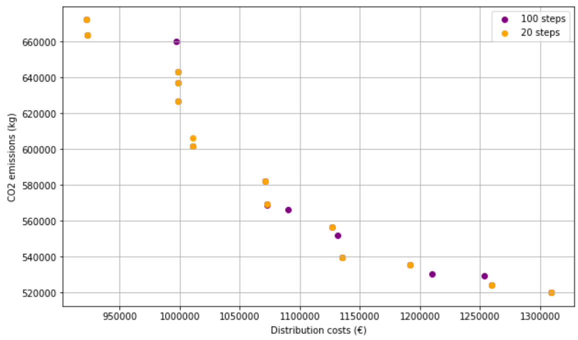
In order to determine an appropriate step size for the ϵ-constraint method, we need the range of CO_2 emissions (f_2^{min}, f_2^{max}). The maximum CO_2 emissions are identified by solving the model with the objective of minimizing distribution costs only, and the minimum CO_2 emissions by minimizing the CO_2 emissions objective only. We determined both of these values in Section 6.1, which result in f_2^{min} = 520,076.28 and f_2^{max} = 672,159.25. In order to determine an appropriate step size, we conducted experiments with different numbers of steps and recorded the run times. The results are shown in Figure 6.3.

We observe that increasing from 10 steps to 20 steps results in the generation of four additional solutions. Therefore, we further increase the number of steps from 20 to 100, resulting in five additional solutions compared to 20 steps. However, when the number of steps is increased from 100 to 200, no additional solutions are yielded.

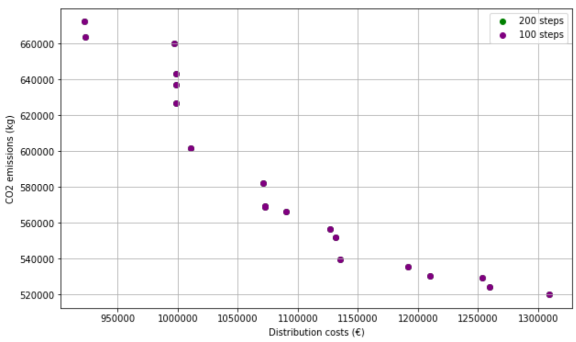
From 200 to 300 steps, we do find one additional solution, but it is approximately the same as the neighbouring solution. In particular, we observe a 0.21% reduction in CO_2 emissions and a corresponding 0.15% increase in costs. Upon increasing the number of steps from 300 to 500, an additional solution is identified. Nevertheless, the solution remains largely identical to that of the neighbouring solution. A reduction of 0.75% in CO_2 emissions was observed, accompanied by a 0.01%



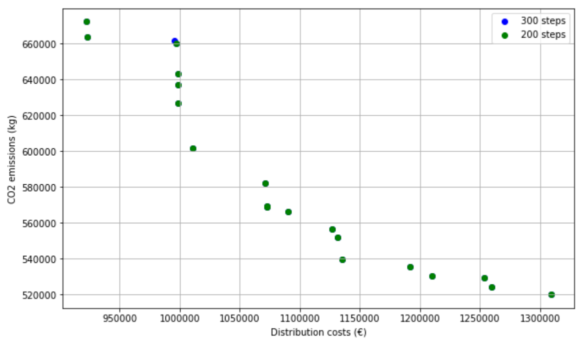
(a) *10 and 20 steps.*



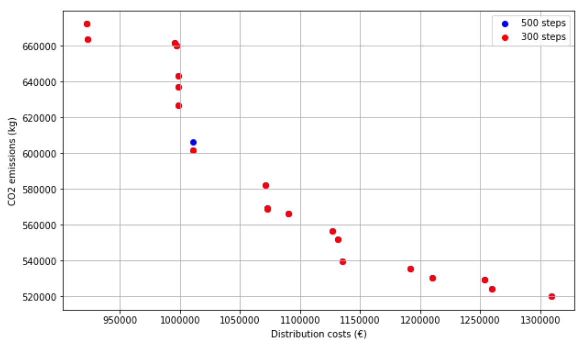
(b) *20 and 100 steps.*



(c) *100 and 200 steps.*



(d) *200 and 300 steps.*



(e) *300 and 500 steps.*

Figure 6.3: *Comparison of the solutions for different numbers of steps.*

increase in costs.

Therefore, we choose a step size of 100, as the percentage of CO_2 reduction for the extra solutions is minimal, and the running time increases significantly with the number of steps (Table 6.2). Moreover, it is unlikely that a company would alter its warehouse locations or invest significant resources in new contracts with logistics service providers for a relatively minor reduction in CO_2 emissions. This results in a step size of:

$$\frac{672,159.25 - 520,076.28}{100} = 1,520.83$$

Table 6.2: *Running times for different numbers of steps.*

Number of steps	Running time (sec.)
10	9,875.29
20	16,857.28
100	79,065.35
200	163,783.26
300	248,800.52
500	412,348.22

6.2.2 Pareto Front Solutions

With this step size, we derive a set of optimal solutions, which are depicted in Figure 6.4. The specific warehouse selections for each solution are detailed in Table 6.3.

The solutions presented in Table 6.3 demonstrate various configurations of warehouses. It is logical to conclude that optimal solutions do not include multiple configurations with the same set of warehouses open but different customer assignments. This is because both objectives aim to minimize the distances, because greater distance result in higher costs and increased CO_2 emissions. Consequently, there is no differentiation in customer assignments when the same set of warehouse locations is utilized. As a result, the Pareto front does not contain solutions where the same warehouses are open but yield different outcomes in terms of objectives.

From the Pareto front presented in Figure 6.4 and the warehouse configuration in Table 6.3, we observe distinct strategies based on the prioritization of objectives. When we prioritize CO_2 reduction, we tend to favor the selection of a greater number of warehouses. Conversely, when our focus is on minimizing distribution costs, the recommendation shifts towards fewer warehouses. This relationship between the number of open warehouses and the two primary objectives is illustrated in Figure 6.5.

Solutions 1 and 19, positioned at the extremes of the Pareto front spectrum, likely represent sub optimal choices due to their extreme nature. In Table 6.4, we demonstrate the CO_2 emissions and the distribution costs per solution. Furthermore, we provide the incremental cost of CO_2 reduction between adjacent solutions.

The most promising solutions are those that achieve a notable reduction in CO_2 emissions while maintaining a relatively low incremental cost. It is important to note that the incremental costs in this table compare adjacent solutions. Nevertheless, in order for a company to make an informed decision, it is essential to evaluate these solutions in relation to their current warehouse locations. This will assist them in determining whether they should reconsider their warehouse locations and, if so, which

Table 6.3: *Warehouse selection per solution.*

Solution	Warehouses
1	Tilburg, Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere
2	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Leeuwarden, Almere
3	Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere
4	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Almere
5	Waterloo, Breda, Arnhem, Hasselt, Leeuwarden, Almere
6	Waterloo, Breda, Arnhem, Hasselt, Almere
7	Waterloo, Arnhem, Hasselt, Rotterdam, Almere
8	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden
9	Waterloo, Breda, Arnhem, Hasselt
10	Waterloo, Arnhem, Hasselt, Rotterdam
11	Waterloo, Breda, Hasselt, Almere
12	Waterloo, Hasselt, Rotterdam, Almere
13	Mechelen, Hasselt, Almere
14	Arnhem, Luik, Rotterdam
15	Arnhem, Leuven, Rotterdam
16	Tilburg, Leuven, Almere
17	Waterloo, Eindhoven, Almere
18	Luik, Almere
19	Leuven, Almere

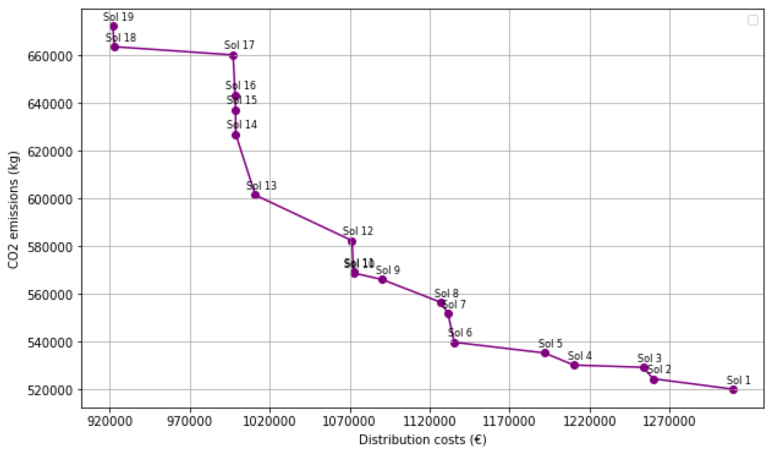


Figure 6.4: *Pareto front resulting from ϵ-constraint method.*

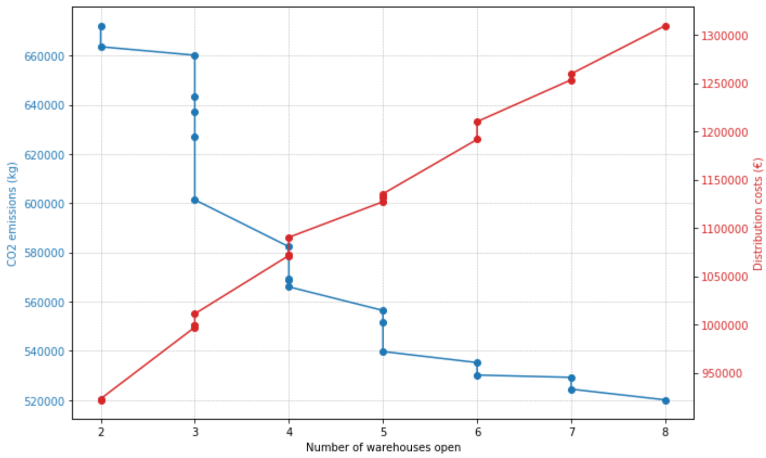


Figure 6.5: *Distribution costs and CO_2 emissions with increasing number of open warehouses.*

Table 6.4: *Comparison of CO_2 emissions, distribution costs, and incremental costs of CO_2 reduction between adjacent solutions.*

Solution	CO_2 emissions (kg)	Distribution costs (€)	CO_2 reduction (kg)	Incremental costs (€)
1	520,076.28	1,309,461.50	4344.52	49,888.18
2	524,420.80	1,259,573.32	4798.79	6,175.44
3	529,219.59	1,253,397.88	934.89	43,328.16
4	530,154.49	1,210,069.73	5077.29	18,381.06
5	535,231.78	1,191,688.66	4477.26	56,300.38
6	539,709.04	1,135,388.28	11993.84	3,940.62
7	551,702.89	1,131,447.66	4710.03	4,297.48
8	556,412.92	1,127,150.18	9595.02	36,793.98
9	566,007.94	1,090,356.20	2744.14	17,953.84
10	568,752.08	1,072,402.37	295.73	4.54
11	569,047.81	1,072,397.83	13266.69	909.67
12	582,314.50	1,071,488.15	19080.73	60,370.46
13	601,395.23	1,011,117.69	25557.07	12,274.87
14	626,952.30	998,842.82	10251.19	50.83
15	637,203.49	998,791.99	6179.52	300.47
16	643,383.01	998,491.53	16773.12	1,295.89
17	660,156.13	997,195.64	3430.25	74,078.41
18	663,586.37	923,117.23	8572.88	1,080.71
19	672,159.25	922,036.52	-	-

locations would be optimal in terms of sustainability, given their sustainability goals and the financial resources available to them.

6.2.3 Comparison with initial warehouse configuration

In the case study, we initially employed two warehouses, in Tiel and Waterloo. This setup, however, is not included in the Pareto optimal solutions, indicating it is sub optimal. The initial configuration, with CO_2 emissions of 700,901.79 kg and costs amounting to €928,806.80, is dominated by other solutions that achieve lower distribution costs and CO_2 emissions, as depicted in Figure 6.6.

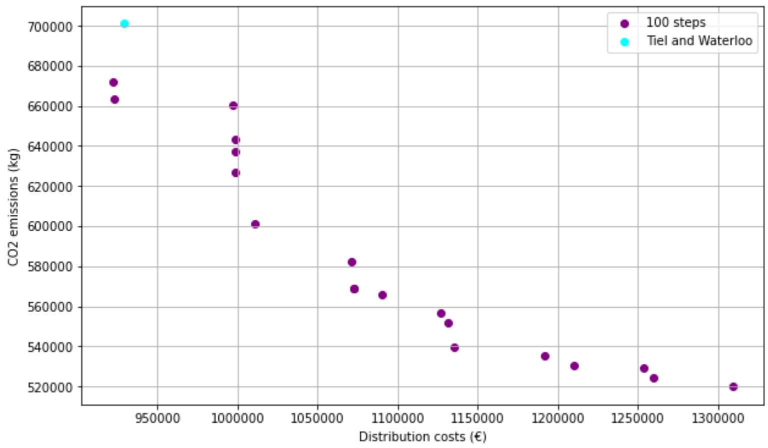


Figure 6.6: *Comparison of initial warehouse configuration with Pareto optimal solutions.*

In Table 6.5, we present the incremental costs of different levels of CO_2 reduction, compared with the initial solution. As the initial configuration of warehouses was sub optimal, solutions 18 and 19 exhibit negative incremental costs. These solutions also involve the operation of two warehouses, in accordance with the initial configuration, however, with lower values of both objectives. This approach enables companies to identify solutions that align with their specific CO_2 reduction targets. In the next chapter, we analyze the impact of varying inputs on the trade-off.

Table 6.5: *Overview solutions for different target levels of CO_2 reduction.*

Target CO_2 reduction	Solution	CO_2 reduction (%)	Incremental costs (€)
20-25%	1	25.80	380,654.71
	2	25.18	330,766.53
	3	24.49	324,591.09
	4	24.36	281,262.93
	5	23.64	262,881.87
	6	23.00	206,581.48
	7	21.29	202,640.86
	8	20.61	198,343.38
15-20%	9	19.25	161,549.41
	10	18.85	143,595.57
	11	18.81	143,591.03
	12	16.92	142,681.36
10-15%	13	14.20	82,310.90
	14	10.55	70,036.03
5-10%	15	9.09	69,985.20
	16	8.21	69,684.73
	17	5.81	68,388.84
	18	5.32	-5,689.57
0-5%	19	4.10	-6,770.27

7

Scenario Analysis

In this chapter, we present various scenario analysis. First, we examine the impact of Temperature-Controlled Logistics (TCL) on the trade-off between the two objectives. Subsequently, we analyze the impact of the new carbon price regulations.The second part of the last research question is answered in this chapter.

How does the trade-off vary with changes in input parameters?

7.1 Temperature-Controlled Logistics

In this section, we present an analysis of the impact of TCL on the trade-off between distribution costs and CO_2 emissions. Given the diverse range of products and their unique characteristics within the FMCG sector, it is essential to understand how TCL impacts the Pareto front. TCL involves managing products within specific temperature ranges to prevent spoilage and ensure efficacy. For instance, dairy products and certain pharmaceuticals require chilled environments, while other items, such as cosmetics, need a stable temperature to maintain their quality. Medicines, in particular, present a wide array of temperature requirements, emphasizing the complexity of TCL (IFC, 2020).

In our case study, we considered a frost-free temperature requirement. However, for a more comprehensive analysis, we examine two additional conditions: chilled and heated environments. Chilled conditions are essential for products requiring cooling, such as dairy, pharmaceuticals, and cosmetics. In contrast, heated conditions are primarily used to maintain a constant temperature and ensure a comfortable working environment in warehouses. Since we assume equal characteristics among both warehouses and trucks, we assume that they each operate under the same temperature condition. Additionally, we assume that within the warehouse and within the truck, they maintain one type of condition.

For the chilled scenario, we analyze the changes in input parameters for both warehouses and trucks, as both need to maintain the necessary cooling conditions. However, for the heated scenario, we focus solely on warehouses. This is because the relatively short distances within the FMCG sector do not necessitate the use of heated trucks to maintain a constant temperature for products during transport.

In the following subsections, we determine the changes in input parameters for the specific temperature conditions for both warehouses and trucks.

7.1.1 Temperature-Controlled Warehouses

Temperature conditions in warehouses, either chilled or heated, significantly impact energy consumption, as shown in Table 7.1. We can directly calculate the shift in CO_2 emissions related to this energy consumption. In order to identify the costs associated with a specific warehouse condition, it is necessary to determine the costs associated with energy. In our case study, we considered a frost-free warehouse with total costs amounting to €70 per m^2 per year. Energy costs represent 15% of the overhead warehouse costs (Ries et al., 2016), amounting to €10.5 per m^2 per year. To estimate the costs associated with chilled or heated warehouses, we first calculate the costs per unit of energy.

$$\text{Cost per unit energy (€)} = \frac{\text{Energy cost (€)}}{\text{Total energy usage (units)}} = \frac{10.5}{27.5 + 3.1} = \text{€}0.343/\text{unit of energy} \tag{7.1}$$

Using this cost per unit of energy, we can calculate the total warehouse costs per m^2 (f) for different temperature conditions as follows:

$$f = 0.343x + 59.5 \tag{7.2}$$

Where x is the energy usage in units per m^2. In Table 7.1, we present the total cost per m^2 for the different warehouse conditions.

Table 7.1: *Energy usage and cost comparison of different warehouse types.*

Warehouse condition	Electricity usage (kWh/m^2)	Gas usage (m^3/m^2)	Total energy usage (units)	Energy cost per unit energy (€)	Fixed costs (€)	Total cost per m^2 (€)
Base case	27.5	3.1	30.60	0.343	59.5	70.00
Heated	32.2	3.8	36.0	0.343	59.5	71.85
Chilled	139.4	3.4	142.80	0.343	59.5	108.50

7.1.2 Temperature-Controlled Trucks

Specific energy usage data for trucks is unavailable. As indicated by Sukkel et al., 2014, the consumption of fuel by refrigerated trucks is observed to increase by 10%. According to the logistics service provider rates database of RHDHV, the costs per kilometer for chilled trucks also increase by 10%.

This means that the transportation costs increase proportional to the fuel consumption. Although not all transportation costs are solely attributable to fuel expenses, refrigerated trucks have a lower capacity than non-refrigerated trucks due to the additional insulation layer required for temperature control, as well as the packaging constraints. Furthermore, the refrigeration unit adds extra weight to the load, thereby impacting the vehicle's movement and speed (Teleroute, 2018). These aspects contribute to a less efficient logistics network which result in higher overall transportation costs, which aligns with the observed 10% increase in fuel consumption.

Therefore, we use an emission factor of 0.213 kg CO_2/km, and transportation cots of €1.30/km for refrigerated trucks. In Table 7.2, we present the parameter settings for each environmental condition, for both the truck and the warehouse, as previously outlined. These parameter settings will be employed to test the two scenarios, chilled and heated conditions. In the subsequent section, we present the results.

Table 7.2: *Overview of parameter settings for each environmental condition.*

		Environmental condition		
Category	**Parameter**	**Base case**	**Chilled**	**Heated**
Truck	Transportation costs (c)	1.18	1.30	1.18
	Emission factor (W_T)	0.194	0.213	0.194
Warehouse	Warehouse costs (f)	70	108.5	71.853
	Electricity usage (E)	27.5	139.4	32.2
	Gas usage (G)	3.1	3.4	3.8

7.1.3 Results

In order to resolve the model for these scenarios, it is necessary to determine the step size once more, as the range of CO_2 emissions is subject to change. In Table 7.3, we present the results when optimizing the objectives individually. In Table 7.4, we present the corresponding step size per scenario.

Table 7.3: *Individual objective optimization results per TCL scenario.*

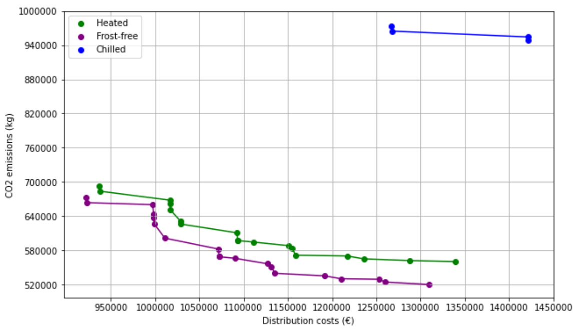
Scenario	Objective	Number of warehouses selected	Distribution costs (€)	CO_2 emissions (kg)
Base case	MC	2	922,036.52	672,159.25
	ME	8	1,309,461.50	520,076.28
Chilled	MC	2	1,266,916.56	973,883.37
	ME	3	1,421,493.33	949,204.83
Heated	MC	2	936,864.23	692,278.68
	ME	8	1,339,116.91	560,315.13

Table 7.4: *CO_2 range and step size per scenario.*

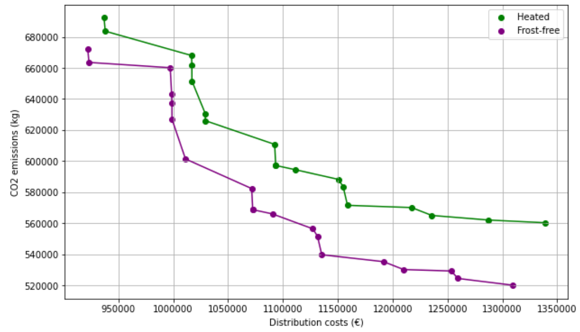
Scenario	CO_2 range	Step size
Base case	152,082.97	1,520.83
Chilled	24,678.54	246.79
Heated	131,963.55	1,319.64

We illustrate the Pareto fronts of the scenarios in Figure 7.1. In Subfigure 7.1a we present the results of all scenarios, while in Subfigure 7.1b we compare the base case (frost-free) and the heated scenario. Subfigure 7.1c highlights the results of the chilled scenario alone.

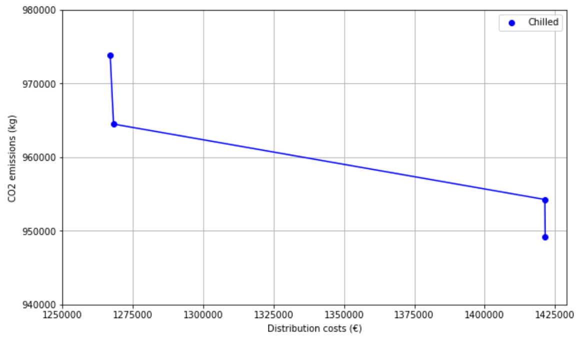
In the heated scenario, distribution costs and CO_2 emissions are slightly higher compared to the base case. However, the warehouse configurations remain consistent, as indicated by a rightward shift in the Pareto front without any alteration in its shape. Notably, the CO_2 range in the heated scenario is smaller, resulting in one fewer solution on the Pareto front.



(a) *Results of all scenarios.*



(b) *Results of frost-free and chilled.*



(c) *Result of chilled.*

Figure 7.1: *Comparison of Pareto fronts across TCL scenarios.*

In contrast, the results from the chilled scenario differ significantly from those in the base case. The narrower range of CO_2 emissions in the chilled scenario necessitates a strategy of minimizing the number of warehouses across both objectives, leading to a distinct warehouse configuration compared to the baseline scenario. This shift results in only four solutions on the Pareto front. The reduced number of solutions stems from the fact that, in the base case, warehouse emissions were lower than transportation emissions. As a result, when minimizing CO_2 emissions, it was advantageous to operate more warehouses, while minimizing costs favored operating fewer warehouses due to lower transportation costs relative to warehouse costs.

However, in the chilled scenario, warehouse emissions increased significantly more than both warehouse costs and transportation emissions and costs. Consequently, even when minimizing CO_2 emissions, it becomes more beneficial to operate fewer warehouses, as the high emissions associated with warehouses outweigh the benefits of having more locations. Additionally, since warehouse costs remain higher than transportation costs, minimizing costs also favors operating fewer warehouses. This explains the limited number of solutions on the Pareto front in the chilled scenario.

In Appendix B, we present the detailed warehouse configurations along with the associated distribution costs and CO_2 emissions in both the chilled and heated scenario.

7.2 Impact of New Regulation Carbon Emissions: ETS2

The European Green Deal aims to cut EU GHG emissions by 55% from 1990 levels by 2030 and achieve net-zero emissions by 2050. Despite overall emissions decreasing by 20% from 1990 to 2019, road transport emissions have risen by over 25%, necessitating more aggressive policies. (Climate Action, 2024).

Carbon pricing, through mechanisms like the EU's Emissions Trading System (ETS), is a critical tool for reducing GHG emissions. The EU ETS has been successful in the power sector and large industrial emitters. To build on this success, the European Commission introduced ETS2, starting in 2027, targeting fuel combustion in buildings, road transport, and small industries. Under ETS2, fuel suppliers are required to monitor and report their emissions and purchase allowances to cover these emissions, aiming to reduce them by 42% by 2030.

The ETS2 introduces a carbon price starting at €45 per ton of CO2 in 2027. This initial price acts as a trigger point set by the Market Stability Reserve (MSR). If the carbon price exceeds €45, the MSR will release additional allowances into the market to stabilize prices and prevent excessive volatility.

However, according to Haywood and Jakob, 2023, to achieve the EU's target of a 42% reduction in emissions by 2030, the carbon price is expected to increase substantially over time. This significant increase is necessary because the initial carbon price increase is projected to reduce emissions by only about 2.2%, far below the required reduction. The low price elasticity of fuel consumption, where demand does not significantly decrease with moderate price increases, suggests that much higher prices will be necessary to drive substantial emission reductions. For example, a carbon price of €100 per ton would result in a roughly 18% increase in fuel prices. If the carbon price rises to €500 per ton, fuel prices are expected to double, representing a 100% increase.

In this scenario analysis, we examine how the trade-off, the Pareto front, shifts when the transportation costs of logistics service providers increase due to the introduction of the ETS2. We assume that fuel suppliers and logistics service providers fully pass on the carbon price.

7.2.1 Results

The CO_2 range, and consequently the step size, remain consistent with the baseline scenario, as fuel costs do not influence the CO_2 range. According to various sources, fuel costs account for approximately 25% of total transportation costs (Comite National Routier, 2019; Ondernemersvereniging Evofenedex, n.d.; Zofío et al., 2014). With current transportation costs at €1.18 per km, this translates to a fuel cost of €0.295 per km. In Table 7.5 we present the transportation costs for each scenario.

Table 7.5: *Impact of CO_2 pricing on transportation costs*

Scenario	Increase in fuel price (%)	Fuel price (€ per km)	Transportation costs (€ per km)
Base case	-	0.295	1.18
€45 per ton CO_2	9	0.32155	1.20655
€100 per ton CO_2	18	0.3481	1.2331
€500 per ton CO_2	100	0.59	1.475

These transportation costs results in the Pareto fronts illustrated in Figure 7.2. As transportation costs increase under various carbon pricing scenarios, we observe a rightward shift in the Pareto fronts, indicating higher overall costs driven by increased transportation expenses. However, this shift does not result in changes to warehouse configurations, as there is no observable alteration in the structure of the Pareto fronts. From our analysis, we conclude that carbon pricing does not have a significant impact on the trade-off between distribution costs and CO_2 emissions. Despite the fact that the fuel supplier and the logistics service provider passes through the whole CO_2 price, this has no significant impact on the trade-off.

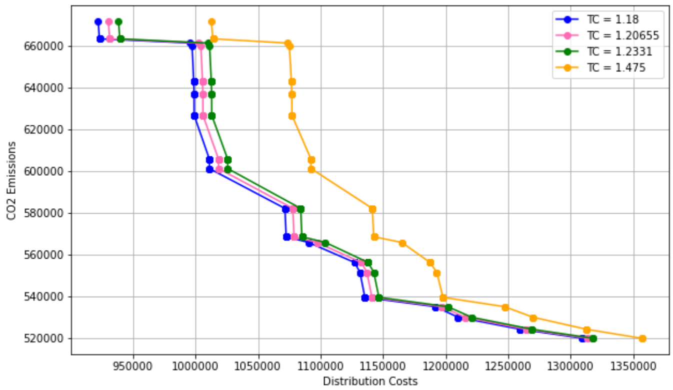


Figure 7.2: *Comparison of Pareto fronts for different transportation cost (TC) levels.*

To determine when the impact becomes significant, we analyzed the results for transportation costs (TC) of €2, €3, and €4 per km, as shown in Figure 7.3. For TC = €2, the Pareto front only shifts to the right but does not change in structure. However, starting from TC = €3, the Pareto front changes, indicating fewer solutions and different warehouse configurations (Appendix D). Specifically, the higher transportation costs involves opening more warehouses because transportation costs outweigh warehouse costs more significantly than in the previous scenarios.

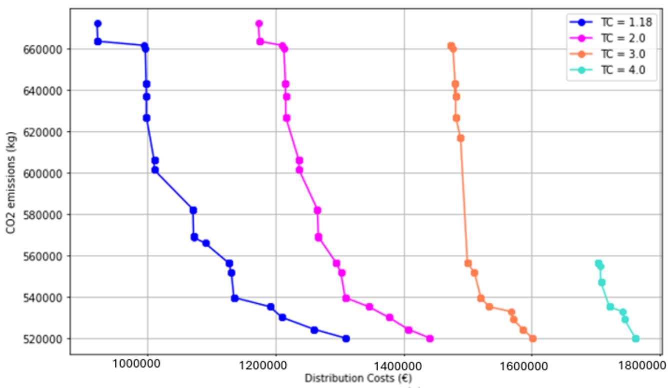


Figure 7.3: *Comparison of Pareto fronts for different transportation cost (TC) levels.*

As the TC increases, the optimization problem gradually shifts towards a single objective. This occurs because, at higher transportation costs, minimizing transportation expenses becomes the dominant objective. Consequently, the trade-off between distribution costs and CO_2 emissions becomes narrower, leading to fewer optimal solutions and a preference for configurations with less warehouses to minimize distribution costs.

8

Conclusions, Limitations and Further Research

In this chapter, we discuss the key findings of our research and we answer the main research question:

How should FMCG companies design their distribution network, considering the trade-off between minimizing distribution costs and CO_2 emissions?

In Section 8.1, we present the conclusions of our research. In Section 8.2, we discuss the limitations and we elaborate on the possible extensions, referred as further research. In the following section, we provide general recommendations for the FMCG industry. In the final section, we address the generalizability of our research.

8.1 Conclusions

In Chapter 1 we defined three sub-research questions. In this section we will address each of them.

1. *What is the most suitable model for selecting warehouse locations in a FMCG network to minimize distribution costs and CO_2 emissions, and how can it be modified for FMCG-specific characteristics?*

In Chapter 2, we introduce the FLP concept. For the FMCG industry considering a shared distribution network, a discrete model is required since warehouse locations of logistic service providers are selected from a predefined set of candidate locations. The multi-facility class of discrete models is the most appropriate, as it determines the optimal number and locations of warehouse facilities, balancing distribution costs and CO_2 emissions. Specifically, the discrete UFLP is the most comprehensive model, allowing for unlimited capacity.

Based on a literature review, the model proposed by Harris et al., 2009 is the most suitable for this research, as it considers the trade-off between minimizing costs and CO_2 emissions with a discrete solution set and unlimited capacity. We made three extensions to this model.

We included a maximum distance constraint to ensure timely deliveries. We also accounted for increased total inventory requirements in a shared network using the SRL. Finally, in Chapter 3, we evaluated that the distance-based method and the site-specific method are most suitable for our case, refining the CO_2 emissions calculation accordingly. This refined model enabled us to address the following research question.

2. *How does the dual objective of minimizing distribution costs and CO_2 emissions impact the selection for warehouses locations and customer assignments?*

In Chapter 5, we explored the dual objective of minimizing both distribution costs and CO_2 emissions and its impact on warehouse locations and customer assignments. When the goal is to minimize distribution costs, the optimal strategy involves operating fewer warehouses, specifically two. Conversely, when the objective shifts to minimizing CO_2 emissions, the model recommends opening eight warehouses to achieve the lowest possible emissions.

In Section 4.3, we determined the trade-off between distribution costs and CO_2 emissions using a Pareto front. We introduced multi-objective optimization and illustrated the trade-off with the Pareto front, employing the ϵ-constraint method. This method balances competing objectives by setting one objective as a constraint and iteratively adjusting it to generate a set of optimal solutions representing different trade-offs.

From the Pareto front, we conclude that as we approach the objective of minimizing distribution costs, it becomes advantageous to choose fewer logistics service providers. Conversely, to minimize CO_2 emissions, selecting a greater number of providers is advisable. This trade-off is further understood by examining total transportation and warehouse costs, as well as emissions. A reduction in logistics providers increases the distance between customers and warehouses, raising transportation costs but reducing warehouse costs. This scenario indicates that transportation costs are less than warehouse costs, leading to the selection of fewer warehouses when minimizing distribution costs. On the other hand, increasing the number of warehouses decreases total CO_2 emissions by reducing transportation emissions, despite the rise in emissions from the warehouses themselves. This shows that transportation emissions are greater than those from warehousing.

The warehouse configuration indicates that selecting warehouses and customer assignments does not result in significant variation in assignments when the same warehouses are chosen. This is due to the shared objective of minimizing distances, which reduces both costs and CO_2 emissions. Consequently, the Pareto front does not contain solutions where the same warehouses are open but yield different outcomes in terms of objectives.

The trade-off between transportation and warehouse costs and emissions can vary depending on specific context factors, such as warehouse types and transportation costs. The next research question will conclude how this trade-off varies when these factors are adjusted.

3. *What are the incremental costs associated with reducing CO_2 emissions in the FMCG distribution network, and how does this trade-off vary with changes in input parameters?*

When comparing the Pareto front solutions with the initial warehouse configuration, we found that the initial setup was suboptimal. Solutions derived from our analysis provided more effective ways to reduce both CO_2 emissions and distribution costs compared to the original configuration. We calculated the incremental costs of different levels of CO_2 reduction, with the highest level of reduction being 25%, at an incremental cost of €380,654.71.

Several conclusions can be drawn regarding the trade-off between distribution costs and CO_2 emissions in different TCL scenarios. Comparing the chilled scenario with the base case, reveals that costs and emissions for both transportation and warehouses are higher in the chilled scenario, especially warehouse emissions. In the base case, transportation emissions were greater than warehouse emissions, while transportation costs were lower than warehouse costs. In the chilled scenario, there is a notable increase in warehouse emissions compared to transportation emissions, shifting the structure of the Pareto front. Thus, selecting fewer warehouses is more advantageous for both cost and emissions objectives.

In the heated scenario, similar to the base case, minimizing costs favors fewer warehouses with lower transportation costs compared to warehouse costs. However, costs and CO_2 emissions are slightly higher in the heated scenario due to increased energy consumption. Minimizing CO_2 emissions still favors opening more warehouses to reduce transportation emissions, maintaining a similar Pareto front structure to the frost-free scenario despite slightly higher operational costs.

The impact of carbon pricing regulations (ETS2) on the trade-off demonstrates a shift in the Pareto front due to increased transportation expenses. Even if fuel suppliers and logistics service providers fully pass on CO_2 emission costs to customers, the trade-off remains unchanged until transportation costs increase to €3 per km. It is unlikely that transportation costs would triple to observe a significant change in the Pareto front structure. Therefore, while carbon pricing regulations might increase transportation costs, the impact on the trade-off is minimal unless transportation expenses reach a significantly higher level.

8.2 Limitations and Future Research

In this section, we discuss the limitations of our research and we propose several future research directions.

Equal warehouse characteristics

Currently, we assume that all warehouses have equal characteristics. This simplification overlooks potential variations in operational costs due to regional differences in labor costs, taxation, and other economic factors. The availability of labour is also becoming an increasingly important topic in this context. It has the potential to lead to automation and mechanisation, which may have a different impact on emissions.

Another assumption we make, is that all candidate warehouses are available in every period. It is, however, important to recognize that the availability of warehouses in the real world can vary. It is possible that logistics service providers who own these warehouses may not always have the capacity to accommodate additional clients. This would result in a smaller set of candidate locations, which would in turn reduce the number of possible solutions and consequently alter the Pareto front. Further research could investigate the impact of these variations on the overall cost and efficiency of the distribution network.

Country specific energy mix

For this study, we did not consider country specific energy mix, which refers to the different energy sources and their respective emission factors used in a country. Since countries vary in their use of renewable energy, the emissions factors for electricity and gas consumption can significantly impact the total CO_2 emissions. For example, nearly half (48%) of the electricity produced in the Netherlands in 2023 came from renewable sources, including solar, wind, and water, leading to lower emission factors for electricity consumption (Netherlands, 2024). In contrast, 39.2% of the energy consumed in Belgium came from renewable sources (International Energy Agency, n.d.). Therefore, Belgium's overall energy mix results in higher emission factors for transportation, electricity, and gas compared to the Netherlands.

If these differences were incorporated into the model, it might show a preference for warehouse locations in the Netherlands due to the lower emissions associated with Dutch energy sources. By including the energy mix, the model could tend to select locations with lower overall emissions, assuming other characteristics are similar. Future research should consider these differences to provide a more accurate assessment of the environmental impact of distribution networks.

Difference in detail of CO_2 calculation for transportation and warehouses

Currently, our CO_2 calculations for transportation are less detailed compared to those for warehousing. The site-specific method for warehouses, including fuel consumption, is more detailed than the distance-based method employed for transportation. As a result, the model might under or overestimate the transportation emissions, impacting the overall assessment of the distribution network. Future studies could provide a more accurate analysis of transportation emissions using the fuel-based method, which could refine the trade-offs between transportation and warehousing emissions and costs.

Exclusion of refrigerant leakage

We excluded refrigerant leakage from our emissions calculations due to the difficulty in obtaining accurate data and its relatively minor contribution to total emissions. However, future research could incorporate refrigerant leakage, which would provide a more comprehensive view of emissions, particularly for TCL.

Impact of product size and weight

Our model currently does not account for the different impacts of product size and weight on emissions and costs. Heavier products increase transportation emissions due to higher weight, which can alter the trade-off. On the other hand, larger products require more warehouse space, potentially leading to higher warehouse costs and emissions. Analyzing these factors could provide more nuanced insights into the trade-offs between transportation efficiency and warehouse requirements. Future research should explore how variations in product size and weight influence the overall cost and emissions of the distribution network.

Considering different warehouse sizes

Analyzing the impact of different warehouse sizes, particularly in scenarios requiring temperature control, could yield important insights. Larger warehouses may be more efficient for heating, while smaller warehouses could be more efficient for cooling. Future research could investigate how these factors influence overall emissions and operational efficiency.

Inbound deliveries and multi-echelon Approach

We focus on optimizing outbound deliveries within a single-echelon environment. Including inbound deliveries in the analysis could provide a more holistic view of the supply chain. For instance, optimizing for CO_2 emissions by increasing the number of warehouses may reduce the distance and emissions associated with inbound logistics, as goods can be transported to a closer warehouse. However, this could lead to increased overall complexity and costs due to more frequent but shorter shipments. Conversely, minimizing distribution costs with fewer warehouses might extend inbound delivery routes, potentially increasing CO_2 emissions and costs related to inbound logistics. Another possibility is that less efficient deliveries could occur due to near-full truckloads being split among multiple distribution centers, particularly if the majority of production occurs overseas. Future research could incorporate a multi-echelon approach, considering both inbound and outbound logistics, to achieve a more comprehensive understanding of the trade-off between these dual objectives.

Impact CO_2 reduction on customer demand

As consumer preferences shift towards more sustainable products, CO_2 reduction could lead to an increase in demand. This could lead to a higher preference for companies to reduce CO_2 emissions. In our study, we did not explore this relationship. Future studies could investigate how fluctuations in customer demand due to sustainability considerations impact the distribution network. Furthermore, an investigation into whether a superior CO_2 footprint is associated with augmented sales could assist in determining the profitability of investing in emission reduction, despite the potential for increased expenditure.

By addressing these limitations and pursuing these future research directions, we can achieve a more comprehensive understanding of the complexities and trade-offs involved in optimizing distribution networks for cost efficiency and environmental sustainability.

8.3 General Recommendations for the FMCG Industry

The findings from our research highlight a clear trade-off between minimizing distribution costs and reducing CO_2 emissions in FMCG distribution networks. To effectively manage this trade-off, FMCG companies should consider the following:

- **Set clear CO_2 emissions reduction goals.**

FMCG companies should decide on specific CO_2 reduction targets and adjust their distribution network accordingly. For instance, if the goal is to reduce CO_2 emissions by a certain percentage (e.g., 10%, 20%, 25%), the analysis shows that expanding the number of warehouses can help achieve these targets by reducing transportation distances, even if it leads to higher warehousing emissions.

- **Expand warehouse network to reduce CO_2 emissions.**

For companies prioritizing sustainability, increasing the number of warehouses reduces transportation distances and associated emissions. More localized networks lead to lower overall CO_2 emissions.

- **Centralize warehousing to minimize distribution costs.**

To cut distribution costs, consolidating operations into fewer warehouses is generally more cost-effective.

- **Tailor the distribution network to specific product temperature requirements.**

For chilled products, where warehouse emissions are higher due to energy-intensive cooling, centralizing operations into fewer warehouses helps reduce both costs and CO_2 emissions. It is advisable that FMCG companies conduct a detailed analysis of energy consumption specific to the temperature requirements of their products to optimize efficiency and sustainability further.

- **Monitor the carbon pricing (ETS2).**

Although carbon pricing under ETS2 is expected to increase transportation costs, the overall impact on the cost-emissions trade-off is likely to remain minimal unless fuel prices rise significantly. FMCG companies should closely monitor developments in carbon pricing and adapt their distribution strategies only in the event of substantial increases in transportation costs, which may necessitate adjustments in warehouse configuration or the selection of logistics providers.

8.4 Generalizability

The findings from our research present a flexible framework that can be applied across various sectors within the FMCG industry and beyond. The model is adaptable to different industries that utilize a shared distribution network. It can be tailored through a variety of parameters, enhancing its applicability to many contexts. For instance, incorporating the maximum distance constraint allows the model to accommodate various service levels. Additionally, different emission factors, such as WtW metrics or those from different countries, can be easily implemented. Consequently, this model can be effectively applied to multiple scenarios, demonstrating its generalizability.

Bibliography

Afshari, H., Sharafi, M., ElMekkawy, T. Y., & Peng, Q. (2014). Optimizing multi-objective dynamic facility location decisions within green distribution network design. *Procedia CIRP*, *17*, 675–679. https://doi.org/10.1016/j.procir.2014.01.147

Ahmadi, M. H., Ahmadi, M. A., Pourfayaz, F., Hosseinzade, H., Acikkalp, E., Tlili, I., & Feidt, M. (2016). Designing a powered combined otto and stirling cycle power plant through multi-objective optimization approach. *Renewable & Sustainable Energy Reviews*, *62*, 585–595. https://doi.org/10.1016/j.rser.2016.05.034

Albitar, K., Al-Shaer, H., & Liu, Y. S. (2023). Corporate commitment to climate change: The effect of eco-innovation and climate governance. *Research Policy*, *52*(2), 104697. https://doi.org/10.1016/j.respol.2022.104697

Alikhani, R., Eskandarpour, M., & Jahani, H. (2023). Collaborative distribution network design with surging demand and facility disruptions. *International Journal of Production Economics*, *262*, 108912. https://doi.org/10.1016/j.ijpe.2023.108912

Atta, S., Mahapatra, P. R. S., & Mukhopadhyay, A. (2019). Multi-objective uncapacitated facility location problem with customers' preferences: Pareto-based and weighted sum ga-based approaches. *Soft Computing*, *23*(23), 12347–12362. https://doi.org/10.1007/s00500-019-03774-1

Caselli, G., Columbu, G., Iori, M., & Magni, C. A. (2022). A mixed integer linear programming model for CO2 emissions minimization in a waste transfer facility location problem [Accessed: 2024-08-25]. *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4141466

CBS. (2018, June). Energie - cijfers - economie [Trends in Nederland 2018].

CBS. (2019). Energieverbruik grootschalig logistiekvastgoed [Accessed: 2024-05-28].

Chandra, S., Vatsa, A. K., & Sarkhel, M. (2020). *Capacitated facility location-allocation problem for effluent treatment in an industrial cluster* (tech. rep. No. WP/02/2019-20/OM & QT). Indian Institute of Management Indore. https://www.iimidr.ac.in/wp-content/uploads/WP-02-2019-20-OMQT.pdf

Climate Action. (2024). Ets2: Buildings, road transport and additional sectors [Accessed: 2024-07-03].

CO2 Emissiefactoren. (2022, April). *Hoe werkt het | co2 emissiefactoren*. Retrieved July 28, 2024, from https://www.co2emissiefactoren.nl/hoe-werkt-het/

CO2 Emissiefactoren. (2024, March). Lijst emissiefactoren | co2 emissiefactoren. https://www.co2emissiefactoren.nl/lijst-emissiefactoren/

Comite National Routier. (2019). The netherlands - the dutch road freight transport sector - 2019.

D'Ambrosio, C., Lodi, A., & Martello, S. (2010). Piecewise linear approximation of functions of two variables in milp models. *Operations Research Letters*, *38*(1), 39–46. https://doi.org/10.1016/j.orl.2009.09.005

Dantrakul, S., Likasiri, C., & Pongvuthithum, R. (2013). Applied p-median and p-center algorithms for facility location problems. *Expert Systems With Applications*, *41*(8), 3596–3604. https://doi.org/10.1016/j.eswa.2013.11.046

Das, S. K., & Roy, S. K. (2019). Effect of variable carbon emission in a multi-objective transportation-p-facility location problem under neutrosophic environment. *Computers & Industrial Engineering*, *132*, 311–324. https://doi.org/10.1016/j.cie.2019.04.037

Demir, E., Bektaş, T., & Laporte, G. (2014). A review of recent research on green road freight transportation. *European Journal of Operational Research*, *237*(3), 775–793. https://doi.org/10.1016/j.ejor.2013.12.033

European Parliament. (2018a, July). Greenhouse gas emissions by country and sector (infographic) [Topics | European Parliament].

European Parliament. (2018b, August). *Reducing carbon emissions: EU targets and policies* [Retrieved on 2024-02-22]. Topics | European Parliament. https://www.europarl.europa.eu/topics/en/article/20180305STO99003/reducing-carbon-emissions-eu-targets-and-policies

Farahani, R. Z., SteadieSeifi, M., & Asgari, N. (2010). Multiple criteria facility location problems: A survey. *Applied Mathematical Modelling*, *34*(7), 1689–1709. https://doi.org/10.1016/j.apm.2009.10.005

Fleischmann, B. (2016). The impact of the number of parallel warehouses on total inventory. *OR Spectrum/OR-Spektrum*, *38*(4), 899–920. https://doi.org/10.1007/s00291-016-0442-2

Gaigné, C., Hovelaque, V., & Méchouar, Y. (2020). Carbon tax and sustainable facility location: The role of production technology. *International Journal of Production Economics*, *224*, 107562. https://doi.org/10.1016/j.ijpe.2019.107562

Greenhouse Gas Protocol. (2024). *About us | ghg protocol*. World Resources Institute. Retrieved July 28, 2024, from https://ghgprotocol.org/about-us

Guo, J., & Liu, X. (2023). Research on the supply chain of fast moving consumer goods industry. *Frontiers in Business, Economics and Management*, *8*(1), 73–76. https://doi.org/10.54097/fbem.v8i1.5850

Haimes, Y., Lasdon, L., & Wismer, D. (1971). On a bicriterion formulation of the problems of integrated system identification and system optimization. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-1*(3), 296–297. https://doi.org/10.1109/TSMC.1971.4308298

Harris, I., Mumford, C. L., & Naim, M. M. (2014). A hybrid multi-objective approach to capacitated facility location with flexible store allocation for green logistics modeling. *Transportation Research Part E: Logistics and Transportation Review*, *66*, 1–22. https://doi.org/10.1016/j.tre.2014.01.010

Harris, I., Mumford, C. L., & Naim, M. M. (2009). The multi-objective uncapacitated facility location problem for green logistics. *IEEE Xplore*. https://doi.org/10.1109/cec.2009.4983285

Harvard Business Review. (2015, November). *Climate business | business climate* [Retrieved on 2024-02-22]. Harvard Business Review. https://hbr.org/2007/10/climate-business-_-business-climate

Haywood, L., & Jakob, M. (2023). The role of the emissions trading scheme 2 in the policy mix to decarbonize road transport in the european union. *Transport Policy*, *139*, 99–108. https://doi.org/10.1016/j.tranpol.2023.06.003

IFC. (2020). Temperature-controlled logistics: Why now? [Accessed: 2024-07-02]. https://www.ifc.org/content/dam/ifc/doc/mgrt/ifc-tcl-notes-tclwhynow-web.pdf

Industrial Real Estate Partners. (2020). Logistics real estate dutch market report 2020 [Retrieved from industrial.nl]. https://www.industrial.nl/wp-content/uploads/2020/03/Logistics-Real-Estate-Dutch-Market-Report-2020-Industrial-Real-Estate-Partners.pdf

International Energy Agency. (n.d.). *Belgium - countries & regions* [Accessed: 2024-07-26]. https://www.iea.org/countries/belgium

Kellner, F., & Igl, J. (2012). Estimating the effect of changing retailing structures on the greenhouse gas performance of FMCG distribution networks. *Logistics Research*, *4*(3–4), 87–99. https://doi.org/10.1007/s12159-012-0063-3

Mavrotas, G. (2009). Effective implementation of the ϵ-constraint method in multi-objective mathematical programming problems. *Applied Mathematics and Computation*, *213*(2), 455–465. https://doi.org/10.1016/j.amc.2009.03.037

Melo, M. T., Nickel, S., & Saldanha-Da-Gama, F. (2009). Facility location and supply chain management – a review. *European Journal of Operational Research*, *196*(2), 401–412. https://doi.org/10.1016/j.ejor.2008.05.007

Minto, B. (1996). *The minto pyramid principle: Logic in writing, thinking, and problem solving*. Minto International. http://ci.nii.ac.jp/ncid/BA58219390

Netherlands, S. (2024, March). *Nearly half the electricity produced in the netherlands is now renewable*. https://www.cbs.nl/en-gb/news/2024/10/nearly-half-the-electricity-produced-in-the-netherlands-is-now-renewable

Ondernemersvereniging Evofenedex. (n.d.). *Brandstofkosten als onderdeel van de vrachtkosten | evofenedex*. Retrieved July 28, 2024, from https://www.evofenedex.nl/kennis/vervoer/duurzaam-vervoer/brandstof/brandstofkosten-als-onderdeel-van-de-vrachtkosten

Rajalakshmi, M., & Umadevi, K. (2020). A study on fast-moving consumer goods (fmcg) - with special reference to kancheepuram district.

Ries, J. M., Grosse, E. H., & Fichtinger, J. (2016). Environmental impact of warehousing: A scenario analysis for the united states. *International Journal of Production Research*, *55*(21), 6485–6499. https://doi.org/10.1080/00207543.2016.1211342

Sukkel, W., van Dijk, S., & van Wijk, K. (2014, March). *Duurzaamheid van een regionale voedselketen* (PPO No. 604) (Report No. 604 for the Sustainable Catering Project (PPO project number: 3250235700)). Wageningen UR, Praktijkonderzoek Plant & Omgeving. Lelystad, Netherlands. https://edepot.wur.nl/299919

Sun, Z., Gao, W., Li, B., & Wang, L. (2020). Locating charging stations for electric vehicles. *Transport Policy*, *98*, 48–54. https://doi.org/10.1016/j.tranpol.2018.07.009

Tadaros, M., & Migdalas, A. (2022). Bi- and multi-objective location routing problems: Classification and literature review. *Operational Research*, *22*(5), 4641–4683. https://doi.org/10.1007/s12351-022-00734-w

Team, C. F. I. (2023). *Fast-moving consumer goods (fmcg)*. https://corporatefinanceinstitute.com/resources/valuation/fast-moving-consumer-goods-fmcg/

Teleroute. (2018). *Vervoer van speciale vrachten: Zaken waar u rekening mee dient te houden*. Retrieved July 28, 2024, from https://teleroute.com/nl-nl/blog/artikel/vervoer-van-speciale-vrachten-zaken-waar-u-rekening-mee-dient-te-houden/

Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research*, *19*(6), 1363–1373. https://doi.org/10.1287/opre.19.6.1363

Verter, V. (2011). Uncapacitated and capacitated facility location problems. In *International series in management science/operations research* (pp. 25–37). Springer. https://doi.org/10.1007/978-1-4419-7572-0_2

Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems*, *51*(2), 262–269. https://doi.org/10.1016/j.dss.2010.11.020

Weber, A. (1909). *Über den standort der industrien*. Tübingen.

Xiao, Y., & Watson, M. (2019). Guidance on conducting a systematic literature review. *Journal of Planning Education and Research*, 93–112.

Xifeng, J., & Peng. (2013). A multi-objective optimization model for sustainable logistics facility location. *Transportation Research Part D: Transport and Environment*, *22*, 45–48. https://doi.org/10.1016/j.trd.2013.03.003

Xi-Feng, T., Wu, J., & Li, R. (2020). Efficient allocation of customers to facilities in the multi-objective sustainable location problem. *Sustainability*, *12*(18), 7634. https://doi.org/10.3390/su12187634

Xu, J., Chen, Y., & Bai, Q. (2016). A two-echelon sustainable supply chain coordination under cap-and-trade regulation. *Journal of Cleaner Production*, *135*, 42–56. https://doi.org/10.1016/j.jclepro.2016.06.047

Yakavenka, V., Mallidis, I., Vlachos, D., Iakovou, E., & Zafeiriou, E. (2019). Development of a multi-objective model for the design of sustainable supply chains: The case of perishable food products. *Annals of Operations Research*, *294*(1–2), 593–621. https://doi.org/10.1007/s10479-019-03434-5

Yu, H., & Solvang, W. D. (2016). An improved multi-objective programming with augmented epsilon-constraint method for hazardous waste location-routing problems. *International Journal of Environmental Research and Public Health*, *13*(6), 548. https://doi.org/10.3390/ijerph13060548

Zofío, J. L., Condeço-Melhorado, A. M., Maroto-Sánchez, A., & Gutiérrez, J. (2014). Generalized transport costs and index numbers: A geographical analysis of economic and infrastructure fundamentals. *Transportation Research. Part A, Policy and Practice*, *67*, 141–157. https://doi.org/10.1016/j.tra.2014.06.009

Appendices

A

Appendix A

We implement the systematic literature review approach of Xiao and Watson 2019, involving:

1. Channel selection
2. Search string formulation

The databases used are Web of Science and Scopus. Within this research framework, we define two exclusion criteria:

- Articles written in non-English.
- Articles from years before 1995, to prevent outdated articles.

The search strings for the initial search are presented in Table A.1.

Table A.1: *Search strings and results per database.*

Search Criteria	*ScienceDirect*	*Scopus*
"Facility Location Problem" AND "Fast-moving consumer goods"	17	48
"Facility Location Problem" AND FMCG	14	30
"Location Allocation" AND "Fast-moving consumer goods"	20	64
"Location Allocation" AND FMCG	13	37
"Multi-objective optimization" AND "Facility Location Problem"	523	1,743
"Multi-objective optimization" AND "Location Allocation"	599	2,208
"Uncapacitated Facility Location Problem" AND "CO_2 Emissions"	7	22
UFLP AND "CO_2 Emissions"	3	1
”Facility location” AND ”Uncapacitated”	1,638	534
”Facility location” AND ”Sustainability”	3,840	224

B

Appendix B

Table B.1: *Warehouse configuration per solution with Distribution Costs and CO2 Emissions, for heated scenario.*

Solution	Warehouses	CO2 Emissions	Distribution Costs
1	Tilburg, Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	560,315.13	1,339,116.91
2	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Leeuwarden, Almere	562,060.80	1,287,313.42
3	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Almere	565,002.36	1,235,752.07
4	Waterloo, Breda, Arnhem, Hasselt, Leeuwarden, Almere	570,079.65	1,217,371.00
5	Waterloo, Breda, Arnhem, Hasselt, Almere	571,520.65	1,158,832.94
6	Waterloo, Arnhem, Hasselt, Rotterdam, Almere	583,514.50	1,154,892.32
7	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden	588,224.45	1,150,594.45
8	Waterloo, Breda, Arnhem, Hasselt	594,461.11	1,111,325.74
9	Waterloo, Arnhem, Hasselt, Rotterdam	597,205.25	1,093,371.91
10	Waterloo, Breda, Hasselt, Almere	597,500.98	1,093,367.37
11	Waterloo, Hasselt, Rotterdam, Almere	610,767.67	1,092,457.70
12	Mechelen, Hasselt, Almere	626,036.40	1,029,277.85
13	Waterloo, Hasselt, Almere	630,624.63	1,029,160.25
14	Arnhem, Luik, Rotterdam	651,593.47	1,017,002.98
15	Arnhem, Leuven, Rotterdam	661,844.66	1,016,952.15
16	Tilburg, Leuven, Almere	668,024.18	1,016,651.68
17	Luik, Almere	683,705.80	937,944.93
18	Leuven, Almere	692,278.68	936,864.23

Table B.2: *Warehouse configuration per solution with Distribution Costs and CO2 Emissions, for chilled scenario.*

Solution	Warehouses	CO2 Emissions	Distribution Costs
1	Mechelen, Hasselt, Almere	949,204.83	1,421,493.33
2	Waterloo, Hasselt, Almere	954,242.43	1,421,363.76
3	Luik, Almere	964,470.87	1,268,107.16
4	Leuven, Almere	973,883.37	1,266,916.56

C

Appendix C

Table C.1: *Total inventory and warehouse costs per number of open warehouses.*

Number of Warehouses	Inventory (m^2)	Warehouse costs (€)
1	5,658	396,060
2	8,002	560,140
3	9,800	686,000
4	11,317	792,190
5	12,652	885,640
6	13,860	970,200
7	14,970	1,047,900
8	16,004	1,120,280
9	16,975	1,188,250
10	17,893	1,252,510
11	18,766	1,313,620
12	19,601	1,372,070
13	20,401	1,428,070
14	21,171	1,481,970
15	21,914	1,534,980
16	22,633	1,584,310
17	23,330	1,633,100
18	24,006	1,680,420
19	24,664	1,726,480

D

Appendix D

Table D.1: *Warehouse configuration and objectives results per solution TC = 1.18, 1.20665, 1.2331, 1.475, 2*

Solution	Warehouses	CO2 Emissions	Distribution Costs
1	Tilburg, Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	520,076.28	1,309,461.50
2	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Leeuwarden, Almere	524,420.80	1,259,573.32
3	Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	529,219.59	1,253,397.88
4	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Almere	530,154.49	1,210,069.73
5	Waterloo, Breda, Arnhem, Hasselt, Leeuwarden, Almere	535,231.78	1,191,688.66
6	Waterloo, Breda, Arnhem, Hasselt, Almere	539,709.04	1,135,388.28
7	Waterloo, Arnhem, Hasselt, Rotterdam, Almere	551,702.89	1,131,447.66
8	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden	556,412.92	1,127,150.18
9	Waterloo, Breda, Arnhem, Hasselt	566,007.94	1,090,356.20
10	Waterloo, Arnhem, Hasselt, Rotterdam	568,752.08	1,072,402.37
11	Waterloo, Breda, Hasselt, Almere	569,047.81	1,072,397.83
12	Waterloo, Hasselt, Rotterdam, Almere	582,314.50	1,071,488.15
13	Mechelen, Hasselt, Almere	601,395.23	1,011,117.69
14	Arnhem, Luik, Rotterdam	626,952.30	998,842.82
15	Arnhem, Leuven, Rotterdam	637,203.49	998,791.99
16	Tilburg, Leuven, Almere	643,383.01	998,491.53
17	Waterloo, Eindhoven, Almere	660,156.13	997,195.64
18	Luik, Almere	663,586.37	923,117.23
19	Leuven, Almere	672,159.25	922,036.52

Table D.2: *Warehouse configuration and objectives results per solution TC = 3.*

Solution	Warehouses	CO2 Emissions	Distribution Costs
1	Tilburg, Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	520,076.28	1,601,249.92
2	Breda, Arnhem, Mechelen, Hasselt, Charleroi, Leeuwarden, Almere	524,420.80	1,586,012.43
3	Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	529,219.59	1,570,312.17
4	Waterloo, Arnhem, Turnhout, Hasselt, Rotterdam, Leeuwarden, Almere	532,850.16	1,568,421.98
5	Waterloo, Breda, Arnhem, Hasselt, Leeuwarden, Almere	535,231.78	1,533,320.74
6	Waterloo, Breda, Arnhem, Hasselt, Almere	539,709.04	1,520,563.78
7	Waterloo, Arnhem, Hasselt, Rotterdam, Almere	551,702.89	1,510,545.25
8	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden	556,412.92	1,499,619.46
9	Arnhem, Luik, Rotterdam, Leeuwarden	616,947.40	1,488,921.63
10	Arnhem, Luik, Rotterdam	626,952.30	1,481,319.01
11	Arnhem, Leuven, Rotterdam	637,203.49	1,481,189.78
12	Tilburg, Leuven, Almere	643,383.01	1,480,425.88
13	Arnhem, Leuven, Rotterdam	637,203.49	1,481,189.78
14	Waterloo, Eindhoven, Almere	660,156.13	1,477,131.25
15	Waterloo, Tilburg, Almere	661,562.48	1,473,298.31

Table D.3: *Warehouse configuration and objectives results per solution TC = 4.*

Solution	Warehouses	CO2 Emissions	Distribution Costs
1	Tilburg, Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	520,076.28	1,761,573.22
2	Arnhem, Mechelen, Hasselt, Charleroi, Rotterdam, Leeuwarden, Almere	529,219.59	1,744,440.89
3	Waterloo, Arnhem, Turnhout, Hasselt, Rotterdam, Leeuwarden, Almere	532,850.16	1,741,920.65
4	Waterloo, Breda, Arnhem, Hasselt, Leeuwarden, Almere	535,231.78	1,721,030.68
5	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden, Almere	547,225.62	1,707,672.64
6	Waterloo, Nijmegen, Hasselt, Rotterdam, Leeuwarden, Almere	554,918.99	1,707,126.97
7	Waterloo, Arnhem, Hasselt, Rotterdam, Leeuwarden	556,412.92	1,704,272.91