Towards electric logistics by optimizing network design and operations

A case study for Heineken tank beer

B.S.G. Lauwers

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by

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to obtain the degree of Master of Science
at the Delft University of Technology,

Student number:	4538706	
Project duration:	September 18, 2023 – 26 April, 2024	
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Preface

With this thesis, I achieve the degree of Master of Science in the field of Complex Systems Engineering and Management at the Delft University of Technology. The opportunity to develop this work in collaboration with Heineken has been both a privilege and a significant challenge, allowing me to immerse myself in the dynamic world of the brewing industry and apply theoretical knowledge to practical, real-world issues.

The journey began with a desire to not only fulfill my academic requirements but to contribute meaningfully to Heineken's ongoing quest for innovation and excellence. As I navigated through the complexities of my research topic, I was fortunate to have the support and guidance of not only my academic advisors but also a team of dedicated professionals at Heineken. Their insights, feedback, and encouragement were invaluable in shaping the direction and outcomes of this thesis.

I am particularly grateful to Stefano Fazi, Petra Heijnen, and Lori Tavasszy, my academic supervisors, for their support and invaluable advice throughout this process. Their expertise and encouragement were critical in overcoming the challenges I encountered along the way.

My colleagues at Heineken deserve special mention for their willingness to share their knowledge and experiences with me. The open and collaborative culture at Heineken provided a fertile ground for learning and innovation, making this journey all the more enriching.

This thesis also could not have been possible without the support of my family and friends, who provided encouragement, understanding, and the occasional much-needed distraction from my studies.

The experience of working with Heineken has not only contributed to my professional development but has also left me with invaluable lessons and memories. I hope that this thesis not only fulfills the academic requirements but also contributes to the broader conversations in the industry and offers insights that may assist Heineken in its future endeavors.

B.S.G. Lauwers
Delft, April 2024

Summary

This research presents a thorough investigation into the incorporation of electric vehicles within a two-echelon network for the transportation of bulk-liquids, with a spotlight on the distribution operations, of Heineken Netherlands. This study meticulously develops a two-echelon location-routing model for bulk-liquid transportation, thoroughly examining the challenges and opportunities that emerge as logistics networks transition towards electric vehicle fleets. This shift is crucial for adhering to the evolving zero-emission regulations, marking a significant step towards sustainable logistics practices. The main research question to be answered is: *" How can a logistic network and truck operations for the delivery of bulk liquids be optimized by implementing a two-echelon network, when transitioning to electric vehicles, aligning with sustainability goals and regulatory constraints, while ensuring efficient operations?"*

The research methodically unfolds through a sequential exploratory strategy, initially leveraging qualitative analysis of the core challenges and opportunities. This phase sets the stage for a subsequent quantitative exploration aimed at assessing the strategic decision-making on network design. Through the application of advanced clustering methods, the study develops a model that enhances the design, operational efficiency, and sustainability of logistics networks. The model is applied to the case of Heineken tank beer in the Netherlands, not only underscoring the practical relevance of the research but also highlighting its applicability and potential for scalability across different sectors facing similar logistical challenges.

The essence of the network design aspect of this research lies in its strategic utilization of various clustering techniques, including the center of gravity, p-median, and k-means. This methodical approach is geared towards identifying the most optimal depot locations. Such strategic integration is pivotal for circumventing the constraints imposed by the operational range and charging necessities of electric vehicles, facilitating seamless and efficient logistics operations. This segment of the study showcases the innovative application of clustering algorithms in optimizing logistics network design for enhanced efficiency and reduced environmental impact, creating a two-echelon network.

The vehicle routing model, the second part of the two-echelon location-routing develops routing strategies that maximize operational efficiency. It takes into account critical factors such as the limited range of electric vehicles, operational constraints of bulk-liquid transportation using multi-compartments, and the specific delivery windows required by customers. By integrating these considerations, the model ensures that vehicle routes are optimized for both efficiency and compliance with operational constraints and regulations. The vehicle routing model is seamlessly integrated into the broader framework of the thesis, highlighting its critical role in achieving the sustainable logistics operations envisioned, creating a two-echelon multi-compartment electric vehicle routing problem with time windows (2E-MCEVRPTW). This integration not only showcases the model's practical applicability but also underscores its importance in formulating a robust response to the challenges of transitioning to electric vehicle fleets in logistics networks.

The case study of Heineken Netherlands illuminates the specific logistical intricacies associated with the company's transition to an electric vehicle fleet for its beer distribution network. This detailed exploration sheds light on operational hurdles, such as vehicle range limitations alongside the nuanced management of diverse tank beer products. The case study serves as a real-world problem of the theoretical models and strategies proposed in the research, providing tangible evidence of its viability and effectiveness.

The discussion of results reveals that the center of gravity method excels in achieving significant kilometer savings and operational efficiencies in network design. Despite these successes, the diminishing returns on kilometer savings with the addition of more hubs indicate that an optimal hub number exists,

underlining the importance of strategic network design. Furthermore, the additional costs of transshipment, driven by the specificities of Heineken's operations, emerge as a significant challenge. These costs outweigh the savings from reduced kilometers across all scenarios, pointing towards an inherent cost in implementing a two-echelon network. Yet, the potential for cost reduction exists, particularly through increased reefer capacity and reduced transshipment times, suggesting areas for operational improvement and cost efficiency but also indicating the vulnerability of the two-echelon network.

The study highlights the specific tailoring to Heineken's operations and the computational challenges of vehicle routing, suggesting that the findings, while insightful, require careful interpretation and may not be directly applicable across different contexts without adjustments of input data for the vehicle routing model. Future research avenues include diversifying data to understand the model's adaptability, developing heuristics for the vehicle routing problem to manage computational complexity, and exploring customer clustering beyond geographic proximity to optimize routing further. Additionally, investigating intermediate charging opportunities at customer locations presents an innovative strategy to enhance electric vehicle utilization in logistics networks.

In conclusion, the research successfully addresses the main research question of optimizing logistic networks and truck operations for the delivery of bulk liquids through a two-echelon network, integrating electric vehicles while aligning with sustainability goals and regulatory constraints. The two-step optimization process, encompassing network design and vehicle routing, shows the complex interplay between strategic and operational logistics. The study underscores the transformative potential of electric vehicles in logistics but highlights the financial and operational hurdles of transitioning to a two-echelon network. These findings provide a foundation for further innovation in sustainable logistics practices.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
2E-LRP	Two-echelon location-routing problem
2E-CLRP	Two-echelon capacitated location-routing problem
2E-FLP	Two-echelon facility location problem
2E-MCEVRPTW	Two-echelon multi-compartment vehicle routing problem with time windows
ALNS	Adaptive large neighborhood search
BIER	Beverage Industry Environmental Roundtable
CAV	connected and autonomous vehicle
CO2	Carbon Dioxide
CH4	Methane
DBE	Draft Beer Equipment
DEFRA	Department for Environment, Food & Rural Affairs
EV	Electric Vehicle
EVs	Electric Vehicles
FMCG	Fast-moving Consumer Goods
GHG	Greenhouse Gas
GLEC	Global Logistics Emissions Council
GRASP	Greedy Randomized Adaptive Search Procedure
HFCs	Hydrofluorocarbons
ITS	Intelligent Transport Systems
LUC	Land Use Change
LRP	Location-routing problem
NDCs	Nationally Determined Contributions
N2O	Nitrous Oxide
PEFCR	Product Environment Footprint Category Rules
PSRP	Petrol Station Replenishment Problem
PSRPTW	Petrol Station Replenishment Problem with Time Windows
PFCs	Perfluorocarbons
RLE	Resource-Link-Echelon
SAA	Sampling Average Approximation
SF6	Sulphur hexafluoride
VRP	Vehicle Routing Problem

1 Introduction

1.1. General information

Global climate change is a critical issue, primarily driven by the increase in greenhouse gas emissions (GHG) from human activities such as the combustion of fossil fuels like coal and oil. This has led to a significant rise in atmospheric concentrations of Carbon Dioxide (CO_2), Methane (CH_4), Nitrous Oxide (N_2O), and Chlorofluorocarbons, with CO_2 being the most prevalent, accounting for 72% of emissions [57]. The rapid increase in CO_2 levels is causing detrimental effects on the environment, including higher global temperatures, sea-level rise, and changes in weather patterns, which threaten the planet's habitability [34]. In an effort to combat these challenges, the Paris Agreement was established in 2015, where 196 countries agreed to work together to limit global warming to well below 2 degrees Celsius, aiming for 1.5 degrees to mitigate climate change risks [59]. Nations commit to this goal by submitting their Nationally Determined Contributions (NDCs) every five years, detailing their plans to reduce greenhouse gas emissions. Despite these commitments, the global trajectory is still not aligned with the Paris Agreement's objectives, highlighting a critical need for increased action and implementation of commitments [50].

Within this global framework, the Dutch government has taken a proactive stance through its national climate agreement, "Het klimaatakkoord." This pact, involving a broad coalition of stakeholders, targets a reduction of CO_2 emissions by 49% by 2030 and 95% by 2050, relative to 1990 levels [34]. This ambitious agenda is part of the Netherlands' commitment to international climate goals and focuses on comprehensive sector-specific strategies. Particularly in the mobility sector, which was responsible for 23.5% of the country's emissions in the second quarter of 2023, the Dutch government aims for a transformative approach to achieve zero greenhouse gas emissions by 2050 [55]. Key initiatives under "Het klimaatakkoord" include the introduction of emission-free zones in urban areas to discourage the use of polluting vehicles and the optimization of the entire supply chain within the mobility sector [55]. These measures represent the Dutch commitment to not only meeting but exceeding the objectives of the Paris Agreement, showcasing a national model of ambitious climate action and sustainability.

1.2. Problem description

A significant development is the establishment of zero-emission zones within inner cities in the Netherlands [36]. These zones restrict access to vehicles emitting pollutants, mandating a transition to zero-emission transportation for all logistics operations within specific urban areas. These zones will exclusively permit the operation of zero-emission vehicles by 2030 and will only allow Euro 6 diesel trucks or zero-emission vehicles from 2025 [36]. This shift poses a substantial challenge for the distribution of goods, especially for specialized distributions that are often not easily adaptable to zero-emission standards. The introduction of zero-emission zones necessitates a comprehensive overhaul of logistics strategies. Traditional distribution networks, heavily reliant on diesel-powered vehicles, must evolve rapidly to incorporate zero-emission vehicles [1]. However, zero-emission vehicles, present unique challenges related to vehicle range, charging infrastructure, and vehicle configurations tailored to specific logistical needs.

The strategic placement of satellites, creating a two-echelon location-routing network, becomes critically important in this new logistics landscape. Depots must be located strategically to serve as efficient hubs for zero-emission distribution. This requirement complicates network design, as depots must accommodate the charging needs of zero-emission vehicles, comply with operational constraints, and the geographical distribution of demand within emission-constrained areas. The design and operation of these depots must consider the limited range of zero-emission vehicles and the need for frequent recharging, posing additional challenges in operational logistics and fleet management [43].

The operational implications of transitioning to zero-emission vehicles are multifaceted. The configurations of electric vehicles, a type of zero-emission vehicle, are constrained by size, weight limits, and the operational requirements of specific types of deliveries. For instance, vehicles equipped with large tanks for the transport of multiple liquid products or those requiring specific configurations for secure delivery of fragile goods must be redesigned to meet zero-emission standards without compromising operational efficiency. Moreover, the transition is influenced by the availability of charging infrastructure and the capacity of the power grid to support overnight charging of a large fleet of electric vehicles, further complicating the shift to zero-emission logistics operations [62].

The transition to a more sustainable and regulatory-compliant logistics operation is not merely a matter of adopting new vehicles. It requires a comprehensive rethinking of network design and vehicle operations. The introduction of zero-emission zones in inner cities is a significant driver of change, pushing logistics operations toward innovative solutions that balance environmental sustainability with operational efficiency and the specific needs of specialized deliveries.

1.3. Literature review

Current research in the domain of logistics and supply chain, particularly on two-echelon location-routing problems and vehicle routing for specialized deliveries, reveals an evolving understanding of the integration between strategic network design and operational vehicle routing. Notably, studies by Ambrosino and Grazia Scutellà [3] and Crainic and Laporte [19] have pioneered in clarifying the interplay between strategic decisions on location and operational transportation choices, highlighting the complexity of integrating these decisions within logistic networks. Further, Salhi and Rand [48] introduced the concept of location-routing problems, enriching the discussion on strategic and operational synthesis in logistics. Recent advancements by Shen and Qi [53] and Klibi, Martel, and Guitouni [33] have contributed significantly to our understanding of the intricate dynamics within two-echelon systems, especially in the face of e-commerce growth and the resultant logistical challenges.

However, despite these comprehensive frameworks and insights, a precise knowledge gap remains in addressing the operationalization of zero-emission vehicles in specialized delivery contexts, particularly within urban areas constrained by zero-emission regulations. The literature has yet to fully explore the operational constraints unique to zero-emission vehicles, such as limited range, dependency on reliable charging infrastructure, and the integration of advanced technologies like flow meters for precise bulk-liquid deliveries. Moreover, the impact of these operational constraints on strategic network design and the adaptability of logistic operations to comply with stringent emission regulations remains underexplored. This gap signals an urgent need for focused research on developing models that consider the specifics of zero-emission logistic operations, including depot placement, vehicle routing, and charging strategies, to ensure the sustainability and efficiency of the supply chain.

1.4. Objective & deliverable

In this section, the objective and the deliverable of the research are discussed. Also, the case study that is part of the research will shortly be introduced.

1.4.1. Introduction to the Heineken case

Heineken Netherlands, a significant subsidiary of the global Heineken N.V., holds a prominent position in the Dutch beer market, servicing a wide array of customers with its innovative and environmentally conscious products, including the notably efficient tank beer system. This system, designed to cater to high-volume hospitality venues, offers a seamless beer dispensing solution that eliminates the need for traditional keg changes, thereby reducing waste and enhancing the quality of service. Specialized, water-cooled tanks and refrigerated pipes ensure the beer remains at the optimal temperature from brewery to tap, a feature that has made the system particularly popular among high-turnover establishments [27]. However, in response to the increasing emphasis on environmental sustainability and the introduction of zero-emission zones within the Netherlands' urban centers, Heineken Netherlands wants to be at the forefront of adapting its logistics and delivery operations. The goal of Heineken Netherlands to transition to electric tank beer trucks represents a significant logistical undertaking, given the operational constraints associated with managing multiple beer brands that cannot be mixed during transport and delivery.

This strategic shift towards electric tank beer trucks for deliveries within urban areas under zero-emission constraints presents a multifaceted challenge. Not only does it require a comprehensive reevaluation of the logistic network to accommodate electric vehicles, but it also involves addressing the operational limitations of these vehicles. Electric trucks come with their unique set of constraints, including limited range, the need for reliable charging infrastructure, and the necessity to integrate advanced technologies such as flow meters for precise bulk-liquid deliveries. These operational challenges, when combined with the requirement to manage multiple beer brands without mixing them during transport, highlight a significant challenge.

1.4.2. Research objective

The objective of this research is to bridge the identified knowledge gap by developing a comprehensive model for optimizing logistics networks and operations to integrate electric vehicles. This research will specifically focus on devising a two-echelon location-routing model optimized for efficiency, sustainability, and compliance with upcoming zero-emission regulations. The goal is to strategically place depots to support efficient operations, taking into account vehicle range, charging needs, and the requirements of specialized deliveries by electric vehicles. The choice is made to focus on electric vehicles since this technique seems to be the most promising in the near future [43]. Through this research, the aim is to improve the operational efficiency and sustainability of logistics, with Heineken Netherlands serving as the case study for adapting distribution networks and electric fleet operations to the constraints of zero-emission zones.

1.4.3. Deliverable

The primary deliverable of this research is the development of a model designed for optimizing two-echelon location-routing logistics networks that incorporate electric vehicles capable of transporting multiple types of liquid products for different industries. This model aims to enhance logistical efficiency and sustainability, particularly within the framework of evolving zero-emission landscapes. By focusing on strategic depot placement and the seamless integration of electric vehicles, the model addresses key operational challenges such as vehicle range limitations, charging infrastructure needs, and the complex requirements of managing diverse liquid deliveries.

Central to this deliverable is the application of the model to a real-world context, with Heineken Netherlands serving as a pivotal case study. The intention is to not only tailor the model to Heineken's specific logistical nuances but also to demonstrate its broader applicability and scalability across various sectors facing similar challenges. This approach underscores the model's versatility in facilitating the transition to electric vehicle fleets, ensuring operational compliance with zero-emission mandates, and fostering sustainability in urban logistics.

Furthermore, the model will encapsulate a comprehensive strategy for fleet operations optimization, emphasizing the adoption of advanced technological solutions to meet the precise demands of bulk-liquid transportation. By considering the operational constraints and potential efficiencies afforded by electric vehicles, the model aspires to offer a forward-looking perspective on logistics network design and fleet management. In delivering this model, this research aims to provide a valuable tool for stakeholders across the logistics and transportation sectors, enabling decision-making regarding network design and operational strategies. Ultimately, the goal is to contribute to the development of sustainable, efficient, and regulation-compliant logistics networks that can adapt to and thrive within the constraints of zero-emission environments.

1.5. Research structure

This research paper is meticulously organized to provide a coherent, comprehensive exploration of optimizing logistics networks for electric vehicles in urban logistics, particularly focusing on the two-echelon location-routing problem. The structure of this paper is delineated as follows:

Chapter 1 sets the stage for the research by presenting the context and significance of the study. It outlines the pressing need for sustainable logistics solutions in the face of rising environmental concerns and stringent emission regulations in urban centers. The section culminates with the research objectives and the specific focus on Heineken Netherlands as a case study for implementing electric vehicle logistics solutions. Chapter 2 delves into existing research and literature related to logistics optimization, electric vehicles transporting liquids, and two-echelon location-routing problems. It identifies the knowledge gap that this research aims to bridge. In Chapter 3, the specific problem description is defined. This includes considerations such as vehicle range, strategic network design, charging infrastructure, and the complexities of managing multiple types of liquid deliveries within zero-emission zones. Then in Chapter 4 the Heineken case study is introduced in more detail. Chapter 5 introduces the methodology and the models developed for this research, detailing the approach taken to design the two-echelon location-routing problem. It also explains the clustering technique used to categorize data and variables relevant to the study, laying out the framework for the case study application. In Chapter 6 the focus is on the data and characteristics of the case study that are used for the model input. It examines the practicalities of transitioning to electric vehicles for tank beer deliveries within two-echelon logistics networks. Chapter 7 presents the findings from applying the model to the Heineken Netherlands case study. It includes data analysis, model outcomes, sensitivity analysis, and experiments. Afterward, Chapter 8 interprets the findings from the numerical analysis, evaluating the implications for logistics optimization, sustainability, and policy compliance. It critically examines the broader applicability of the model and its relevance to the logistics and transportation sectors at large. Finally, Chapter 9 summarizes the key findings, contributions to the field of logistics, and the specific insights gained regarding Heineken Netherlands' case. It also outlines recommendations and potential areas for further exploration based on the study's limitations and outcomes.

2 Literature study

The second chapter aims to gain knowledge, explain the scientific problem to study, and finally formulate a knowledge gap that needs further investigation. As a scientific approach is sought to deal with the specific problem description, the literature regarding the subjects of the deliverable is consulted. Much research has been done with regard to strategic network optimizations and there appear to be many methods for modelling and optimizing logistics networks. Mostly the methods are cost-driven but other aims, like maximum level of service or maximum reach, are treated in the literature as well. Each model requires different inputs and produces different optimal solutions. Next to this, there are also many approaches concerning vehicle operations. The delivery of bulk liquids is quite specific, therefore, a search is done to find the best method for this specific vehicle operation, keeping in mind the configuration of the truck and the objective to transition completely to zero-emission vehicles. This section attempts to provide an overview of the most recent and relevant studies regarding the subjects of interest and identifying a knowledge gap.

2.1. Literature review process

First, the available literature was explored by reading all kinds of literature that are available with a focus on the logistics networks, and electrical vehicles in the context of network optimization and fleet operations. The exploration was done by using multiple search engines and databases but mainly focusing on Scopus, and Google Scholar. Second, a more specific approach was used to focus more on scientific articles with regard to the subject. For the more specific approach, keywords like a two-echelon model, hub and spoke network, fleet optimization, vehicle routing, multi-compartment, and electrification were used to identify the most suitable literature.

2.2. Two-echelon location-routing

The Two-Echelon Location-Routing Problem (2E-LRP) is an advanced optimization problem that combines elements of facility location and routing decisions within a two-level distribution system. In a 2E-LRP, decisions need to be made on two main fronts:

- **Location decisions**: This involves determining the optimal locations for facilities at two hierarchical levels. The first level usually involves locating central depots or warehouses, and the second level involves locating local distribution centers or satellite facilities.
- **Routing decisions**: This part concerns determining the best routes for vehicles to follow. The routing decisions are made at two levels as well. The routes from the central depots to the local distribution centers, and from these centers to the final customers.

The objective of the 2E-LRP is typically to minimize the overall system cost, which may include the fixed costs of opening facilities, the transportation costs between facilities and from facilities to customers, and possibly the vehicle costs, all while adhering to various constraints [60]. The 2E-LRP is particularly relevant in scenarios where direct distribution from a central facility to customers is not efficient or possible, and an intermediate level of distribution points like satellite facilities or urban consolidation centers can help reduce costs, improve service levels, or decrease environmental impact.

Strategic decisions and operations are becoming increasingly intertwined, as highlighted by Ambrosino and Grazia Scutellà [3] and Crainic and Laporte [19]. At the strategic level, decisions revolve around, for instance, locations, while the operational level entails transportations. The amalgamation of these two levels into a location-routing problem (LRP) has shown promise in enhancing optimized network design, as introduced by Salhi and Rand [48] and discussed more recently by Shen and Qi [53] and Klibi, Martel, and Guitouni [33].

The literature explores various variants of LRPs, differing in the number of distribution echelons. There are echelons involved in location decisions, capacity planning decisions, and the granularity of transportation integration under different demand considerations. Comprehensive surveys on distribution problems and classification schemes are available in Prodhon and Prins [44], Drexl and Schneider [21], and Cuda, Guastaroba, and Speranza [20].

Most LRPs predominantly rely on a single-echelon distribution structure. However, attention to two-echelon distribution structures, particularly in the context of e-commerce growth, has increased in recent years. Initial contributions to two-echelon structures were made by Madsen [35] and Jacobsen and Madsen [30], addressing the 2E-LRP in newspaper distribution. Subsequent studies, such as Sterle [56], Boccia et al. [7], Contardo, Hemmelmayr, and Crainic [15], and Schwengerer, Pirkwieser, and Raidl [49], delved into the 2E-Capacitated Location-Routing Problem (2E-CLRP), considering platform costs and capacity limitations.

Capacity planning decisions, treated as strategic design decisions determining platform capacity allocation, are integrated into certain variants of distribution network design problems [18, 26, 5]. Dynamic distribution design problems, as explored by Jena, Cordeau, and Gendron [32] and Pimentel, Mateus, and Almeida [41], further investigate these decisions. Most LRPs and 2E-LRPs assume simultaneous decision-making for design and transportation without considering structure. Some papers, however, adopt a hierarchical approach, building on the facility location problem (FLP) to the two-echelon FLP. Notably, Winkenbach, Kleindorfer, and Spinler [64] and Janjevic, Winkenbach, and Merchán [31] present a variant of the 2E-CLRP designed for urban distribution networks.

The literature has explored various exact and heuristic solution methods for two-echelon distribution problems. Exact methods utilize mathematical programs, including Mixed Integer Programming (MIP) solvers and algorithms like Branch-and-cut and Benders decomposition. Heuristic approaches, such as Greedy Randomized Adaptive Search Procedure (GRASP) and Adaptive Large Neighborhood Search (ALNS), offer efficient solutions for larger instances [13]. Despite this progress, further advancements are needed to efficiently solve real-size instances of 2E-CLRP. The Sampling Average Approximation (SAA) method, Shapiro [52], has proven successful in addressing stochastic models. While most research on two-echelon distribution structures primarily deals with deterministic-static settings, Snoeck, Winkenbach, and Mascarino [54] and Ben Mohamed, Klibi, and Vanderbeck [5] introduce stochastic and multi-period into variants of the 2E-CLRP.

2.3. Vehicle routing

The Vehicle Routing Problem (VRP) is a classic optimization and logistics challenge that focuses on the most efficient way to deliver goods or services to a set of destinations using a fleet of vehicles. Originating from the broader family of combinatorial optimization problems, the VRP seeks to determine the optimal set of routes to use for a fleet of vehicles to meet certain objectives, typically minimizing total distance traveled, total time, or overall costs while satisfying a set of constraints. The Petrol Station Replenishment Problem (PSRP) is a specialized variant of the Vehicle Routing Problem and presents distinctive characteristics to the problem description due to the liquid characteristics of the products that are transported[16].

One fundamental aspect explored in the literature is the composition of the vehicle fleet. Dantzig and Ramser's pioneering work in 1959 initially framed the problem using a homogeneous fleet, where a single type of vehicle was employed for petrol deliveries. In recent years, however, there has been a shift toward investigating heterogeneous fleets, as evidenced in studies by Chowmali and Sukto [13] and Ng et al. [38]. These works delve into the intricacies of fleet heterogeneity, which involves utilizing a variety of vehicles with different capacities and configurations. This shift in perspective highlights the practicality of using diverse vehicles tailored to specific delivery needs, a crucial consideration for modern fuel distribution operations.

The number of customers served in a single delivery route is another critical dimension examined in PSRP research. Brown and Graves [9] advocated for a strategy where each delivery route served a single customer, leading to routes consisting of precisely one customer per delivery. This approach was well-suited for scenarios in which each order filled an entire truck. Conversely, Wang et al. [60] introduced a more flexible approach, permitting vehicles to visit one or two customers in each route. This transition from single-customer routes to multi-customer routes reflects the evolving dynamics of the fuel distribution landscape and necessitates adapting optimization approaches to manage the increased complexity associated with multiple stops.

Another crucial area of focus within the PSRP literature is the integration of time windows. Time windows play a pivotal role in logistics problems and have been a central element in the evolution of the PSRP. Cornillier et al. [17] took a significant step by introducing the Petrol Station Replenishment Problem with Time Windows (PSRPTW), wherein customers specify certain times in which they must be served. The inclusion of time windows adds an additional layer of complexity, requiring efficient scheduling to meet customer constraints, adhere to delivery windows, and optimize route planning to minimize overall costs.

The PSRP literature has also delved into multi-depot scenarios, extending the problem's boundaries. Bruggen, Gruson, and Salomon [10] ventured into this territory by addressing the transportation network of a large Dutch oil corporation. Their approach assigned each customer to a specific depot, introducing strategic considerations related to depot allocation, fleet size, and route planning. Multi-depot scenarios bring an added layer of complexity to the PSRP, necessitating decision-making regarding which depot should serve each customer, how the fleet should be divided among depots, and how routes should be optimized to ensure efficient and cost-effective delivery.

Furthermore, several studies have expanded beyond the traditional single-day perspective, examining multi-period PSRP. Popović, Vidović, and Radivojević [42] optimized replenishment operations over several days, considering the changing needs of petrol stations over time. This multi-period analysis aligns with the operational complexities faced by fuel distribution companies operating in dynamic environments, where the demand for different fuel products at petrol stations can fluctuate throughout the week or month. Accounting for these temporal dynamics is crucial in devising effective replenishment strategies.

The PSRP literature encompasses a wide spectrum of problem-solving approaches. While some studies, such as Avella, Boccia, and Sforza [4], Zhang et al. [65] and Carotenuto et al. [12] have harnessed mathematical optimization techniques like integer programming and mixed-integer linear programming to achieve precise solutions, others, like Chowmali and Sukto [13, 14] have introduced innovative heuristic algorithms. These heuristic methods, inspired by practical problem-solving strategies, have been developed to address the challenges posed by the PSRP, especially when mathematical optimization becomes computationally intensive.

In conclusion, the rich and diverse literature on the Petrol Station Replenishment Problem reflects the complexities of real-world distribution challenges. Researchers have ventured into various dimensions of the problem, including fleet composition, the number of customers per route, integration of time windows, exploration of multi-depot scenarios, and adaptation to multi-period analysis. Furthermore, the choice between exact mathematical optimization and heuristic methods demonstrates the adaptability of research to the evolving needs of fuel distribution.

2.4. Knowledge gap

In this research, the switch to electric vehicles brings additional crucial constraints due to the range constraints and the necessity of electric charging and charging infrastructure. Next to this, there is the need to monitor the precise flow of liquids since multiple customers need to be supplied with one truck and often have a precise amount of product that can be delivered. The inclusion of flow meters in the optimization process is crucial for ensuring the accurate and precise delivery of liquid products. Ensuring that the right amount of product is delivered to each customer within the required quality standards is of great importance for customer satisfaction and efficient operations. Addressing these aspects in the literature can provide valuable insights into how to design and manage delivery operations with flow meter-equipped vehicles, particularly in industries where liquid quality and quantity are critical factors.

The two-echelon location-routing problem combines the strategic- and operational levels of the logistics network and operations. The literature on the two-echelon location-routing problem covers multiple forms of the problem. Still, it lacks the study of deliveries using multi-compartment electric vehicles with different liquid commodities as part of the operational level of the two-echelon location-routing problem.

While the literature on the PSRP has explored various dimensions, including fleet composition, the number of customers per route, integration of time windows, and multi-depot scenarios, a notable knowledge gap exists in the context of fleet operations and specific truck configurations. Existing studies have focused on fleet composition and routing strategies but have not focussed on new vehicle types like electric trucks and their operational constraints. No restrictions on the maximum number of droven kilometers of trucks per route or charging necessities have been studied. Next to this, the incorporation of flow meters, which enable the exact delivery of product has only been applied in a few studies. The literature especially fails to make the combination of the two-echelon location problem, combining strategic decisions with electric vehicle operations for multi-product bulk liquid deliveries.

Therefore, the existing literature lacks research that specifically addresses the combination of strategic network challenges and operational fleet challenges for liquid transportation related to specific operational constraints of electric vehicles. Bridging this knowledge gap can lead to more effective strategic- and operational strategies for sustainable deliveries.

2.5. Research questions

Regarding the literature and the knowledge gap discussed, the following section introduces the main research question of this research, followed by the sub-questions developed to answer this main research question.

2.5.1. Main research question

This research not only reflects a commitment to sustainability but also responds to upcoming regulatory requirements. This study focuses on combining strategic decisions for hub locations and specific operational constraints for the electric transportation of bulk liquids, creating a two-echelon location-routing model. In this context, the central question emerges:

"How can a logistic network and truck operations for the delivery of bulk liquids be optimized by implementing a two-echelon network, when transitioning to electric vehicles, aligning with sustainability goals and regulatory constraints, while ensuring efficient operations?"

2.5.2. Sub-questions

To answer the main research question, the following sub-questions are formulated:

1. *What are the key challenges and opportunities in the logistic network and operations that should be considered when transitioning to a two-echelon location-routing with electric vehicles for the delivery of bulk liquids?*

   This sub-question aims to map the different criteria that should be taken into account when transitioning to electric vehicles. There are multiple criteria per subject to address, for instance, the operational requirements like range and weight capacity, loading infrastructure, costs, etc.

2. *How can logistics networks be improved by the implementation of satellites in the logistic network design, creating a two-echelon network?*

   This sub-question addresses the optimization of the logistics network for bulk-liquid delivery. It explores the potential benefits of introducing hub locations with regard to efficiency and costs. While doing so, it takes into account the specific constraints and requirements associated with electric vehicles.

3. *What is the effect of different network optimization techniques on the efficiency of logistic networks?*

   This sub-question addresses the outcomes of the different network optimization methods that are used in the research. It tries to grasp the different characteristics of the methods used and the effect on the complete network.

4. *What is the effect of an electric fleet on the operations of bulk liquid delivery considering regulatory- and customer constraints, assuming a two-echelon network?*

   This sub-question delves into the operational part of the deliveries. It considers various operational constraints, such as range, load capacity, and charging infrastructure, while assuming a two-echelon logistic network. The objective is to identify the key attributes and challenges of the electric operations of bulk liquids.

5. *What is the interaction between the different strategic placements of satellites and the operations and fleet characteristics in the model?*

   This sub-question aims to identify the interaction between strategic network design decisions and operational decisions about fleet configurations and operational performance.

6. *What is the overall feasibility of the proposed optimizations and how does it score on key performance indicators?*

   This sub-question focuses on the feasibility of the proposed optimization process. It aims to identify potential obstacles or factors that could affect the successful transition to electric vehicles and the optimization of the logistics network for bulk liquids delivery. By addressing the feasibility, the research aims to develop robust strategies for network optimization and transition to an electric fleet.

7. *What is the best strategy when optimizing a two-echelon location-routing model concerning the network and operations for the electric delivery of bulk liquids?*

   The last sub-question aims to advise on the best strategy to adopt. How can the findings of the research be translated into feasible strategies to optimize logistic networks and electric vehicle operations?

The research framed by these research questions seeks not only to address the immediate operational and strategic needs of Heineken Netherlands but also to contribute to the broader discourse on sustainable logistics practices in multiple industries. By exploring the intricacies of transitioning to electric vehicles within the specific context of bulk liquid deliveries, this research aspires to uncover insights that apply to multiple industries. The research needs to develop a two-echelon location-routing model that complies with the constraints of transportation of bulk liquids using electric vehicles. The findings of this study are anticipated to offer valuable guidance to Heineken Netherlands in its pursuit of sustainability and efficiency, but also adaptable to the evolving landscape of regulatory constraints and technological advancements, setting a precedent for other sectors facing similar challenges.

3 Problem description

The aim of this chapter is to delineate the complex problem that forms the core of our research. In the face of evolving environmental policies and the advent of zero-emission zones, the logistics and transportation industry stands at a pivotal crossroads. This chapter sets out to unpack the multifaceted challenges involved in integrating electric vehicles for multi-product liquids transportation into a redesigned two-echelon distribution network. This chapter focuses on identifying the critical aspects that constitute the problem at hand. By carefully defining the problem space, this chapter aims to establish a clear understanding of the logistical, strategic, operational, and environmental challenges that the research seeks to address.

3.1. Problem description

The demand for sustainable logistics solutions, propelled by increasing environmental awareness and stringent regulatory mandates, necessitates a comprehensive overhaul of traditional distribution frameworks. Urban centers worldwide are rapidly adopting zero-emission zones as a means to combat pollution and reduce carbon footprints, thereby compelling logistics operations to pivot towards greener alternatives [61]. This evolution in urban logistics is underscored by the critical need to integrate electric vehicles into distribution networks, a move that presents a unique set of challenges and opportunities for optimizing logistics in adherence to new environmental standards. The centerpiece of this transformation is the conceptualization and implementation of a two-echelon logistics network that can effectively navigate the complexities of distribution while aligning with sustainability objectives.

At the heart of this logistics paradigm shift is the design of a two-echelon network, a structure that fundamentally redefines the flow of goods from producers to consumers. Central to this model is the existence of a single depot that acts as the primary hub for distribution activities. The critical challenge lies in determining the optimal number and strategic placement of satellite facilities that will serve as intermediary distribution points, effectively bridging the gap between the central depot and the ultimate delivery destinations. These satellite nodes are essential for facilitating the efficient distribution of goods and charging opportunities, especially within areas where direct access may be hindered by traffic restrictions or environmental regulations.

Transportations from the central depot to these satellite locations is able to use specialized, high-capacity trucks. Designed for bulk liquid transport, these vehicles are pivotal in minimizing the number of trips required for distribution, consolidating transportation, and thereby optimizing logistics operations. At the satellite, the bulk liquids are transshipped to specialized vehicles to finally supply the customers. However, the transition from satellite facilities to final customers introduces an intricate layer of complexity, it facilitates the operational constraints associated with electric vehicles. These specialized electric delivery vehicles, adept at carrying multiple types of liquids in segregated compartments, must confront and overcome challenges such as limited operational range and the imperative need for reliable, accessible charging infrastructure.

The operational intricacies of electric vehicles are further compounded by the constraint of overnight charging. Given the limited range and endurance of current electric vehicle technology, these vehicles necessitate charging at the end of each day, at their home facilities. This requirement not only influences the strategic placement of satellite facilities, which must now function as charging points but also impacts the overall efficiency and feasibility of the delivery routing. The charging itself is not part of this problem but the necessity of ending a trip at a hub location because of the charging needs is part of the problem. Also, the integration of customer-specific time windows into the delivery schedule introduces a sophisticated layer of routing optimization, necessitating meticulous planning and dynamic routing strategies to ensure timely deliveries within the constrained operational parameters of electric vehicles. Next to this, the trucks need to be cleaned as well due to the transportation of liquids and strict quality standards that are often applicable to the transportation of liquids.

Navigating these challenges presents a multifaceted problem that can be stated as a two-echelon multi-compartment electric vehicle routing problem with time windows (2E-MCEVRPTW). Creating opportunities to pioneer innovative solutions in logistics, steering the industry toward a more sustainable and efficient future. By developing a comprehensive model to optimize a two-echelon location-routing problem, this research aims to blueprint a model that exemplifies operational efficiency, environmental sustainability, and compliance with emerging emission standards. Such a model must holistically consider the strategic placement of depots and satellites, the routing of electric vehicles, the operational constraints of transporting different liquid types, and the incorporation of time windows, to develop a future-proof logistics network.

4 Case study

As mentioned in Chapter 1 this research entails a case study of the tank beer operations of Heineken Netherlands. The model presented in Chapter 5 is fit for multiple systems within logistic systems transporting bulk liquids and transitioning to electric vehicles.

4.1. Company introduction

Heineken N.V., established by Gerard Heineken in 1864, achieved global recognition a century later under the leadership of his grandson, Freddie. Its international expansion continued into the 21st century, culminating in Heineken becoming Europe's largest and the world's second-largest brewing company. With a network of 165 factories worldwide and soaring global demand, managing logistics becomes an intricate operation. Heineken's products are distributed to over 190 countries, encompassing a portfolio of more than 300 different brands. To facilitate logistics, Heineken utilizes a combination of truck, train, and ship transportation to move products from breweries to consumers [40].

4.1.1. Heineken Netherlands

Heineken Netherlands is an operational company that falls under Heineken N.V. and is responsible for the Dutch market. With a market share of 50%, Heineken dominates the Dutch beer market [8]. One of the products that Heineken sells is tank beer. Tank beer is a user-friendly tap system without keg changes. Special water-cooled tanks and refrigerated pipes ensure you always have cold beer on tap. It is ideal for hospitality operators with high beer sales. The supply of tank beer is done with specialized tank beer trucks that can ship around 10.000 liters every shipment. Heineken delivers five different tank beer brands to its customers, Heineken, Heineken Silver, Amstel, Brand, and Bira Moretti. Since those different beer brands logically cannot be mixed during all processes, it brings operational constraints the the logistic activities.

The Heineken Netherlands out-of-home services team is responsible for the logistic operations regarding tank beer. All tank beer deliveries are currently done from the brewery in Den Bosch. Here, all the logistic operations start by filling up the specialised tank beer trucks that are active. The configurations of those trucks can differ from one big tank to two medium tanks and three small tanks. With a hose and flow meters, meters that monitor the outflow of beer, these tank beer trucks can deliver the exact amount of liters ordered by customers into their tank beer tanks.

A large part of the tank beer customers of Heineken are located in the inner cities of the Netherlands. Amsterdam and Utrecht are currently the two cities that have weight limitations for traffic in the inner cities due to their vulnerable quays. Amsterdam and Utrecht respectively have weight limits of 7.5 tonnes and 2 tonnes per axis for all traffic in the inner city [24, 25]. Therefore, in the current situation, there is a city hub located in Amsterdam where reefers with a capacity of 30.000 liters coming from the brewery in Den Bosch transfer the beer into smaller electric tank beer trucks that can carry up to 3000 liters. The smaller electric tank beer trucks are dedicated to the customers in the Amsterdam inner city. In Utrecht, a specialized tank beer truck with an extra axis supplies the inner city directly from

Den Bosch. In this way, the imposed weight restrictions by the municipalities are met and the logistic operations are made more sustainable due to the electrification of the last-mile deliveries.

4.2. Key stakeholders

The mobility sector is involved in both the private- and public domains. Public entities manage essential infrastructure such as roads, rail lines, and public transit systems, ensuring broad accessibility and compliance with regulatory standards. Meanwhile, private carriers, as a critical component of the private domain, offer specialized logistics and transportation services for goods and people. They operate within the public infrastructure, adapting to regulatory environments while striving for operational efficiency, cost-effectiveness, and service innovation.

Additionally, private companies outside of traditional carriers also contribute significantly to the sector through vehicle technology advancements, ridesharing services, and app-based navigation tools, propelled by market competition and profit motives. This multifaceted interaction is crucial for the sector's evolution. Public investments and policies not only provide the framework for private sector operations but are also influenced by the innovations and trends developed by these private entities [45]. For instance, the surge in electric vehicles, primarily driven by private companies, prompts public investments in charging infrastructure. Conversely, public strategies like urban congestion charges can direct private mobility and carrier choices. This complex interplay, when effectively managed, fosters a mobility ecosystem that is efficient, sustainable, and responsive to evolving transportation needs.

4.2.1. Power-interest grid

In the case of Heineken and its tank beer network and operations, multiple stakeholders influence the operations. To map out the stakeholders and their role within the operations of Heineken, a power-interest grid is made.

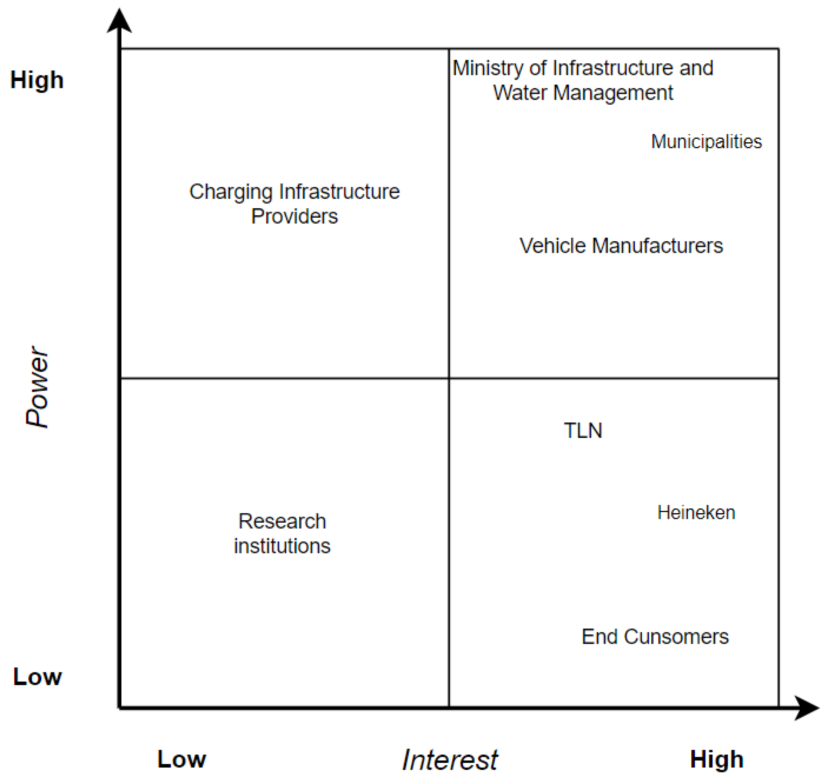

Figure 4.1: Power interest grid

To elaborate a bit more on the positions of the different stakeholders, a more extensive explanation for each stakeholder is given.

- **Ministry of Infrastructure and Water Management**: As the governmental body responsible for transportation policies and regulations, they have significant power and interest in shaping and enforcing emission constraints and the adoption of electric vehicles to meet the sustainability goals within the transportation sector.
- **Vehicle Manufacturers**: Companies that produce vehicles will be directly affected by emission regulations that are developed by governmental bodies and will need to innovate to comply. Also, transportation companies are relying on the production of those electric vehicles and their specifications, positioning them as powerful and highly interested stakeholders.
- **Municipalities**: They have the power to implement local regulations and initiatives that align with national policies. Think of time windows for certain heavy-duty transport in inner cities. Their interest is also high due to the public pressure for sustainable urban planning.
- **Charging Infrastructure Providers**: These stakeholders have the power to enable the transition to electric vehicles by providing the necessary charging infrastructure. Their interest might be considered lower because their primary goal is profit, although this could increase if the market for electric vehicles expands due to the new regulations.
- **Heineken**: As a major beer producer, Heineken has a significant interest in reducing emissions and transitioning to electric vehicles to adhere to sustainability goals and regulations. While they might not have regulatory power, their corporate decisions can have considerable influence over their supply chain.
- **End Consumers**: Consumers are increasingly interested in sustainability, but individually, they have limited power to influence regulations or corporate strategies, collectively their power could increase. Next to this, regulatory constraints could affect the supply of the end consumers therefore their interest is high.
- **Research Institutions**: They have an interest in studying and developing sustainable technologies and networks but may have limited power to influence policy or industry practices directly.
- **TLN (Transport and Logistics Netherlands)**: As an industry association, they wield considerable power through their influence on transport policies and practices but might have varied interests across their members depending on how the transition affects their operations.

From the power interest analysis it becomes clear that multiple stakeholders have different interests and other means of power within the system. The links and collaborations between different actors in the system are interdependent, making it of high importance to map the key stakeholders and their goals.

4.3. Performance criteria

To comprehensively evaluate the performance of the proposed two-echelon location-routing model, this section discusses a set of developed performance indicators. These indicators are designed to quantify the performance of the network design and the vehicle routing. The indicators are categorized into the performance indicators for the network design and the vehicle routing.

4.3.1. Network design

- **Savings in kilometers:** This indicator measures the reduction in total kilometers traveled as a result of consolidating transportation movements by high-capacity vehicles within a two-echelon network structure. It captures the efficiency gained through strategic distribution planning, where goods are initially transported to intermediate hubs before final delivery, as opposed to direct shipments from the origin to all destinations. The savings are quantified by comparing the total kilometers traveled in the traditional single-echelon system against the kilometers traveled in the proposed two-echelon system.
- **Additional operational costs**: Operational costs are critical in evaluating the financial viability of the network design. This research assesses:
    - *Transshipment handling costs*: Costs associated with the handling of goods during transshipment at hubs, which include labor and equipment usage.

- *Extra transportation costs*: The additional costs incurred for transportation movements that are necessary within the two-echelon structure, such as movements between hubs and the brewery for materials or cleaning.
- *Savings in kilometer*: Reduction in transportation costs achieved through decreased kilometers traveled, considering fuel consumption, vehicle usage, and other variable costs.

4.3.2. Vehicle Routing

- **Kilometers of the routes**: This metric evaluates the total kilometers driven to satisfy the demand of all customers within the network. It reflects the direct impact of routing decisions on fuel consumption, vehicle wear and tear, and driver hours, offering insights into the operational efficiency of the vehicle routing plan.
- **Operational costs per hectoliter**: Operational costs per hectoliter of product delivered serve as a critical indicator of cost efficiency in the logistics process. This ratio provides an understanding of how effectively resources are utilized in delivering goods to customers, highlighting the balance between operational expenditure and service level.
- **Truck efficiency**: Truck efficiency is gauged by the utilization ratio of the truck's capacity on each route. This indicator not only reflects the effectiveness of load planning but also impacts fuel efficiency and operational costs. High utilization rates indicate efficient use of available capacity, minimizing the number of trips required and thereby reducing overall transportation costs.

5 Methodology

The methodology chapter delineates the research design, and analytical procedures employed to address the research questions outlined in the preceding section. The choice of methodology is crucial, as it underpins the reliability and validity of the research outcomes, ensuring that the findings can be trusted to inform both theory and practice. In the context of designing a strategic logistic network together with the operational constraints of specialized electric vehicles, a multifaceted methodological approach is warranted.

5.1. Research design

The research design section will elaborate on the conceptual framework that structures the investigation. It will describe the sequential, exploratory strategy adopted to first understand the key challenges and opportunities through qualitative analysis and then quantify the impact of different strategic choices using quantitative methods. A quantitative modeling approach is chosen since it has several advantages in the pursuit of this research objective. It provides a logical and systematic framework for analyzing the network design and additionally, it enables the construction of a simplified representation of a real-world system, facilitating the efficient exploration of diverse alternatives and the search for optimal solutions [51]. However, it is important to state that the modeling approach does have its limitations and one notable challenge is the accurate reflection of real-world situations within the model [63]. Furthermore, due to the inherent simplification of reality within the model, the outcomes obtained may be susceptible to bias. Therefore, careful consideration must be devoted to the selection of appropriate model elements to ensure the production of accurate and reliable results. Given the complexity of the logistical challenges and the pioneering nature of integrating sustainability goals in strategic- and operational efficiency. This approach allows for a comprehensive exploration of the strategic design and operational dimensions of the transition to electric vehicles within the logistics network.

The research flow, as illustrated in Figure 5.1, serves as a visual representation of the research methodology adopted in this study, delineating the sequential stages within the research process. This diagram places particular emphasis on the two-step optimization strategy and outlines the strategic- and operational fundamentals that are included in this study.

First, the system of the research is described to set the stage for the modeling research steps and the most important factors for design are discussed. Afterward, the first strategical optimization step is taken where the network design model is going to be developed at first. After that, the network design alternatives are generated and serve as input for the next operational optimization steps where the vehicle routing is conducted. Here the first step is to develop a vehicle routing model that complies with the specific characteristics of this case study. The vehicle routing model is then applied to all different network design alternatives and results will be generated. The research flow shows the interplay between strategic- and operational optimization to align both parts.

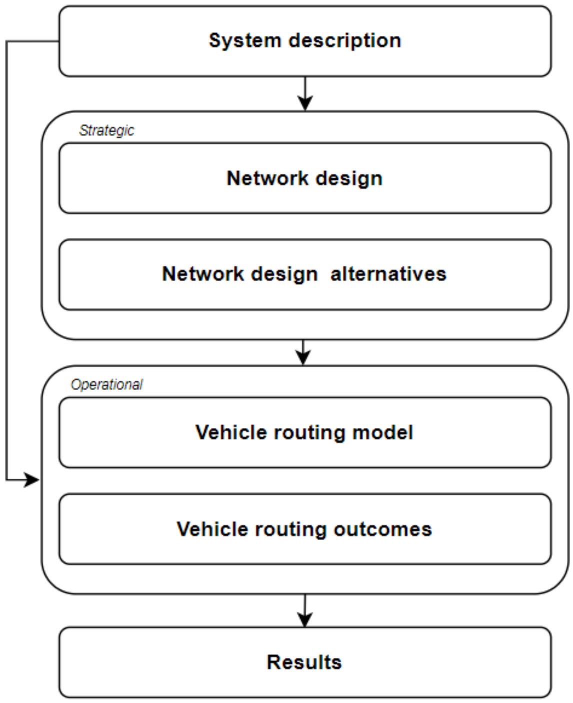

Figure 5.1: Research flow

5.2. Key challenges and opportunities

At the beginning of the research lies the identification of key challenges and opportunities that inform the research design. These elements not only serve as the initial step in the investigative process but also as crucial input for the subsequent modeling stages.

One of the foremost challenges encountered in this research is the creation of accurate model inputs that reflect the specific nuances of this problem. The complexity of integrating electric vehicles into logistics networks necessitates a nuanced approach to model formulation. This involves a careful consideration of the operational range of electric vehicles, charging infrastructure, and the scheduling constraints imposed by customer delivery windows. The precision of these inputs is critical, as they directly influence the model's ability to generate viable, actionable solutions.

Further complicating the research design are the constraints inherent to the models themselves. Each logistic model comes with its own set of assumptions and limitations, which in turn impact the scope and applicability of its outputs. Navigating these constraints requires a deep understanding of the models' theoretical underpinnings and an approach to adapting them to the unique requirements of electric vehicle-based distribution networks. Another significant challenge lies in the adoption of various techniques to construct a two-echelon location-routing network that is both efficient and sustainable. The choice of technique has profound implications for the network's design and performance. The transportation of bulk liquids presents its own set of specific constraints and challenges, underscoring the need for specialized solutions. The requirement to keep different liquid types segregated throughout the transportation process, coupled with the need for precise delivery volumes, demands a level of accuracy that goes beyond traditional logistic models.

Despite these challenges, the research to optimize a two-echelon location-routing network for electric vehicles and bulk liquid transportation has opportunities. It offers a chance to pioneer innovative solutions that could set new benchmarks for sustainability and efficiency in logistics.

5.3. Network design

The primary objective of the network design is to improve performance and overcome the range and charging restrictions of electric vehicles. The methodology was predicated on the premise that the only means for enhancing the network's efficiency was through the strategic integration of additional depots or hub locations creating a two-echelon network. The vehicles employed for transportation from the location where products are supplied to the hub locations are characterized by a higher freight capacity relative to those utilized for final delivery to customers from the depot, consolidating transportation activities. However, the operational handling is more complex due to an extra layer in the network, which potentially results in higher operational costs [6]. Figure 5.2 shows the differences in a single-echelon network and a two-echelon network, where the WPs are the depots and the DPs are the satelites of the network.

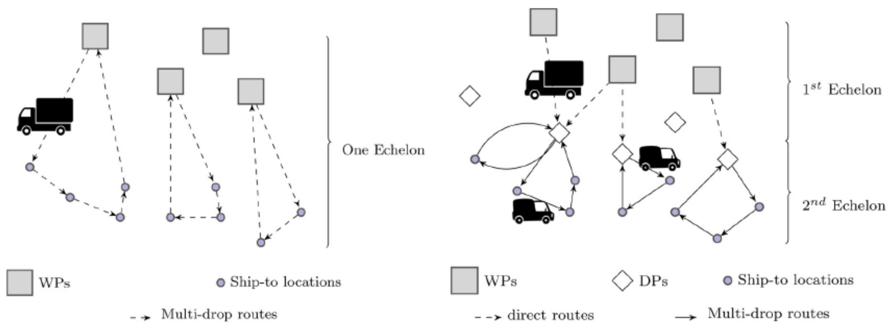

Figure 5.2: One-echelon vs two-echelon network design [6]

To find the optimal hub locations multiple clustering techniques are selected for this study to identify clusters of customers that are assigned to a hub location. The different methods include the center of gravity, p-median, and weighted k-means, each chosen for their unique ability to group data points. The three different clustering methods don't have huge differences that separate them, because locations and demand are the drivers of the clustering. Nevertheless, the three different clustering techniques will gain valuable insights into the different performances of the network optimizations and ensure more robust outcomes. The network design model calculates the savings in kilometers to establish the quantity and placement of the hubs. For each clustering technique, multiple scenarios including different numbers of clusters are run. For each scenario, the model is run 200 times and the design with the highest savings in kilometers is chosen to be the design for this number of clusters. The model was subjected to reflection of real-world operations. For each proposed hub location generated by the clustering algorithms, multi-performance indicators are generated. This analysis considers the various performance indicators discussed in Chapter 4.

5.3.1. Center of gravity

The center of gravity Method is a strategic method mainly used in logistics, supply chain management, and marketing to address location problems and cluster entities based on their geographical locations and demand. This approach is particularly beneficial in customer clustering, where it enables the determination of the optimal placement for services or distribution centers by analyzing the geographical distribution of their customer base [11]. The ultimate goals are to minimize transportation costs, enhance service delivery efficiency, and boost customer satisfaction. The following characteristics can be drawn:

- **Geographical optimization:** This method aims to find a central point that minimizes distance or cost to all points (customers) in a specified area, focusing on geographical optimization.
- **Simplicity and flexibility:** Known for its straightforward calculation process, it is easy to apply and can be adapted to suit various business models and customer distributions.
- **Cost-efficiency focus:** By optimizing the location based on the center of gravity, businesses can potentially reduce transportation and operational costs.

- **Dynamic adaptation:** It allows for re-evaluation and adjustments as customer bases grow or shift geographically, making it a versatile tool for businesses.

The mathematical notation of the center of gravity method is discussed. Let x_i, y_i represent the coordinates of customer location i, and let w_i represent the weight for location i, which could be the demand, the volume of goods to be delivered, or any other relevant metric. The center of gravity (X_{CG}, Y_{CG}) is calculated as:

$$X_{CG} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{5.1}$$

$$Y_{CG} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{5.2}$$

,where n is the total number of customers.

The center of gravity method does have some limitations. The method mainly emphasizes geographical closeness and might not consider additional expenses such as those arising from traffic conditions, physical obstacles, or variations in transportation fees. It also captures a momentary picture based on existing data, without naturally incorporating predictions about potential growth or geographical shifts of customer bases.

5.3.2. Center of gravity clustering

The center of gravity method is used within the clusters to determine the potential hub location, but the clustering of the customers is also of importance. The function used is designed for clustering data points by considering their center of gravity, with the capability to fix one of the centers of gravity beforehand, the main depot, from which the hub locations are supplied. A breakdown of the steps is made below:

1. **Initialization:** Randomly assign each data point to one of the clusters with random initial centroids, ensuring the fixed CoG is always included in the initial set of centroids.
2. **Iteration:**
    - For each data point, calculate its distance to each centroid.
    - Assign each data point to the cluster associated with the nearest centroid.
    - Update the centroid of each cluster by recalculating the center of gravity.
    - If the cluster assignments do not change between iterations, stop the process.
3. **Output:** The final cluster assignments and centroid locations are returned.

5.3.3. P-median

The p-median method is a strategic approach employed in operations research, logistics, and supply chain management, aimed at identifying the optimal placement of a predefined number of facilities. Here, 'p' denotes the number of facilities or locations that are to be determined and is determined beforehand. The method minimizes the overall distance or cost between these facilities and a set of demand points, thereby enhancing the efficiency and effectiveness of service delivery and logistics operations. The p-median method addresses the complexity of selecting specific locations from potential candidates to optimally serve multiple demand points [23]. The following points outline its main characteristics:

- **Optimal facility placement**: At its core, the p-median method strategically determines the best locations for the specified number of facilities to efficiently service demand points, analyzing distances or costs to ensure minimization of the aggregate distance or cost from demand points to their closest facility.
- **Enhanced service efficiency**: By optimizing the placement of a fixed number of facilities, the method aims to reduce service times, lower transportation costs, and thus improve the overall efficiency and responsiveness of delivering services or goods to customers for the whole network.

- **Cost reduction**: Focusing on minimizing operational and transportation costs through strategic facility placement, the p-median approach distinctively tackles the challenge of selecting among multiple potential locations to efficiently meet distributed demand.

This method is applicable in a variety of scenarios, including logistics and distribution network design where optimal resource allocation significantly impacts operational efficiency and customer satisfaction. The complexity of solving the p-median problem increases with the number of potential locations and demand points.

The mathematical notation of the p-median method is discussed here. Let d_{ij} be the distance between customer location i and potential facility location j, and let x_{ij} be a binary variable that equals 1 if customer location i is served by facility location j, and 0 otherwise. Let m and n be the sets of customer- and facility locations. The objective is to minimize the total distance:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} d_{ij} x_{ij} \tag{5.3}$$

Each customer location is served by exactly one facility:

$$\sum_{j=1}^{m} x_{ij} = 1, \quad \forall i \tag{5.4}$$

Exactly p facilities are selected:

$$\sum_{j=1}^{m} y_j = p \tag{5.5}$$

,if a facility is selected at location j, then $y_j = 1$; otherwise, $y_j = 0$.

5.3.4. P-median clustering

The p-median clustering aims to minimize the distance between points and their designated cluster centers, while also taking into account the demands associated with each point for the calculation of these centers. The process unfolds as follows:

1. **Initialization**:
   - The 'p' is selected and 'p' points from the dataset at random to serve as the initial centroids.
2. **Iteration**:
   - Distances between each data point and all centroids are calculated.
   - Each data point is assigned to its nearest centroid.
   - New centroids are updated by calculating the center of gravity within each cluster, incorporating the demands and distances associated with each customer.
   - After updating the centroids, the algorithm checks for changes in their positions compared to the previous iteration. If no changes are observed, indicating convergence, the iterative process is terminated.
3. **Adjustment for fixed point**: Post iteration, the function ensures that one of the centroids corresponds to the predetermined fixed point, the depot. This involves identifying the cluster whose centroid is nearest to this point and setting that cluster's centroid to the fixed point. This adjustment allows for adherence to specific constraints or business logic requirements, integrating a fixed point into the clustering solution.
4. **Output**: The function returns the cluster assignments for each data point and the final positions of the centroids, including the fixed point.

This approach modifies the classic p-median problem by incorporating demand in the centroid calculations and enforcing a constraint for a fixed location. It aims to reflect both geographical distribution and the significance of each point, providing a nuanced clustering solution that considers location and importance.

5.3.5. K-means

K-Means algorithms belong to the class of unsupervised learning techniques used to identify distinct clusters within a dataset. The advantage of unsupervised learning is its capability to uncover patterns without necessitating pre-labeled data. A core principle of clustering is to organize data points such that they exhibit greater similarity to members within their cluster than to those outside it. This similarity is commonly gauged through distance metrics, making these methods apt for tasks like clustering data points. K-means is recognized as a partitional clustering algorithm, which presupposes a specific number of clusters and segregates the data accordingly [11]. This approach guarantees that each cluster is populated and every data point is exclusively associated with one cluster. It is noteworthy that k-means algorithms are inherently non-deterministic, potentially leading to varied outcomes with each execution.

The k-means algorithm follows an iterative process to partition a dataset into 'k' distinct, non-overlapping clusters [29]. Below are the typical steps involved in executing a k-means algorithm:

Let x_i represent customer location i, which could include coordinates and demand. Let C_k be the set of all points assigned to cluster k, and let μ_k be the centroid of cluster k, which is the mean of the points in C_k. The objective of k-means is to minimize the total within-cluster variance:

$$\min \sum_{k=1}^{K} \sum_{x_i \in C_k} ||x_i - \mu_k||^2 \tag{5.6}$$

The algorithm iteratively updates the cluster assignments and the centroids until it converges:

1. **Initialization**: Select k initial centroids.
2. **Assignment step**: Assign each x_i to the nearest centroid.
3. **Update step**: Recalculate centroids as the mean of all points assigned to each cluster.
4. **Repeat**: Repeat steps 2 and 3 until convergence.

Key characteristics of the k-means algorithm are that the k-means algorithm is guaranteed to converge, but it may find a local rather than a global minimum. This characteristic underlines the importance of the initial selection of centroids. Also, the outcome of the algorithm can be sensitive to the initial placement of centroids. While k-means can handle large datasets, it becomes computationally intensive with increasing data size and dimensionality. K-means is versatile and applicable in a wide range of scenarios, including market segmentation and document clustering. However, it might not always be representable for the real-world data.

5.3.6. K-Means clustering

The k-means clustering for this problem description is adjusted, to fit the right specifics. The following steps are conducted in the k-means clustering process:

1. **K-means clustering**: The k-means clustering function performs a standard k-means as described in Section 5.3.5.
2. **Calculate weighted centroids**: After the k-means clustering, the centroids are adjusted based on the demand of the cluster.
3. **Adjustment for fixed point**: It is identified which cluster includes the fixed point and the centroid of this cluster is changed to the fixed point. This is critical for scenarios where a fixed point must be included in the final clustering results.

As stated there are similarities between the three clustering methods but the main differences are also clarified above. The p-median focuses on minimizing the sum of the actual distances from the customers to the centroids, minimizing travel time or costs. The k-means minimizes the squared distances, which leads to minimizing the variance. Therefore, the k-means approach focuses on balancing the spread of points around the centroids which might not always yield the minimum total distances. The center of gravity method focuses on minimizing the transportation costs, including the weight of the points. Due to the importance of the customer weights in the research, the centroids in each clustering method are slightly adjusted therefore reducing the differences between the three methods.

5.4. Network model

In this section, we introduce a comprehensive network model designed to encapsulate the complexities and dynamics of real-world systems. The aim is to accurately capture the system's most critical aspects and dynamics well enough to draw meaningful insights and conclusions. The inherent limitations of modeling mean that, while we strive for accuracy and relevance, some nuances of the real-world situation might not be fully represented in the model.

To construct and analyze our network model, we use Jupyter Notebook. This is a powerful tool that allows for the integration of code, computational output, and rich text elements within a single, interactive environment. Jupyter Notebook is particularly well-suited for this task due to its capability to blend documentation with code. This not only makes the model more accessible for review and understanding but also simplifies replication and modifications for future research.

As we delve into the specifics of the network model, it's important to highlight that the primary purpose of the model is to serve as a tool for analysis and decision-making. By abstracting the real-world situation into a structured and manipulable format, we can simulate various scenarios, test hypotheses, and evaluate potential outcomes much more swiftly and precisely than would be possible through direct experimentation in the real world.

5.4.1. Model outline

The main aim of the network model is to measure the performance of clustering the customers and adding hub locations for those clusters. As stated in Chapter 4 the performance of the network is measured in kilometers that are saved by consolidating the shipments from the depot to the hub locations and the additional operational costs of the implementation of the hub locations. For the savings in kilometers, the assumption is made that in general, trucks would normally serve a certain area during one day. This area can be seen as the cluster area and the centroids of the clusters can be seen as the central starting point for the original routes. Therefore the savings in kilometers are the savings that are made on the distance between the depot and the proposed hub locations, which are placed on the centroid locations of the different methods. Next to this savings in kilometers, there are extra handlings that need to be performed due to the two-echelon network. Normally the trucks are filled up at the depot from which they would serve the customers directly. Now an intermediate step is added to this process since there are reefers filled up at the depot that drive to the hub location and at the hub location the trucks are loaded from the reefers and then serve the customers within the cluster. The costs of the extra handlings at the hub location and the additional transportation costs are included in the model.

Next to this, there is no need to add a hub location in the cluster that includes the depot. This is a fixed point in the research that cannot be adjusted. Therefore, in all experiments, this point is fixed beforehand and included in the clustering process.

5.4.2. Mathematical model network

The model is initialized with a set of input variables reflecting the costs and operational parameters relevant to logistics and distribution:

Variables Definition and Units

Variable	Definition	Unit
C_{km}	Cost per kilometer for transportation	euro/km
W_h	Wage per hour paid to the workforce	euro/hour
v	Average speed of the vehicles	km/hour
T	Transshipment time for every truck transshipment	minutes
T_{travel}	Travel time of a round trip	minutes
C_{et}	Cost per hour for operating an electric truck	euro/hour
C_{rt}	Cost per trip for using a reefer for consolidated transport	euro/trip
Cap_r	Capacity of a reefer in units of demand	hectoliters
Cap_t	Capacity of a truck in units of demand	hectoliters
F	Scaling factor for distances	dimensionless
D_d	Distance from centroid to the fixed centroid (depot)	kilometers
D_s	Savings in km using a 2-echelon instead of 1-echelon network	kilometers/year
Q_c	Demand for a certain cluster	hectoliters/year

Table 5.1: Definition and units of variables

Formulas

Kilometer Savings

These functions compute the logistical efficiency gains by contrasting distances traveled with and without utilizing a distribution hub.

Kilometers driven without a hub (D_{se}): Distance traveled if each demand point was directly served from the depot using a single echelon network, considering a round trip, representing the current network.

$$D_{se} = \left(\frac{Q_c}{Cap_t}\right) * D_d * 2 \tag{5.7}$$

Kilometers with hub (D_{te}): Represents the reduced distance for a cluster when implementing a two-echelon network assuming efficiency scales with the truck-to-reefer capacity ratio.

$$D_{te} = D_{te} * \left(\frac{Cap_t}{Cap_r}\right) \tag{5.8}$$

Savings in kilometers (D_s): The net distance saved per cluster by using a two-echelon network.

$$D_s = D_{se} - D_{te} \tag{5.9}$$

Total savings in kilometers ($Total\_D_s$): Sum of all net distance cluster savings.

$$Total\_D_s = \sum_{i=1}^{n_{clusters}} D_{s_i} \tag{5.10}$$

Operational Hub Costs

Assesses the cost implications and savings from employing a hub by considering various operational expenses.

Number of reefer trips (N_{trips}): Required trips to satisfy the demand, highlighting the logistical load on the hub.

$$N_{trips} = \left(\frac{Q_c}{Cap_r}\right) \tag{5.11}$$

Round trip distance (D_{rt}): The total distance for a round trip per hub location.

$$D_{rt} = D_d * 2 \tag{5.12}$$

Travel time (T_{travel}): Duration required for a round trip.

$$T_{travel} = \frac{D_{rt}}{v} \tag{5.13}$$

Reefer usage cost (C_{ru}): Additional expenses related to reefer transport. Since the trucks drive from the hub location to the customers the deployment of the reefers is additional and does not replace another truck. Therefore, extra costs need to be identified.

$$C_{ru} = C_{et} * T_{travel} \tag{5.14}$$

Wage cost per kilometer (W_{km}):

$$W_{km} = \frac{W_h}{v} \tag{5.15}$$

Cost savings in kilometers ($C_{savings\_km}$): Financial savings from decreased travel emphasizing the economic benefit of a hub.

$$C_{savings\_km} = D_s * (C_{km} + W_{km}) \tag{5.16}$$

Transshipment cost per unit (C_{trans_unit}): The transshipment cost in euros for every truck transshipment.

$$C_{trans\_unit} = W_h * T \tag{5.17}$$

Transshipment cost (C_{trans}): Transshipment costs per hub location.

$$C_{trans} = \left(\frac{Qc}{Cap_t}\right) * C_{trans\_unit} \tag{5.18}$$

Transport and cleaning cost (C_{tc}): Comprehensive costs for additional transport for materials and cleaning at hub locations.

$$C_{tc} = 2 * 52 * (D_{rt} * (C_{km} + W_{km})) + N_{trips} * (C_{rt} + C_{ru}) \tag{5.19}$$

This structured presentation not only clarifies the mathematical relations but also assists in comprehending the interdependencies and interactions between different variables within the network model. This comprehensive discourse, coupled with the mathematical formulations, sheds light on the multifaceted analysis conducted to evaluate the logistical and economic consequences of integrating a hub into a distribution network.

5.5. Vehicle routing model

In this section, the second part of the optimization process, the vehicle routing is covered. As discussed in Section 5.1 the network design outcomes, where the number and the placement of the hub locations are determined, serve as an input for the vehicle routing model. This part of the research has focused on the operational aspects of the logistic system rather than on the strategic part. The main goal is to develop a vehicle routing model with accompanying constraints for specific transportation and apply it to the optimized network. This vehicle model only focuses on the second echelon of the two-echelon network. The primary objective of vehicle routing is to schedule the most efficient routes that satisfy the demand of the customers complying with operational- and customer constraints. The vehicle routing in this research aims to minimize the cost of the routing, which entails the minimization of the amount of kilometers driven. The operational constraints of this research are specified for bulk liquid transportation. One of the most specific constraints is the fact that trucks have multiple compartments in which different bulk liquids can be transported to the customers. Also, the research aims to electrify all logistics activities that result in overnight charging and range constraints.

Vehicle routing problems due to the exact calculations and the specifics of truck configurations and operations translated into constraints make it NP-hard. NP-hard problems are a classification highlighting the complexity and challenges of certain computational tasks. NP-hard signifies that solving these problems is at least as difficult as the hardest problems that can be verified in polynomial time, although they may not necessarily adhere to this constraint for solution verification. These problems are crucial for understanding the limits of what can be feasibly computed. Unlike NP-complete problems, which are both solvable and verifiable in polynomial time, NP-hard problems do not require a feasible solution method to exist, making them a fundamental concept in assessing computational difficulty and the feasibility of algorithmic problem-solving [39]. Therefore, the vehicle routing problem cannot be executed on a large dataset and a different approach is needed to perform the vehicle routing in this research.

The individual clusters of the network design serve as an input for the vehicle routing model. The customer size of the clusters is problematic for the performance of the vehicle routing. Therefore, the choice is made to overcome this by sub-clustering the customers within an individual cluster again within the north clusters. The same clustering techniques are used to perform the sub-clustering and eventually, the customers are reallocated to ensure a maximum sub-cluster size. These smaller sub-clusters can be used as input for a specific vehicle routing run. Figure 6.2 visualizes the flow of the data from the input of the network model outcomes to the performance of the vehicle routing per re-allocated sub-cluster. Steps 1,2 and 3 are input or filtering specific data out of the data in the previous step.

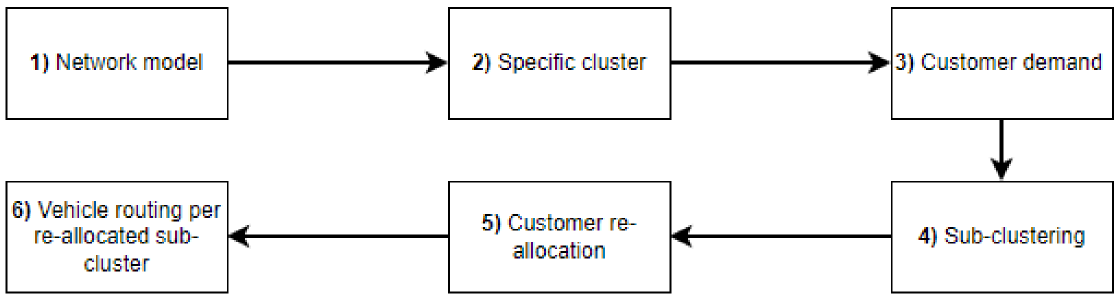

Figure 5.3: Vehicle routing data flow methodology

Following the sub-clustering phase, customer re-allocation is conducted to balance the distribution of customers among the available sub-clusters. This re-allocation step is critical for maintaining operational efficiency, as it ensures that no sub-cluster is overburdened with too many customers while others have not reached their capacity. The re-allocation mechanism is straightforward: customers from overpopulated sub-clusters are reassigned to the nearest sub-cluster that has not yet reached the maximum threshold of the maximum customers. The criterion of proximity ensures that the re-allocation not only balances the customer load but also maintains routing efficiency by minimizing additional travel distances. The re-allocation process iterates until an equilibrium is reached across all sub-clusters, achieving a uniform size distribution. This meticulous balancing act ensures that each vehicle routing operation can be conducted with maximum efficiency, with each sub-cluster optimized for the most effective distribution and service fulfillment.

The core of our vehicle routing strategy is grounded in the use of Mixed Integer Linear Programming (MILP), which allows for the detailed mathematical formulation of the routing challenges. This includes specifying linear constraints and integer variables to define vehicle routes, time windows, and load capacities, and to minimize objectives such as total travel distance. MILP's comprehensive framework enables us to accurately model the complexities inherent in vehicle routing in this specific case study, providing a structured means to identify optimal or near-optimal solutions. The vehicle routing model is tailored to encapsulate the essential elements and dynamics of the logistics systems. The objective is to construct a representation that accurately reflects the key factors and constraints influencing routing performance and efficiency. Recognizing the intrinsic limitations of any model, acknowledgments are made that some subtleties of the real-life logistics environment may not be entirely captured like traffic or the complete road network. Nonetheless, the model aims to offer substantial accuracy and relevance to derive meaningful insights.

For the construction, analysis, and visualization of our vehicle routing model, Jupyter Notebook is used with the Gurobi optimizer package. The adaptability of Jupyter Notebook is particularly beneficial for modeling complex systems. Jupyter Notebook not only aids in elucidating the model for review but also streamlines any future similar research that may require model replication or alteration.

5.5.1. Mathematical model vehicle routing

In this subsection, the mathematical model for the vehicle routing is introduced. The vehicle routing model is employed to one cluster at a time since it only focuses on the second echelon network. Therefore, the sets will only have one depot that represents the hub location of the cluster. First, the sets and indices, the parameters, the objective function, and the decision variables are shown thereafter and the constraints are summarized. These constraints collectively form a comprehensive framework that ensures the Multi-compartment ElectricVehicle Routing Problem with Time Windows solutions are not only cost-effective but also operationally viable, considering vehicle capacities, customer demands, product types, and scheduling requirements.

Sets and indices

- N: Set of customers only.
- V: Set of all nodes including the depot.
- P: Set of all product types.
- K: Set of all trucks.
- C: Set of all compartments.
- $A = (i, j), \forall (i, j) \in V, i \neq j$: Set of arcs representing possible routes.

Parameters

- d_{ij}: Distance between nodes i and j, adjusted by a scaling factor and calculated using the Haversine formula.
- F: Scaling factor for distances.
- q_{np}: Demand of product type p at customer node n for a certain day.
- e_i: Start of the time window in which the product needs to be delivered, at node i.
- l_i: End of the time window in which the product needs to be delivered at node i.
- s_i: Service time at node i.
- n_t: The total number of trucks available.
- C_t: The total capacity of the truck, which is equal for all trucks.
- n_c: Number of truck compartments, which is equal for all trucks.
- $compartment\_capacity$: The capacity of the compartments within the trucks, which is equal for all compartments.
- $cost\_per\_km$: The cost per km includes wages and truck operating costs.
- $max\_distance$: The range constraint due to the use of electric vehicles.

Objective Function

Minimize the total cost, primarily based on distance traveled by all vehicles, with a cost per kilometer that incorporates wages, truck costs, and fuel costs:

$$\textit{MIN} : cost\_per\_km * \sum_{\forall (i,j) \in A} (d_{ij} * x_{i,j,k}), \forall k \in K \tag{5.20}$$

Decision Variables

- $x_{i,j,k}$: Binary variable, 1 if truck k travels from node i to node j, 0 otherwise, where $(i = 1, 2, .., V), (j = 1, 2, .., V), (i \neq j), (k = 1, 2, .., K)$
- $t_{i,k}$: Continuous variable representing the time node i is visited by truck k, where $(i = 1, 2, .., V), (k = 1, 2, .., K)$
- $y_{k,p}$: Binary variable, 1 if truck k carries product type p, 0 otherwise, where $(k = 1, 2, .., K), (p = 1, 2, .., P)$.
- $z_{k,c,p}$: Binary variable, 1 if compartment c of truck k is used for product type p, 0 otherwise, where $(k = 1, 2, .., K), (c = 1, 2, .., C), (p = 1, 2, .., P)$

Constraints
Now all the constraints that are applicable to this problem description are presented.

Depot departures and arrivals
Ensure each vehicle departs from and returns to the depot at most once, limiting unnecessary movement and focusing on efficiency. The depot is zero for i and j.

$$\sum_{j \in N} x_{0,j,k} \leq 1, \forall k \in K \tag{5.21}$$

$$\sum_{i \in N} x_{i,0,k} \leq 1, \forall k \in K \tag{5.22}$$

Visit each customer once
This ensures every customer is visited exactly once, promoting equitable service distribution and operational consistency.

$$\sum_{j \in V, k \in K} x_{i,j,k} = 1, \quad \forall i \in N \tag{5.23}$$

Flow conservation
A vehicle that enters a node must also leave it, maintaining route continuity.

$$\sum_{j \in V} x_{i,j,k} - \sum_{j \in V} x_{j,i,k} = 0, \quad \forall i \in V, k \in K \tag{5.24}$$

Travel distance limit
Limits the total distance a vehicle can travel, ensuring routes are within operational capabilities and promoting cost efficiency.

$$\sum_{(i,j) \in A} (d_{ij} * x_{i,j,k}) \leq max\_distance, \quad \forall k \in K \tag{5.25}$$

Vehicle capacity
The total demand for each product type on a route must not exceed the vehicle's capacity, ensuring all goods can be safely and efficiently transported.

$$\sum_{j \in V} (q_{np} * x_{i,j,k}) \leq C_t * y_{k,p}, \quad \forall i \in N, k \in K, p \in P \tag{5.26}$$

Compartment usage
Each compartment within a vehicle can be used for at most one product type, ensuring product integrity.

$$\sum_{p \in P} z_{k,c,p} \leq 1, \quad \forall k \in K, c \in C \tag{5.27}$$

Truck and compartment activation
Activates a truck and its compartments for use if they are involved in any transportation, ensuring resources are allocated only when needed.

$$\sum_{i,j \in V} x_{i,j,k} \geq \sum_{p \in P} z_{k,c,p}, \quad \forall k \in K, c \in C \tag{5.28}$$

Compartment product type assignment
Ensures compartments are assigned to product types based on actual route demand, optimizing space and resources.

$$\sum_{(i,j) \in A} x_{i,j,k} \geq z_{k,c,p}, \quad \forall k \in K, c \in C, p \in P \tag{5.29}$$

Total capacity for each product type
The total demand for each product type must not exceed the total allocated capacity across all compartments, ensuring logistical feasibility.

$$\sum_{(i,j)\in A}(q_{np} * x_{i,j,k}) \leq compartment\_capacity * \sum_{c\in C} z_{k,c,p}, \quad \forall k \in K, p \in P \tag{5.30}$$

Time window constraints
Ensures deliveries and pickups occur within predefined customer time windows, promoting customer satisfaction and operational efficiency.

$$(t_{i,k} + s_i + (t_{j,k} - t_{i,k})) \leq t_{j,k}, \forall i, j \in N, k \in K, i \neq j \tag{5.31}$$

$$t_{i,k} \geq \mathsf{e}_i, \qquad \forall i \in N, k \in K \tag{5.32}$$

$$t_{i,k} \leq \mathsf{l}_i, \qquad \forall i \in N, k \in K \tag{5.33}$$

Following the introduction of the mathematical model for the vehicle routing problem addressed in this research, it is crucial to discuss the assumptions that underly the model. These assumptions are pivotal in shaping the model's structure and its potential applications, and they are also critical for understanding the model's scope, its limitations, and the interpretability of its outcomes.

In crafting the vehicle routing, the following important assumptions are made:

- **Road distance calculation**: The road distances between nodes, essential for plotting routes and estimating travel times, are computed using the Haversine function. The same scaling factor F is used as in the network modeling.
- **Operational time constraint**: A 24-hour operational window for each vehicle's routing activity is assumed. Within this time frame, each vehicle can only complete a single route. This constraint is reflective of real-world operational limits, including drivers' working hours regulations, and vehicle usage policies.
- **Depot start and finish**: Each vehicle must start from and return to a central depot within the 24-hour operational window. The assumption here also includes the necessity for vehicles to finish at the depot, stemming from the requirement for recharging, which is especially relevant in the context of electric vehicles. This aspect also has implications for how the route is structured and the distance a vehicle can cover within its operational time frame.

These assumptions play a significant role in framing the model's operational context. They limit the solution space to feasible and practical routes that align with real-world constraints, such as the physical limitations of vehicles and time windows. By setting these parameters, we also ensure that the VRP is attuned to the logistical considerations pertinent to a fleet of electric vehicles, which must adhere to charging requirements and range constraints that do not apply to conventional internal combustion engine vehicles.

6 Case study data

In Chapter 4 the Heineken case study was introduced and the performance criteria were established. In this chapter the data that serves as input for the model is discussed, focusing on the Heineken customer data and the Dutch road network.

6.1. Network

The current network of Heineken tankbeer was in general a single-echelon network where the brewery in Den Bosch is the starting point of every distribution. Due to the change in weight regulations for vehicles in the inner city of Amsterdam, the distribution of tank beer needed to be adjusted [24]. Heineken introduced a hub location near the city center of Amsterdam to supply customers within the inner city with smaller vehicles that comply with the weight restrictions. Therefore, currently, the network consists of one hub location near Amsterdam that is supplied with big reefers, tanks with a capacity of 30 hectoliters, and a brewery in Den Bosch. For the tank beer deliveries, the Dutch road network is used.

6.1.1. Dutch road network

The Netherlands, with its robust infrastructure, features a road network that is a linchpin for its logistics operations. Renowned for its high density and exemplary maintenance, the network includes an extensive series of motorways that seamlessly link major urban centers and rural areas, underscoring the network's centrality to efficient cargo movement. The complete road network has a length of 139.294 kilometers. The proximity of economic hubs to each other is a distinctive feature of this network, augmenting the reliability and promptness of logistics operations [28].

The Dutch road network is a foundational component of the country's logistics operations. Its strategic design, innovative management, and sustainability initiatives ensure its ability to fulfill the contemporary demands of the logistics industry and anticipate future developments. Figure 6.1 gives a visualization of the train stations, railroads, highways and country roads in the Netherlands in 2022.

In the context of the model, a scaling factor of 1.2 is applied to the result of the direct distance calculations to account for the differences between direct, and the actual distances traveled along roads within the Dutch road network [37]. This scaling factor adjusts the calculated distances to be more representative of real-world travel distances in the Netherlands, where roadways do not always follow the shortest path due to various geographical and infrastructural factors.

Figure 6.1: Infrastructure Netherlands 2022 [28]

6.2. Validation of the Heineken Case

The model outlined in Chapter 5, designed to enhance the efficiency and sustainability of logistics systems transitioning to electric vehicles through a two-echelon network, finds a fitting application in the case of Heineken Netherlands. The operational intricacies and logistical challenges inherent in Heineken's tank beer delivery operations present a robust case environment for validating the model's applicability and effectiveness.

The specialized nature of Heineken's tank beer trucks, which are tasked with transporting multi-liquid products across densely populated urban areas, including zero-emission zones, exemplifies the logistical complexities the model seeks to address. Moreover, the necessity of navigating regulatory constraints while maintaining operational efficiency further underscores the relevance of applying a two-echelon network strategy within this context and can provide valuable insights into optimizing routing and depot placement strategies. Next to this, the model's focus on vehicle routing for specialized electric trucks capable of transporting multiple liquid products applies to Heineken's logistical operations.

Through the case study of Heineken Netherlands, the research aims to illustrate how the model can facilitate the strategic placement of hubs within a logistic network and create vehicle routes for specialized trucks transporting liquids, thereby creating a more efficient and sustainable two-echelon system. This approach is anticipated to not only meet the immediate needs of Heineken's tank beer distribution but also serve as a blueprint for other cases facing similar challenges in the transition to electric vehicle fleets.

6.3. Model input

To make the model fit for the Heineken case, the data that is put in the model is of great importance. The data is mostly gathered from contracts that Heineken has with logistic providers and the tank beer powerBI dashboard, where each order, with all the necessary characteristics, is saved. The different inputs of the model can be separated by the model input for the network design, and the vehicle routing.

6.3.1. Network model input

The model is initialized with a set of input variables reflecting the costs and operational parameters relevant to logistics and distribution:

- v = 60
- T = 3
- Cap_r = 300
- Cap_t = 105
- F = 1.2

These parameters serve as the foundation for the subsequent calculations and analyses conducted within the model, aiming to optimize logistics and distribution strategies in a cost-effective and efficient manner for the Heineken case.

6.3.2. Vehicle routing model input

The outcomes of all three clustering methods, that are used for the network design, serve as an input for the vehicle routing model. The choice is made to focus only on the northern cluster of each network design for the vehicle routing since applying the vehicle routing on other clusters would be repetitive. As discussed in Chapter 5 the customer size of the clusters is problematic for the performance of the vehicle routing since the number of customers in one cluster is too big. The data input for the network model is the customer base of 2023 including locations and yearly demand. To focus on the vehicle routing the demand of one specific week is taken out of this customer data set, where each customer in this data set is only served once. One week is taken as data input due to its average demand. The customers are reallocated to ensure a maximum cluster size of 10 customers since this is a feasible number of customers for which the vehicle routing model can still solve the model within a decent amount of time. These smaller sub-clusters can be used as input for the vehicle routing model. Figure 6.2 visualizes the flow of the data from the input of the network model outcomes to the performance of the vehicle routing per re-allocated sub-cluster

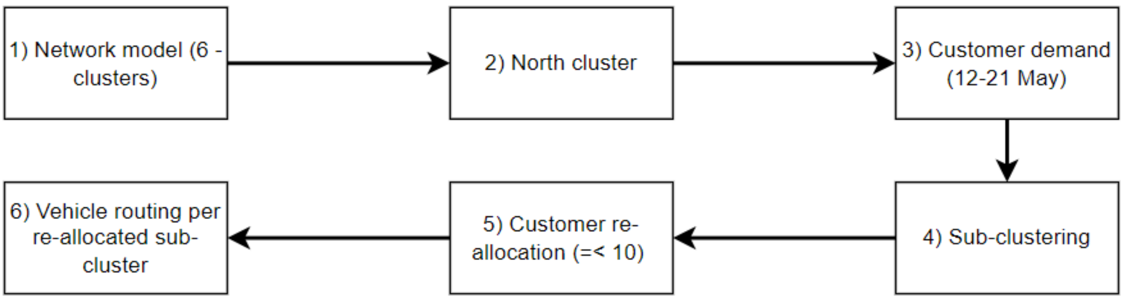

Figure 6.2: Vehicle routing data flow

The model is initialized with the data set discussed above that includes the demand, location, and time windows of specific customers. Next to this customer data, there are other input parameters that are specified in the case of Heineken.

- F = 1.2
- n_t = 20
- C_t = 105
- n_c = 3
- $compartment\_capacity$ = 35
- $max\_distance$ = 300

The current trucks of Heineken have a range of 100 kilometers. Long-haul trucks already have a range of 350 kilometers but those trucks cannot be used in the inner cities due to their size. Therefore, the expectations in the coming years for the medium-duty and heavy trucks used for tank beer deliveries are that their range is around 300 kilometers on one battery [58].

7

Numerical section

7.1. Results

In this chapter, the results of the Heineken case that is applied to the model that is developed in Chapter 5 are discussed. The model input is discussed and shown in Chapter 6 and following up on this input the results of the base case and sensitivity analysis are discussed in this chapter.

7.1.1. Network model

For each clustering method, the performance of the network with a pre-defined number of hubs is calculated. The additional placement of hub locations goes from 2 locations, so the brewery and a hub location, up to 10 locations. The two performance indicators are the savings in kilometers and the additional operational costs for hubs. Both indicators are the results of the application of the two-echelon network yearly, so the savings in kilometers per year and the additional operational costs per year.

Savings in kilometers

The results concerning the savings in kilometers are shown below. It is clear that all three methods show the same pattern, where the savings in kilometers increase drastically when adding the first hub locations. Eventually, the additional savings stagnate, and not many extra kilometers are saved by adding extra hub locations. The savings in kilometers for 2 clusters are higher for the center of gravity method than for the other methods, but when the number of clusters is increased, the savings tend to be more similar. In Figure 7.2 the focus is on the stagnation of the savings. For both the center of gravity- and the k-means method a clear decrease in the growth of the additional kilometers savings can be seen at 6 clusters. For the p-median method, a clear decrease can be seen at 7 clusters.

Clusters	COG	p-median	k-means
2	443769	237413	236505
3	575424	588185	588580
4	633037	629934	624260
5	679703	662163	630536
6	701839	682237	661027
7	707961	703653	672065
8	710278	708773	682432
9	713174	712322	685866
10	715214	714550	691039

Table 7.1: Savings kms by clustering method

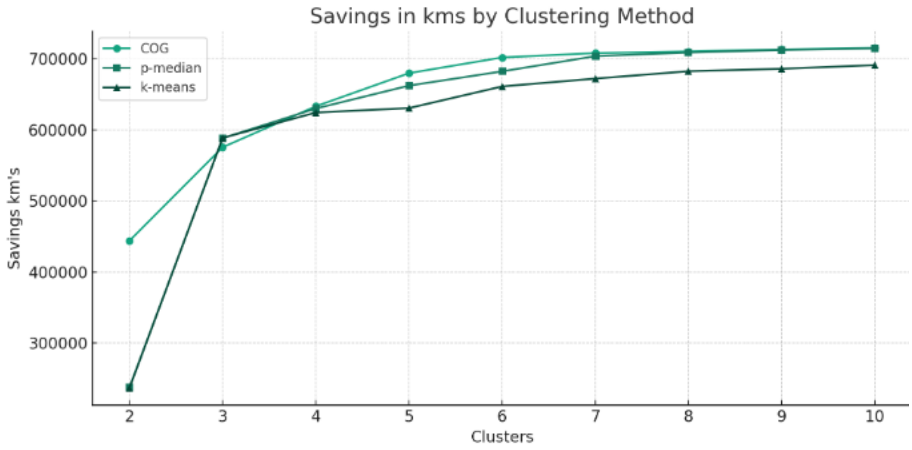

Figure 7.1: Savings in kms by clustering method

Figure 7.2: Savings in kms by clustering method 3-10

Opertional costs

The additional operational costs of opening hub locations consist of the extra costs that are made due to extra handling costs at the hub locations and the extra transportations that need to be made to the hub locations for the supply of materials and cleaning. Next to these additional costs, there are savings in operational costs due to the savings in kilometers that are dependent on the placement of the hub locations. Table **??** and Figure **??** show the additional operational costs for each clustering method. In the graph can be seen that the additional operational costs do not follow a linear or another expected path. For instance, the additional operational costs first decline when moving from 2 to 3 clusters and then increase again for the center of gravity method. Three main points influence these additional operational costs:

- The higher the demand for a cluster, that is not the cluster that contains the brewery, the higher the transshipment costs that are made. Each liter of tank beer needs to be transshipped at the hub locations which has a major effect on the cost implications.
- The further away a hub location is from the brewery, the higher the cost savings due to kilometer savings. If the consolidated reefer transport covers a longer distance, more kilometers are saved due to fewer transportation movements.
- The further away a hub location is from the brewery, the higher the additional operational costs for transportation and cleaning costs. These are movements that need to be made to supply the hub locations and keep the operations running.

Since the clustering methods are purely based on clustering instead of on minimizing the additional operational costs the progression of the graphs can be explained. Some network designs for a certain amount of clusters perform better with regard to additional operational cost due to a better balance between transshipment costs, transportation and cleaning costs, and cost savings in kilometers.

Additional operational cost breakdown

To get more insights into the additional operational costs, a breakdown of the additional operational costs is made for each method. The center of gravity cost breakdown differs from the cost breakdown of the p-median and k-means methods. The additional operational costs for the p-median and the k-means method for 2 clusters are way less than for the center of gravity method. Also, the cost savings from kilometers are way less.
It is clear that all three methods have around the same additional costs for each cluster count. Only for the second cluster count a big difference between the center of gravity method and the p-median and k-means method is found. This difference was already discovered, but when analyzing in more detail the main reason for this difference is the placement of the initial hub locations for the second cluster count. As can be seen in the figures and table below, the initial placement of the hub location in all methods is different but especially the placement of the hub location in the center of gravity method is different. The cluster of the hub location includes the 'Randstad' and therefore the demand is two times bigger than the demand in the other cluster. Since only in the center of gravity method the 'Randstad' is included in the cluster of the hub location, the transshipment costs and transportation and cleaning costs are higher for this method and don't outweigh the cost savings in kilometers.

Network design

As discussed in Chapter 5 the network design serves as an input for the vehicle routing of the research. Therefore, a choice needs to be made for which network design with a certain amount of clusters serves as a starting point for vehicle routing. Two main performance indicators need to be taken into account when making this decision, the savings in kilometers and the additional operational costs.
If the focus is on the additional operational costs, it is clear that those costs are preferably as low as possible. This would mean in the current case that the number of clusters is around 2 or 3, depending on the clustering method. The aim of the methods chosen is to cluster in the best way possible and maximize the savings in kilometers. The choice is made to focus on this performance indicator in combination with the focus on minimizing additional operational costs. The additional operational costs do not exponentially get higher when adding more clusters but are within a decent cost range. Therefore the network designs of the different clustering methods that serve as an input for the vehicle routing part will contain 6 clusters due to the combination of high savings in kilometers and no exponential increase in addiational costs. In Figures **??**,**??**, and **??**, the different network designs are visualized.

Next to this, the methodology of the network design concerning the placement of the hub locations entails that the hub locations are placed in the place of the centroids. Since this is the most central place considering locations and demand for each method and due to the method of calculating savings in kilometers, the assumption is made that from this place the customers in the cluster are served, leaving out other analyses on hub placement.

Conclusion

In conclusion, the network model balanced the intricacies of logistic efficiencies against the granularity of the additional operational variables, encapsulating key components such as cost per kilometer, average speeds, and labor costs. This allowed for an analysis of the consequences of hub integration, with additional operational costs and kilometer savings serving as primary performance indicators.

The results underscore the importance of strategic hub placement, revealing that while the addition of initial hub locations yielded significant kilometer savings, the marginal gains diminished with each subsequent hub, indicating a point of diminishing returns. This pattern was observed across different clustering methods, with a notable convergence in savings as the number of clusters increased.

The additional operational cost analysis painted a more complex picture, affected by a multitude of factors including demand, distance from the brewery, and the inherent costs of transshipment and maintenance operations and cost savings from savings in kilometers. The non-linear progression of these costs, attributable to the various influences and the clustering methods' focus on spatial consolidation rather than cost minimization, required a careful balancing of efficiency and expense.

Ultimately, the decision to utilize a six-cluster network design was selected by a preference for maximizing kilometer savings, while still maintaining the additional operational costs within a reasonable range. This strategic choice, rooted in the analytical insights gained from the model, sets the stage for further refinement and optimization of the distribution network, promising an improvement in overall efficiency and cost-effectiveness.

7.1.2. Vehicle routing model

For the three different network model outcomes the northern cluster has been clustered into sub-clusters of equal size with a maximum of 10 customers. After this, a vehicle routing for each sub-cluster is performed. Since the characteristics of each northern cluster, and subsequently the sub-clusters, differ, the performance needs to be measured effectively to ensure comparisons between the different clustering methods. First, the characteristics of each sub-cluster are discussed after which the performance indicators are discussed. Since the vehicle routing model is NP-hard, the choice is made to run each vehicle routing problem for a maximum of 3 hours. The maximum cluster sizes, already significantly decreased the computational time, but still, for some experiments, the gap to the optimal solution was high. However the choice was made to include the solutions of those experiments in the results as well due to minor expected improvements.

The efficiency of the model is based on multiple factors that are discussed in Chapter 4. Since the clustering methods are used again for the sub-clustering and those sub-clusters form the input for the vehicle routing, the effect of the sub-clustering on the vehicle routing is fairly large. So it is important to grasp the independent performance effect of each clustering method on the vehicle routing. Next to this, the performance of the vehicle routing needs to be analyzed as well.

Daganzo approximation

Since the vehicle routing problem is NP-hard, it is difficult to indicate or calculate the exact performance of a vehicle routing problem. An approximation method that is sometimes used in these approximations is the Daganzo approximation. The Daganzo approximation, developed by Carlos F. Daganzo, is a seminal framework in logistics and transportation, aimed at estimating the minimum number of vehicles required for delivery with a certain amount of kilometers driven within a specified area. Daganzo's foundational work, as outlined in his 1984 study, introduces a formula to approximate the minimum fleet size and total distance driven, considering delivery density and vehicle capacity constraints [47].

The application of the Daganzo approximation across various sectors has significantly enhanced vehicle routing efficiency. By employing this framework, logistics operations can optimize fleet utilization, and routing schedules, and ultimately, reduce additional operational costs. The methodology underscores the importance of strategic resource allocation and network optimization [2]. The vehicle routing problem. The Daganzo approximation for the CVRP distance is formulated as follows:

$$\text{CVRP distance} \approx \left(0.9 + \frac{kN}{C^2}\right) \cdot \sqrt{AN}, \tag{7.1}$$

where N represents the total demand, A is the total area for the deliveries that is calculated by using the coordinates of the customers located in a (sub-)cluster, C denotes the vehicle capacity, and k is a constant that accounts for the area shape efficiency in delivery coverage, which is kept 1 for all areas. Due to its nature, the Daganzo approximation is mostly used to indicate the minimum number of kilometers that have to be driven to supply a certain area so with a high-performing vehicle routing model. In this research, the performance of the vehicle routing is therefore compared to the Daganzo approximation outcomes for that same area.

Sub-cluster characteristics

As Table **??** shows there are noticeable differences in the amount of customers and the total demand of those customers between the different clustering methods. Due to the methodological differences between the three methods it could also be assumed that different clusters would be generated. Nevertheless, it can be seen that the center of gravity- en p-median methods have quite similar outcomes. The number of sub-clusters is chosen before the re-allocation is executed. The maximum cluster size is 10 but to overcome the re-allocation to sub-clusters that are geographically far apart from each other within the cluster more sub-clusters are generated instead of filling each sub-cluster to exact 10 customers.

Performance

For the performance of the vehicle routing, the Daganzo approximation is a good measurement of the efficiency of the vehicle routes that are conducted in the experiments. There are two Daganzo approximations conducted. For the $Dag.cluster$, the complete area covered by the northern clusters is taken as input, and for the other approximation, $Dag.sub - cluster$, the area covered by the sub-clusters is taken as input. This is done to see what the effect of the area input is on the Daganzo approximation and how it performs against the experiment outcomes. As can be seen in Table **??**, the approximated number of kilometers for the vehicle routing is significantly less for the sub-cluster approximation than for the cluster approximation. Since the Daganzo approximation has the aim to give a close to the minimum number of kilometers for a vehicle routing the approximation using the sub-clusters performs better.

Next to this, Table **??** and **??** show that the k-means outperforms the center of gravity- and the p-median method in total kilometers and additional operational costs. However, the total number of customers and the total demand is significantly lower for the k-means experiment and therefore there needs to be looked at the $Dag.performance$ value. This performance value shows how many more kilometers the vehicle routing experiments have as an outcome in comparison with the kilometers of the Daganzo sub-cluster approximation. The center of gravity method model, for instance, has 1,44 times as many kilometers as is approximated by the Daganzo formula. This performance measure levels out the differences in demand and area size. The p-median outperforms both other methods for this indicator. As we look at the additional operational costs it is clear that the k-means scores best on this indicator as well in terms of total operational costs. This is because the northern cluster of the k-means network design includes fewer customers and therefore has lower additional operational costs. If you look at the indicator operational cost per hectoliter that is delivered to the customers the center of gravity outperforms both other methods, indicating a more efficient routing.
Figure **??** shows the distribution of the distances of all routes that are generated for each method. The center of gravity and the p-median distribution are quite similar. The k-means distribution of route distances is more divided. The truck performance indicates how many trucks are used to supply all customers in the clusters and how much of the capacity of the trucks is used for each route. The total amount of trucks used is in line with the expectations due to the total demand of each cluster. On the efficiency, the center of gravity method and the p-median outperform the k-means method.

Conclusion

Through rigorous application and analysis of different clustering methods and subsequent vehicle routing, several crucial insights have emerged. Firstly, the center of gravity method consistently outperforms other approaches in various metrics of efficiency and cost-effectiveness. It yields the lowest additional operational costs and total kilometers in the experiments, coupled with a higher ratio of demand served per kilometer traveled, making it the most effective strategy among those tested. However, it's important to note the overall efficiency of trucks remains a concern. The efficiency measured by the capacity utilization of each truck route is relatively low. This suggests that there's still significant room for improvement in optimizing route planning and vehicle loading. One contributing factor could be the limited cluster size, which, while a necessity to manage the computational load of NP-hard vehicle routing problems, inherently restricts the capacity utilization per truck. Trucks may be departing with suboptimal loads, leading to a higher number of routes and, consequently, reduced overall efficiency.

Secondly, despite it is not the goal of this research, a major finding is the fact that sub-clustering emerges as a highly effective strategy to enhance the precision of the Daganzo approximation. By breaking down larger clusters into sub-clusters, and approximating the delivery area more precisely, the approximation's accuracy in estimating the necessary kilometers for delivery becomes significantly refined. This refinement is evident in the reduced kilometers driven according to the Daganzo approximation when sub-clusters are utilized as the basis for calculation, compared to larger, more inclusive cluster models. This indicates that sub-clustering, by its very nature of creating more geographically compact groupings, can lead to a more accurate and efficient vehicle routing process that is closer to the ideal minimal routing distances as predicted by theoretical models.

7.2. Sensitivity analysis

In this section different scenarios for the network model and the vehicle routing model. By testing the model on different scenarios, the sensitivity of the model, how the model works, and the potential impacts of different input parameters can be identified. This could serve as potential input for managerial decisions on certain investments or implementations of the model. For the network model, different input values for the reefer capacity and the transshipment costs are tested since these have the most impact on the kilometer savings and additional operational cost performance indicators of the network model according to the formula set up. The following scenarios are tested:

- Reefer capacity of 350 hectoliters, an increase of 17% against the base case
- Reefer capacity of 400 hectoliters, an increase of 33% against the base case
- Transshipment cost decline with 20%
- Transshipment cost decline with 10%
- Transshipment cost increase with 10%
- Transshipment cost increase with 20%

For the vehicle routing model the difference in input data is partly responsible for the different performances of the cluster methods. Therefore, the choice is made to execute the vehicle routing model again with the northern cluster data of the center of gravity method. So, if we look at the vehicle routing data flow in Figure 6.2 steps 1 to 3 are now performed with the center of gravity data for all methods. In step 4 the different methods for sub-clustering are used again. The characteristics of the northern cluster are the same since the same input data is used. Also, the amount of sub-clusters, which can be determined on the forehand, is set to 16 for all methods.

7.2.1. Network model sensitivity analysis

The network model sensitivity analysis have impacts on the performance of the network design. The performance of the network in the different scenarios is divided into the savings in kilometers and the additional operational costs. For both indicators, the effects of the scenarios are discussed.

Savings in kilometers

The savings in kilometers are only affected by the change in reefer capacity since a higher capacity will decrease the logistic activity to the hub locations and not by changes in transshipment cost. Therefore, only the reefer capacity sensitivity analysis is discussed.

Clusters	COG	p-median	k-means
2	443769	237413	236505
3	575424	588185	588580
4	633037	629934	624260
5	679703	662163	630536
6	701839	682237	661027
7	707961	703653	672065
8	710278	708773	682432
9	713174	712322	685866
10	715214	714550	691039

Table 7.2: Savings kms by clustering method

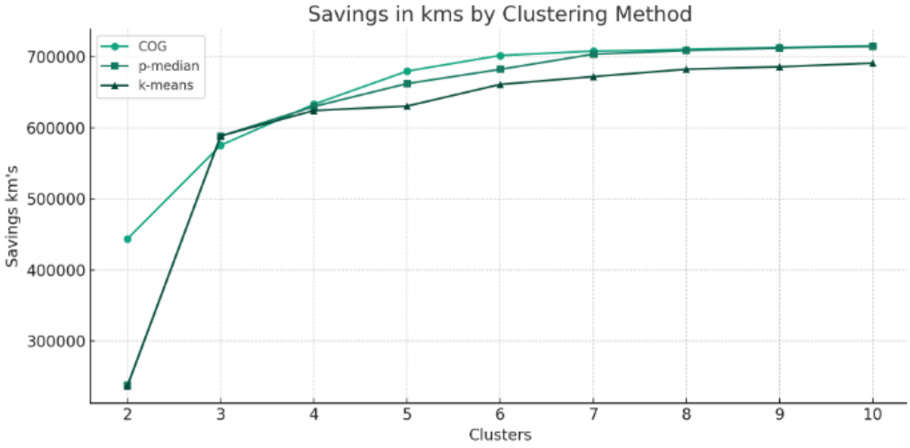

Figure 7.3: Savings in kms by clustering method

The reefer capacity has an effect on the savings in kilometers since it consolidates the amount of product that was transported by multiple vehicles into one vehicle. The truck-to-reefer ratio influences the amount of kilometers that are saved. To show the effect of the reefer capacity on the savings in kilometers the following formulas are discussed:

- **Kilomters driven without hubs:** These are the kilometers driven without the use of reefers and hubs from the depot to the centers of the clusters.

$$D_{se} = \left(\frac{Q_c}{Cap_t}\right) * D_d * 2 \tag{7.2}$$

- **Kilometers with hub:** Represents the reduced distance when employing a hub, assuming efficiency scales with the truck-to-reefer capacity ratio. Here the reefer capacity has an impact on the kilometers driven with hubs.

$$D_{te} = D_{te} * \left(\frac{Cap_t}{Cap_r}\right) \tag{7.3}$$

- **Savings in kilometers:** The net distance saved by using a hub system.

$$D_s = D_{se} - D_{te} \tag{7.4}$$

Table 7.3 shows the truck/reefer ratios the difference for each scenario, where the effect of the higher reefer capacity on the ratio is increased by respectively 17% and 33%.

Reefer capacity	Truck capacity	Reefer/truck ratio	Delta ratio
300	105	2.86	0%
350	105	3.33	17%
400	105	3.81	33%

Table 7.3: Truck/reefer ratios

Clusters	Base case	Reefer capacity (350)	Reefer capacity (400)
2	443769	477905	503507
3	575424	619687	652884
4	633037	681731	718253
5	679703	731987	771202
6	701839	755826	796318
7	707961	762421	803264
8	710278	764915	805894
9	713174	768033	809179
10	715214	770231	811493

Table 7.4: Analysis of Reefer Capacities savings in kilometers - COG

Clusters	Base case	Reefer capacity (350)	Reefer capacity (400)
2	237413	255676	269373
3	588185	633430	667364
4	629934	678391	714733
5	662163	713098	751301
6	682237	734717	774077
7	703653	757780	798376
8	708773	763294	804186
9	712322	767117	808213
10	714550	769514	810740

Table 7.5: Analysis of Reefer Capacities savings in kilometers - p-median

Clusters	Base case	Reefer capacity (350)	Reefer capacity (400)
2	236505	254698	268342
3	588580	633855	667812
4	624260	672281	708296
5	630536	679039	715418
6	661027	711876	750012
7	672065	723763	762534
8	682432	734927	774299
9	685866	738625	778193
10	691039	744193	784063

Table 7.6: Analysis of Reefer Capacities savings in kilometers - k-means

Base case	Reefer capacity (350)	Reefer capacity (400)
0%	8%	13%

Table 7.7: Analysis of Reefer Capacities savings in kilometers percentual

The outcomes of both scenarios for the three methods, the effect of the reefer capacity on the savings of kilometers is the same. For the reefer capacity of 350, the savings in kilometers go up by 8% for all cluster counts and by 13% for the scenarios with a reefer capacity of 400. It means that a bigger capacity for the reefers has a positive effect on the savings in kilometers, which was expected. However, the capacity of the reefer doesn't correspond directly with the savings in kilometers since the reefer capacity in both scenarios respectively go up by 17% and 33%. Therefore, in the next subsection, the additional cost savings from the savings in kilometers should be analyzed precisely to see if an investment in reefers with a higher capacity is beneficial.

Opertional costs

The effect of the different scenarios on the additional operational costs is shown in the tables below. The percentual change of additional operational costs in comparison with the base case of Table **??** are shown per method.

From the outcomes of the sensitivity analysis, it can be clearly stated that the reefer capacity and the transshipment costs have a major effect on the additional operational costs of the network design. A notable trend is the diminishing percentual change in additional costs as the number of clusters increases.

Moreover, the methodological differences between center of gravity, p-median, and k-means provide insightful variations in cost implications, emphasizing the importance of selecting an appropriate network design strategy tailored to specific operational objectives. Each method's response to the different scenarios underscores the value of robust scenario analysis in guiding strategic decision-making to optimize network designs.

The additional operational cost breakdown is discussed, but the effect of the different scenarios on the additional operational cost is not discussed yet. The following formulas affect the different operational costs:

- **Cost savings in kilometers:** Financial savings from decreased travel, emphasizing the economic benefit of the hub.
$$C_{savings\_km} = D_s * (C_{km} + W_{km}) \tag{7.5}$$
- **Transshipment cost:** Expenses incurred at the hub for goods transfer between transportation modes.
$$C_{trans} = \left(\frac{Qc}{Cap_t}\right) * C_{trans\_unit} \tag{7.6}$$
- **Transport and cleaning cost:** The comprehensive costs for additional transport for materials and cleaning at hub locations.
$$C_{tc} = 2 * 52 * (D_{rt} * (C_{km} + W_{km})) + N_{trips} * (C_{rt} + C_{ru}) \tag{7.7}$$

The transportation costs scenarios only have a direct effect on the transshipment costs, therefore these scenarios are not discussed in more detail. The reefer capacity scenarios affect multiple operational cost formulas as discussed. The cost savings in kilometers are driven by the savings in kilometers, the cost per kilometer, and the wage per kilometer. Next to this effect, the reefer capacity also has an effect on the transport and cleaning costs. The number of trips is affected by the reefer capacity since the demand of a certain cluster can be shipped to the hub locations with fewer transport movements.

- **Number of reefer trips:** The required trips to satisfy the demand, highlighting the logistical load on the hub.
$$N_{trips} = \left(\frac{Q_c}{Cap_r}\right) \tag{7.8}$$

Tables **??** and **??** show the percentual difference in the three additional cost parts for both reefer capacity scenarios for the center of gravity method. The percentual differences for the other methods are proportional to the differences in network characteristics. The cost savings in kilometers are in the same proportions as the kilometer savings which was expected and the differences in both scenarios are also proportional to the difference in capacity. As expected the cost savings in kilometers are directly influenced by the savings in kilometers and therefore the percentual effect is the same as the effect on the kilometer savings. The effect on the transportation and cleaning costs declines as the cluster count increases. This indicates that the number of trips does affect the transport and cleaning costs but its share decreases since the round trip distance gets higher when there are more hub locations.

7.2.2. Vehicle routing model sensitivity analysis

Performance

Table **??** shows the total amount of kilometers for each method. Here the center of gravity method performs best, followed by the k-means method. What is interesting to see is the difference in the values of the Daganzo approximation using the sub-clusters. The different methods are used for the sub-clustering and according to the Daganzo approximation, the p-median needs fewer kilometers to supply all customers. If we look at the Daganzo performance indicator we see that the p-median scores less than the center of gravity- and k-means method. This means that in ratio the p-median performs less than is expected from the Daganzo approximation.

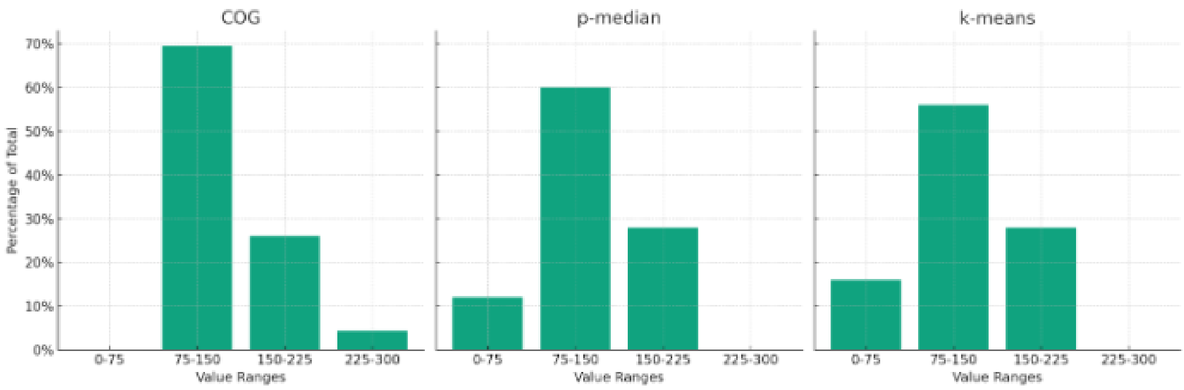

Figure 7.4: Distribution route distances COG scenarios

In terms of additional operational costs the center of gravity outperforms both other methods. The center of gravity method also performs better on the truck performance indicators. Fewer trucks are used to supply the customers and therefore also the capacity of the truck that is used is higher for the center of gravity method.

It is difficult to compare the kilometers that are driven in this modeling scenario with the kilometers that were actually driven last year to supply the customers that are part of this dataset. Mainly because there are customers that are not in the northern cluster that were supplied in the same routes in 2023 and other potential reasons for extended routes, like emergency deliveries. Still, this comparison indicates the savings in kilometers that can be established when creating a two-echelon network, including the constraints of the vehicle routing.
As can be seen from Table **??** the savings due to the established two-echelon network in this comparison are more than 9000 kilometers on the routes of this one week in May 2023. Of course, the demand that is supplied with the 2023 routes is higher but even when adjusting for this demand the kilometers that could potentially be saved is still over 5000 kilometers.

7.2.3. Conclusion

In summary, the sensitivity analysis has explored the complexities and outcomes of vehicle routing and network design within the context of delivering a specified product, tank beer, using electric vehicles. Through rigorous application and analysis of different clustering methods and subsequent vehicle routing, several crucial insights have emerged.

Moreover, the reduction in transshipment costs is identified as a pivotal element in diminishing additional operational expenses. This finding accentuates the importance of streamlining logistics processes to achieve cost-effectiveness, thereby reinforcing the value of investing in more efficient transshipment facilities and technologies. Additionally, the expanded reefer capacity demonstrates a dual benefit by positively impacting additional costs and savings in kilometers due to better consolidation of transshipments between the depot and the hub locations. This observation suggests that investments in reefer technology and capacity are not merely operational enhancements but strategic assets that can drive down costs while boosting service levels.

In the realm of vehicle routing, the center of gravity method distinctly outperforms other techniques when tested with identical data inputs. This superiority highlights the method's effect in optimizing route planning to further enhance kilometer savings and operational efficiency. However, despite these advancements, the efficiency of the trucks remains an area requiring attention. The low utilization rate suggests the potential for improvement, possibly through better load management or larger customer sets. Also, the center of gravity has more routes with fewer kilometers in comparison with the other two methods. Lastly, the distribution of brands, predominantly limited to one or two per delivery, points towards a narrow product mix being transported. This finding may indicate opportunities for diversification in transport strategies, such as mixed loads, which could lead to better asset utilization and customer service.

These insights collectively illuminate the path forward for Heineken and similar enterprises aiming to refine their distribution strategies. Embracing technological advancements, optimizing vehicle capacities, and streamlining costs are pivotal steps toward achieving sustainability and efficiency in the competitive landscape of logistics and distribution.

8 Discussion

In the discussion chapter, the focus is on the conclusions from Chatper 7. It's essential to interpret the implications of the findings, acknowledge the limitations inherent in the study, and identify opportunities for future research.

8.1. Discussion

The results in Chapter 7 illustrate the higher performance of the center of gravity method in achieving significant kilometer savings and operational efficiencies in network design. It has to be stated that the differences in performance are not drastically big in both the base case, the sensitivity analysis, and the experiment. Particularly, the initial addition of hubs produced substantial savings, however, it is clear that after a certain point, further additions of hub locations had a diminished impact on kilometer savings. This observation suggests an optimal number of hubs exists beyond which the benefits plateau. This has considerable implications for strategic network design and underscores the need to find a balance between the extent of the two-echelon network and the returns on investment in terms of kilometer savings. Section 7.1 also shows the importance of the initial placement of hub locations. Due to the model setup, where the savings in kilometers are calculated with the distances between the brewery and a hub location and the demand of that specific cluster, the calculated savings can differ quite a lot between the different methods. This effect levels out when adding more hub locations. With regard to the reefer capacity experiments, the percentual changes in kilometer savings are equal for all methods, but the ratio of capacity enlargement is higher than the effect on the total kilometer savings due to the no effect on the kilometers driven without the implementation of hubs, which are part of the kilometer savings calculations.

With regard to the vehicle routing, the center of gravity again outperforms the other two methods. The best comparison can be made between the outcomes of the models when the center of gravity network design is used for the different vehicle routing methods. Here the center of gravity method outperforms the other methods and ensures fewer kilometers driven, less operational costs, and the usage of fewer trucks to supply all customers within the cluster. The implementation of sub-clustering as a strategy to enhance the precision of the Daganzo approximation for vehicle routing yields insights into the potential for better high-level approximations for vehicle routing performance, but this finding does not affect the performance of the model. This vehicle routing model points to the value of creating more compact and geographically sensible customer groupings to facilitate route planning. For the number of brands that are transported per truck, it can be stated that mostly there are one to two different brands transported, potentially giving insights into the opportunities of other tank configurations within the trucks, instead of using three different compartments.

Section **??** showcases that the driven kilometers for the two-echelon network are significantly less than the kilometers driven last year to supply the same customers. It highlights the benefits of a two-echelon network and the compliance of the performance of the model that is created in this research.

8.2. Limitations

This study, while providing valuable insights by the development of a two-echelon location-routing model, faces several limitations which highlight the need for caution in interpreting the results and need to be discussed.

Firstly, the overall limitations of modeling in this context are notable. Modeling, by its nature, simplifies real-world scenarios to fit within computational and theoretical frameworks. This simplification means that not all factors, especially those unpredictable or external, are accounted for. Such limitations can lead to discrepancies between modeled outcomes and real-world experiences, particularly in the dynamic and complex field of logistics and distribution.

The method of calculating kilometer savings and operational cost savings has its limitations. The calculations are heavily dependent on the model's assumptions and input data, such as the distances between hubs and customers and the specific demands of each cluster. Also, the study highlights the high effect of cluster characteristics on the outcomes, including the hard rule that a customer must be served from a specific hub location. This rule can restrict the flexibility of the distribution network, potentially leading to inefficiencies or increased costs in scenarios where alternative hub assignments could be more effective. These calculations might not fully capture the nuances of real-world operations, such as varying road conditions, traffic patterns, and vehicle performance, which can affect actual savings.

The use of specific customer data for the Heineken case brings to light another limitation. While this data provides a concrete foundation for the study, it also means that the findings are particularly tailored to Heineken's operations and may not be directly applicable to other companies or industries without significant adjustments. This specificity can limit the generalizability of the study's conclusions.

Lastly, the computational boundary of the vehicle routing presents the most significant limitation. The complexity of vehicle routing problems increases exponentially with the addition of more customers and constraints, making it computationally challenging to find optimal solutions for large-scale operations. This limitation not only restricts the solution space but also creates boundaries for the number of customers that can be added to one experiment. As a result, the study's findings may be constrained by the computational capabilities available, preventing exploration of potentially more effective distribution strategies that lie beyond these computational boundaries.

8.3. Further research

To expand upon the discussion, the potential for future research is discussed. Several subjects are suggested that could further enhance the understanding and efficiency of this research topic.

This research only runs the vehicle routing model on the data of one specific week for Heineken tank beer demand. Also, the network design is based on the Heineken tank beer data of 2023. Diversification of data could provide insights into the adaptability of the two-echelon network model, highlighting the potential need for model adjustments to cater to specific operations. This exploration could also create insights into seasonal variations in logistics demands, offering a more comprehensive understanding of the challenges and opportunities in logistics and distribution networks.

Given the NP-hardness of the vehicle routing problem identified in this study, there is a need to overcome this computation boundary. The development of heuristics could be beneficial for this type of research. These heuristics would aim to provide near-optimal solutions within a reasonable computational time, thus overcoming the inherent computational challenges. The focus could be on creating algorithms that account for the unique characteristics of the distribution network, such as the specific constraints of electric vehicle routing for bulk liquids, including range limitations, charging requirements, and compartment usage.

The efficiency of routing could potentially be improved by clustering customers not solely based on geographic locations but also considering other characteristics, such as customer demand patterns, the brand types being delivered, or specific customer preferences for delivery times. This approach could lead to more efficient route planning and reduced operational costs. Future studies could explore the implications of such clustering strategies on the overall performance of the distribution network.

An intriguing area for further research is the investigation of the potential benefits of intermediate charging opportunities at customer locations. Given the extended service times at certain delivery points, there is a possibility to utilize this time for charging electric vehicles, thus extending their range and operational efficiency. This strategy could potentially enable non-stop deliveries by mitigating the need for overnight charging, thereby increasing the utilization and efficiency of the fleet. Since customers for tank beer mostly have multiple suppliers, including suppliers for their food and other products, tank beer trucks are not the only truck that stops at their location. Wireless charging of electric vehicles, where there does not have to be a physical connection between the vehicle and the charging device, has gained interest in the last few years. In short, the vehicle parks above a wireless charging transmitter, and by means of a receiving part in the vehicle, the vehicle will be charged [46]. When these locations are used by multiple suppliers it could be benificial. Future studies should examine the feasibility, cost implications, and logistical challenges of implementing intermediate charging stations, including the potential need for partnerships with customers or third-party providers.

The exploration of these areas not only addresses the limitations identified in the current study but also opens up new pathways for innovation in the field of logistics and distribution. By focusing on these subjects, future research can contribute to the development of more resilient, efficient, and sustainable distribution networks.

9
Conclusion

9.1. Conclusion

In the pursuit of sustainable logistics solutions within the increasing emission regulations for transportation, this research embarked on an exploration of optimizing a two-echelon location-routing network tailored for the distribution of bulk liquids using electric vehicles. At the core of this study were two intertwined research objectives: firstly, to design an optimized logistics network that leverages the benefits of a two-echelon system, and secondly, to develop a vehicle routing strategy that maximizes the efficiency and sustainability of electric vehicle use for bulk-liquid transportation. A Heineken case study was applied to the model and generated outcomes and valuable insights. This section aims to draw conclusions from the research and answer the main research question:

”How can a logistic network and truck operations for the delivery of bulk liquids be optimized by implementing a two-echelon network, when transitioning to electric vehicles, aligning with sustainability goals and regulatory constraints, while ensuring efficient operations?”

The research hinged on a two-step optimization process, a methodological approach designed to dissect and address the complex logistics problem systematically. The first step of the model researched multiple clustering techniques for the placements of hub locations, designing a two-echelon network. The initial phase of network design utilized three clustering methods, the center of gravity method, the p-median method, and the k-means method. The center of gravity method outperformed the other methods, saving more kilometers and having less additional operational costs. The main reason for this performance is the ability to factor in the depot’s location from the starting point. This capability proved crucial, not only for the strategic clustering of customers but also for the initial placement of satellite facilities which affected the overall performance of the network. It became evident that the placement of hub locations is instrumental in dictating the overall efficiency and effectiveness of the logistics network. By integrating the depot location in the first stage of network design, and the nature of the center of gravity, combining distance and demand, the profound impact of foundational decisions on the subsequent operational logistics framework.
Next to kilometers savings, the two-echelon network design also brings additional operational costs due to extra handling in the transportation network. A significant revelation of this study was the substantial financial implications posed by transshipment costs. These costs emerged as a big challenge, exerting considerable pressure on the feasibility of the two-echelon network. The financial strain introduced by transshipment underscores the need for innovative solutions aimed at reducing these costs to ensure the economic viability of the proposed logistics model.

Furthermore, the experiments conducted revealed the reefer capacity’s critical role in the network’s performance. Increasing the capacity of reefers, thereby consolidating more goods for transport from the depot to the hub locations, was identified as a particularly effective strategy for achieving savings in kilometers and reducing operational costs. This finding emphasizes the potential benefits of optimizing reefer utilization within the logistics network. Also, the different scenarios impacting the transshipment cost, which is bounded by the time it takes to pump liquids from reefers to trucks, have a major impact on the operational costs. The exploration of methods to streamline or optimize the transshipment process could significantly decrease operational expenses, pointing to an area for potential investments for Heineken. Therefore, it can be stated that a two-echelon network for bulk-liquid transportation brings a lot of uncertainties. The operational costs of the model are really volatile for changes as for positive and negative changes. It is of great importance to understand the volatility of the additional handling when developing a two-echelon network.

The second part of the research model focused on vehicle routing, where the specific operations of multiple bulk-liquid transportation with electric vehicles with multiple compartments were addressed. This part incorporated sub-clustering to generate viable data sets for vehicle routing due to the NP-hardness of the vehicle routing problem. The meticulous application of sub-clustering not only facilitated the creation of input for the vehicle routing experiments but also significantly improved the accuracy of the Daganzo approximation outcomes, underscoring the technique's potential in refining high-level estimations of vehicle routing performance in logistic networks.

The center of gravity method's application within vehicle routing emerged as the most effective strategy, yielding the best outcomes in terms of operational efficiency, scoring the best on the performance indicators, traveling fewer kilometers to supply all customers, and decreasing operational costs. However, the realization of the trucks' relatively low efficiency, is a finding attributed to the computational constraints imposed by the vehicle routing process, notably the maximum limit of ten customers per route. This limitation, coupled with the observation that vehicles predominantly transported one or two brands despite having the capacity for three, suggests an opportunity to re-evaluate truck configurations. Exploring alternative configurations, such as trucks with two compartments, may offer pathways to enhance operational efficiency and better utilize vehicle capacity.

Furthermore, in the Heineken case the routes designed are compliant with the 300 km range constraint of electric vehicles, it's notable that in the six-cluster setting, some routes are already surpassing 225 km. This proximity to the upper range limit warrants attention as reducing the number of clusters thereby increasing cluster sizes could pose challenges when operating with electric vehicles. Such changes might lead to routes that exceed the electric vehicles' range capability, raising concerns over the feasibility and sustainability of the transportation model. A careful balance must be struck to ensure that the operational modifications do not impede adherence to the range constraint, which is a critical component of the logistical framework. Also, adaptability with regard to changes in electric vehicle range capacities in the future needs to be ensured. The network design and the vehicle routes are influenced by this limited factor and need to be carefully reiterated when changes in the range constraint of electric vehicles occur.

In conclusion, this research presents a detailed framework for refining a two-echelon location-routing logistics network specifically tailored for the distribution of bulk liquids with electric vehicles. The research thoroughly addressed the primary questions through a structured two-step optimization model, showcasing the intricacies and prospects within the construction of sustainable logistics systems. This model incorporated an initial phase of network design, which demonstrated the superior performance of the center of gravity method over other clustering techniques. Crucially, the study highlights the importance of identifying the optimal number of hubs, a tipping point where distance savings are nearly maximized without incurring unnecessary additional operational costs. Also, the effect of higher capacity reefers and faster transshipment times can have a major positive impact on the additional operational costs of a two-echelon network and provide great opportunities for Heineken.

The subsequent vehicle routing phase took on the challenges posed by the NP-hard nature of the problem, employing sub-clustering as an effective strategy to craft feasible routing plans. This approach also served to enhance the accuracy of the Daganzo approximation, further substantiating its validity in high-level logistics planning. Next to this, the MILP model is showcased to grasp all specific constraints of the transportation of bulk liquids.

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A
Heineken sustainability

While logistics plays a pivotal role in the value chain, it's important to acknowledge that it also leaves behind a carbon footprint. In 2021 Heineken announced their Brew a Better World 2030 strategy, which has three pillars that guide Heineken on their path to zero impact on the environment, an inclusive fair, and equitable world, moderation, and no harmful use. The main goal of Heineken with regard to sustainability is to reach net-zero carbon emissions by 2040. Other near-term targets are to reach net-zero in scope 1 and 2 emissions and reduce scope 3 emissions by 21% by 2030 [22]. Heineken's calculation scope and principles are compared to the requirements of three relevant protocols: the GHG Protocol Product standard, the GHG Protocol Corporate Standard (scope 1 and 2), and the GHG Protocol Corporate standard (scope 3). Heineken accounts for relevant GHG emissions along its production: carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), sulphur hexafluoride (SF6), perfluorocarbons (PFCs), and hydrofluorocarbons (HFCs). Heineken has worked closely with BIER (Beverage Industry Environmental Roundtable) to develop GHG emissions sector guidance to standardize GHG reporting. Logistics covers both inbound transport of raw agricultural inputs, processed inputs, and packaging materials to our breweries as outbound distribution of beverages to the point of sale consumer, and warehouse energy consumption. It includes the logistics network, both controlled and not controlled by Heineken, to get the finished product to the point of sale and back, with returnable packaging. In 2022, logistics is still 11% of the whole carbon footprint [50].

Heineken strives to report the Carbon Footprint as accurately, consistently, and completely as possible. Due to inherent limitations in relation to the uncertainty of measurement equipment and/or availability of actual data, Heineken applies extrapolations and uses estimates, assumptions, and judgments in reporting. Estimates, assumptions, and judgments are based on historical data. Data, certificates, or emission factors applied may be provided by other parties such as vendors or specialized firms. The following significant estimates are used to report the emissions of Heineken:

- To calculate emissions of production operations, data provided by energy and fuel suppliers is used. If this data is not available, the 2006 IPCC Guidelines for National Greenhouse Gas Inventories for emission factors of fossil fuels are used, most recent International Energy Agency data, for country grid emission factors, and the Department for Environment, Food & Rural Affairs (DEFRA) emission factors for biofuels.
- The transport emissions reporting has limitations for all transport modes. For fleets within the control of Heineken, fuel-based data is used in countries where telematics systems are in place. For contracted partners, Heineken receives data on kilometers driven and the type of vehicle used, and emissions are calculated based on a Global Logistics Emissions Council (GLEC) framework-accredited emission factors in g CO2-eq/km. For contracted partners where data on distance traveled is not available, calculations are based on estimates. For inbound transport, emissions are calculated for the biggest categories such as glass bottles, aluminum cans, malt, and adjuncts.
- Emissions at outsourced logistics sites also have limitations. For such sites where data on electricity consumption and fuel consumption for Forklift trucks is not available, estimations are used.

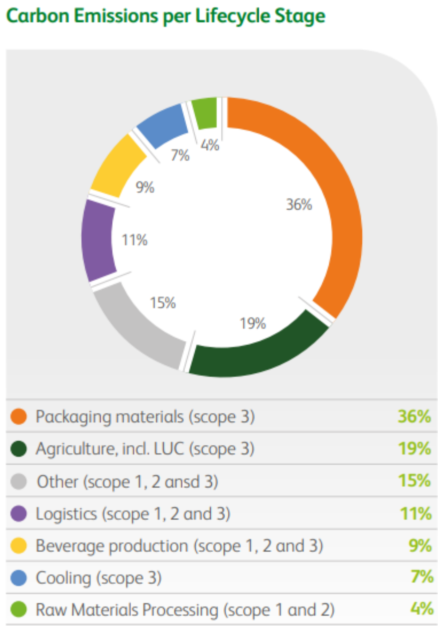

Figure A.1: Carbon Emissions per Lifecycle Stage Heineken 2022

- Packaging emissions are based on a circular carbon footprint formula incorporating upstream production, use, and end of life of the product. As glass bottles and aluminum cans are Heineken's most significant emissions contributors, suppliers making up 80% of these emissions provide information about the carbon intensity of their production locations supplying Heineken. For the remainder of our Packaging materials, an industry-approved Product Environment Footprint Category Rules (PEFCR) emissions factor is applied.
- Agriculture and processing emissions reporting has limitations. External party inputs for Land Use Change (LUC) emission factors per country and per crop. Based on the available data per supplier shed base and per crop in the external party database, a weighted average emission factor per crop is calculated. This weighted average emission factor is applied to calculate the emission per crop for all countries. For processing, data is collected from suppliers. In case there is no data available, the emission factor per material group is estimated.
- To calculate cooling emissions, the lifetime of fridges and Draft Beer Equipment (DBE) is assumed to be seven years. We calculate DBE emissions based on the actual number of DBEs in the market. Emissions of fridges are based on the total number of fridges purchased in the last 7 years (2016-2022). Also, home cooling emissions are estimated based on the volume sold via non-keg pack types and the percentage sold via home cooling versus fridges. For goods purchased for resale, it is assumed that these have a similar carbon footprint as Heineken-produced products. For assets under construction, it is assumed that these have a similar carbon footprint as current capitalized assets. For employee commuting distance and methodology, regionally produced government statistics are used.

B
Zero-emission zones regulations

One of the key drivers to electrify the deliveries that are subject to this research is the zero-emission zones that are introduced within inner cities. A precise overview of the regulations is given below.

B.0.1. Regulations

The transportation sector in the Netherlands is undergoing a transformative shift towards sustainability, propelled by an emergent framework of regulations designed to mitigate environmental impact. Central to this transformation is the introduction of Zero-Emission Zones (ZEZs) within urban landscapes. Effective from the 1st of January, 2025, these zones epitomize an ambitious governmental directive to curtail vehicular emissions, specifically targeting particulate matter and CO2 (Business.gov.nl, 2024). The ZEZ initiative delineates city centers and adjoining neighborhoods as areas where only vehicles devoid of emission outputs—namely electric or hydrogen-powered—are permissible (Business.gov.nl, 2024).

Accompanying the ZEZs are Transitional Regulations that allow a phased integration of emission standards. Vehicles conforming to Euro 5 and Euro 6 emission criteria have been granted extensions until January 1, 2027, and January 1, 2028, respectively, with certain Euro 6 trucks being given a leeway up to January 1, 2030 (Business.gov.nl, 2024). These temporal provisions acknowledge the logistical and economic challenges of immediate compliance while maintaining a trajectory towards emission-free transport.

In parallel, a system of Exemptions and Dispensations seeks to balance the rigorousness of ZEZs with pragmatic considerations for vehicles not meeting the stipulated emission standards. These allowances facilitate the continued operation of heritage vehicles and those outside the transitional regime, subject to specific conditions (Business.gov.nl, 2024). Financial stimuli, such as the Subsidy scheme for zero-emission commercial vehicles (SEBA), underscore the government's commitment to incentivize the transition. These economic measures aim to offset the cost differentials associated with procuring emission-free commercial vehicles, nudging enterprises towards modernizing their vehicular assets (Business.gov.nl, 2024).

The harmonization of Low Emission Zones (LEZs) is another pivotal stride, aligning with European emissions standards since January 1, 2020. The LEZ framework classifies zones into 'yellow' and 'green' standards, based on the Euro emissions benchmark, with an upward adjustment anticipated in 2025. A 'purple' zone, applicable to trucks adhering to Euro 6 standards, is slated for implementation from 2022 onwards (European Commission, 2020).

Furthermore, municipalities are empowered to enforce Access Regulations, introducing car-free zones and transit bans to alleviate urban congestion and atmospheric pollution (urbanaccessregulations.eu, 2024). In essence, the Dutch transportation policy reflects a holistic and forward-looking approach, intertwining regulatory rigor with adaptive mechanisms to facilitate a transition to a low-carbon future. The regulations manifest an acute awareness of the ecological exigencies of urban transport, establishing the Netherlands as a vanguard of environmental stewardship within the sector.