Redesign of the Car Distribution Process: a Dutch case study

A Holistic Approach in a Capacitated Vehicle Routing Problem to Reduce Direct CO_2 Emissions

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March 2024

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Redesign of the Car Distribution Process: a Dutch case study

A Holistic Approach in a Capacitated Vehicle Routing Problem to Reduce Direct CO_2 Emissions in a Truck-Based Car Distribution Process

by

W.S.Koopal

to obtain the degree of Master of Science
at the Delft University of Technology
to be defended publicly on Wednesday March 27, 2024 at 10:15 AM.

Master thesis

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Date defended	March 27, 2024
Report number	2024.TIL.8908

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Preface

This master thesis marks the milestone for the end of my Master's in Transport, Infrastructure, and Logistics at Delft University of Technology. To conduct this thesis, I closely collaborated with Pon Automotive, an import company of the Volkswagen group. This partnership was the perfect blend of my keen interest in cars, logistics processes, and my academic skills. The practical data from Pon, conversations with experienced specialists, and access to information about certain decisions have been of significant value. As Pon works closely with transportation companies and dealer holdings, an overarching perspective was applied. I had the freedom to visit various dealer locations, work together with specialists for multiple days, and use Pon's contacts. As a result, well-founded adjustments have been identified, substantiated, and validated at the stakeholders. Thanks to the excellent collaboration with Pon, I was able to investigate aspects of the distribution process that Pon currently needs. The findings of this study serve as the foundation to reduce direct CO_2 emissions in the short term, helping Pon advance towards CO_2-neutral auto distribution.

This thesis would not have been possible without my graduation committee. I would first like to thank Jan van Assen for his help in specific knowledge, new insights, and assistance in finding suitable approaches. I truly valued our pleasant meetings, and your engagement with my research helped me enormously. It was a pleasure working with you. Additionally, I want to thank my second supervisor, Maarten Schneider, for his business-minded and critically sharp comments that increased the value of my research. Also, I'd like to thank the people of Dealer and Sales Support for their support, enjoyable moments, and open culture.

Furthermore, I want to thank Jaap Vleugel for the excellent collaboration during my thesis. I value the direct and to-the-point feedback, supportive advice, swift communication, and the meetings that began with a half-hour of catching up before talking about my research. Second, I want to thank Frederik Schulte for the supportive feedback, professionalism, and insights into suitable methods for my research. Your advice consistently challenged me, adding significant value to my research. Also, I am thankful for the guidance of Rudy Negenborn, which included insightful critiques and valuable advice, assisting in the refinement and improvement of my work.

Finally, I want to extend a special thanks to my parents for their endless support throughout my entire study period.

Enjoy reading this research.

W.S. Koopal
Amsterdam, March 2024

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Summary

The dynamic automotive industry is characterized as one of the largest goods movement industries. Large amounts of cars are imported by countries, especially in the Netherlands. Annually, 320 thousand new cars are imported in the Netherlands [73]. The COVID-19 pandemic affected car production, but in 2022 a 17.8% increase in car registrations is reached. However, this resurgence has presented challenges, as the adaptability of the supply chain is difficult due to standardized procedures [56] [38]. This results in inefficiencies, also affecting the car distribution processes. The majority of the cars is transported by truck due to the flexibility in routes [6]. In the Netherlands, after the import of cars, all cars are distributed to car dealers by trucks. From environmental point of view, trucks and busses are responsible for 28% of the direct CO_2 emissions from road transport in the EU. Therefore, in 2019, the European Parliament published a regulation establishing CO_2 emission reduction targets for the entire heavy-duty vehicle fleet by 2030, and companies must prove starting implementing new measures by 2025 [72]. Tailored supply chain strategies and improved route planning could help for short-term improvements.
The need for these improvements is emphasized by the the short-term targets of the European Commission [72], but scarce emphasizes is provided on short-term alternatives in truck-based distribution processes of cars in literature. Especially, research is done from specific perspectives of stakeholders, but a holistic approach lacks. This gap is particularly critical in light of the need to develop improvement plans by 2025 to reduce future direct emissions [72]. In additions, evaluation methods applicable for the car distribution processes on large scale lacks. Due to the complexity and size of Capacitated Vehicle Routing Problems (CVRP), modeling real world situations is complex. State-of-the-art meta-heuristics are suitable, but not directly in large scale car distribution processes, due to the need for a split delivery function as car dealers are served by multiple trucks.

This research addresses these gaps with (1) the identification of bottlenecks in the context of direct CO_2 emissions of trucks and (2) the contribution to literature with applying the state-of-the-art Hybrid Genetic Search meta-heuristic, specialized for a Capacitated Vehicle Routing Problem (HGS-CVRP), including a split delivery function suitable on large scale problems. This enables the evaluation of proposed short term improvement of in the truck based car distribution. The main research question was:

"To what extent can redesigning car distribution processes reduce direct CO_2 emissions emitted by transportation vehicles?"

This research is executed in three main phases, of the System Engineering (SE) framework of Dym, Brown, and Little [34]. First, in the **Problem Identification** the current state is mapped out and interpreted to identify bottlenecks and to formulate potential improvements. Second, a **Solution Approach** is developed, based on the current distribution processes, with the aim to develop an representative model of the system. This model is verified on small scale by comparing the performance with a benchmark, a CVRP model using an exact method including split delivery function. Third, the **Future Designs** with proposed improvements of the problem identification is evaluated by applying the model in a real-life situation.
The real-life situation is applied on the national car distribution in the Netherlands from distribution hub to car dealers, using a case study at Pon Automotive, the largest car import company of the Netherlands. The problem identification indicates that the three main stakeholders — the import company, the transportation company, and car dealers — are aiming to achieve their objectives but lack adequate collaboration. Limited route flexibility and daily transport executed by car dealers strongly contributes to redundant direct CO_2 emissions. These inefficiencies occur due to forced route constraints and a lacking car priority system on specific car details. These insights, in combination with the system functions and requirements, formed 2 new policies: Unlimited stops for transportation trucks and a priority system including the Not-Ride-Before (NRB) period of cars, to relax truck stops and reduce the dealer transport. With the development of the solution approach, the proposed policies are evaluated. The application

of the solution approach to case study at Pon Automotive demonstrates that modifying policies can have a significant effect on car distribution processes. Adding more flexibility to transportation vehicles leads to a decrease in CO_2 emissions by an average of 2.1%. Transportation trucks undertake fewer lengthy unnecessary routes because more trucks are making shorter trips. Car prioritizing based on the NRB-period, results in a 6.4% decrease in direct CO_2 emissions, as cars are prioritized to external locations or car dealers more efficiently. This highlights the effectiveness of aligning car dealer needs with distribution strategies. Both policies offer potential for improvements of the distribution processes and positive environmental impacts. However, the increase in the number of trucks used in Policy 1 may lead to higher operational costs, whereas Policy 2's reallocation of transportation responsibilities could streamline dealer operations and reduce dealer costs. Scenarios are designed to validate the model and identify improvement areas. Also real data is used to validate the model outcome on large scale. The expected growth in electric vehicle popularity strongly affects the number of transportation trucks because the influence of the load factor on truck capacity. Also, it is observed that the model's efficiency decreases when nodes relatively close tot the distribution center contains moderately a priori groups, potentially resulting in a reduced solutions space as diversity of solutions is a ranking criteria.

This research offers several recommendations for improving environmental impact, operational efficiency, and stakeholder collaboration in car distribution. For distribution companies, it is recommended to increasing transparency on NRB-periods of cars at the prioritization department of the central distribution hub. By prioritizing cars, based on the NRB-period, a direct CO_2 emission reduction of 6.4% can be achieved. Also, the communication and integration of these car details to production processes of manufacturers is recommended to minimize the risk of accumulation further down the supply chain. Transportation companies are recommended to reconsider the maximum number of stops to a flexible number of stops per route to potentially lower emissions by 2.1%. Also, provide car dealers with accurate delivery schedules, to align work schedules. Furthermore, consider the impact of more frequent stops on more potential damages and maintenance costs. Car dealers should enhance communication with distribution companies for more efficient car dealer capacity usage and align workforce schedules with delivery times. From a modeling perspective, incorporating time-related variables, extending the modeling time frame, and improving the Hybrid Genetic Search for the Capacitated Vehicle Routing Problem (HGS-CVRP) algorithm to include integrated split deliveries are recommended, instead of using dummy variables. Utilizing actual road distances, exploring the combination of E-trucks and self-driving cars, and researching the impact of geographical positioning on HGS-CVRP performance could further optimize distribution. Additionally, maximizing dealer capacity and exploring deliveries from external parking locations may offer further reductions in transport requirements. These recommendations aim to provide a comprehensive strategy for increasing the car distribution system while acknowledging the complexity and interdependence of the various stakeholders involved.

Contents

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Acronyms

CO_2eq	A metric measure used to compare the emissions from various greenhouse gases
CSRD	Corporate Sustainability Reporting Directive
CVRP	Capacitated Vehicle Routing Problem
GHG	Greenhouse gasses
HGS-CVRP	Hybrid Genetic Search algorithm, specialized for CVRP
HVO	Hydrotreated Vegetable Oil
IDEF-0	Integration DEFinition for Function - 0
KPI	Key Performance Indicator
NRB-period	Not-Ride-Before period
PDI	Pre-Delivery Inspection
SDCVRP	Split Delivery Capacitated Vehicle Routing Problem
TOC	Theory of Constraints
TPL	Transportation Parking Lot

Definitions

Case Study	Detailed analysis of a specific subject within its real context.
Central distribution hub	Central storage from where the cars are transported to dealer locations.
Dealer capacity	The available space at a car dealer.
Dealer holding	Overarching company, with multiple car dealers.
Dealer locations	The delivery locations (car dealer and external parking).
Dealer transport	The transport motions between car dealers and external parkings.
Exact Method	Precise algorithms seeking optimal solutions in routing and logistics challenges.
External parking	Extra storage for car dealers.
Key Performance Indicators	Quantifiable metrics used to evaluate success in achieving objectives.
Load Factor	Ratio of cargo volume to total vehicle capacity, based on size and weight.
Meta-heuristic	Approximate algorithms for finding near-optimal solutions efficiently.
NRB-period	”Not Ride Before” period. The contractual determined period a car cannot drive on the road.
Solution approach	Systematic approach to calculate and evaluate a system.
Split delivery	The model function to use multiple vehicles to serve a single location.
System Engineering	Systematic approach to developing and managing complex systems.
Transportation Van	Small vans owned by car dealers to distribute cars between external parkings and car dealers.
Truck	Transportation truck applied for car distribution.
Validation	Ensuring research findings’ applicability and correctness in real-world contexts.
Verification	Confirmation of research findings’ accuracy through empirical evidence.

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1
Introduction

This chapter introduces the research focusing on improving and redesigning the truck-based car distribution process with the aim to reduce the direct CO_2 emissions. First the background of this research is elaborated. Second, the scientific and practical background of the research is described, followed by the research scope. Consequently, the objectives, questions, and outline are described.

1.1. Background research

In the dynamic landscape of the automotive industry, importing vehicles plays a significant role in serving consumers efficiently end effectively. In the Netherlands, there are nearly 9 million registered vehicles, consisting of dozens of different brands [84]. With the recent declaration of bankruptcy of the only car manufacturer in the Netherlands, and considering 350 active automotive brands world wide, a large number of cars is imported [97]. Annually, 320 thousand new cars are imported in the Netherlands [73]. From 2020, COVID-19 has lead to a decrease in car production, mainly caused by personnel shortage and shortages of materials. As a result, a down-drop of new vehicle registrations for two years[64]. Currently, the number of car registrations in the European Union has increased by 17.8 percent between June 2022 and 2023 [83]. Germany, being Europe's largest passenger vehicle market, experienced a 24.8 percent year-on-year increase in car sales in 2023 [64]. However, due to relatively low production levels during the COVID-19 years, the supply chain is not configured to accommodate these significant differences in production. Car dealers and import companies are forced to rent additional inventory areas to store the cars temporally, and the delivery of the right vehicles to car dealers is time consuming.

Despite the large flow fluctuations, processes in the automotive sector are automated to fulfill the high demand for cars in each country, allowing for mass production [56] [38]. This strategy for car manufacturing uses diverse methods and techniques to achieve mass production, to ensure the creation of large quantities of standardized or similar items with uniform quality [56]. However, car manufacturers must be flexible as market trends, component availability and technological improvement results in varying fluctuations demand. For example, BMW allows modification up to seven days before productions at models with more than 1000 different configurations [18]. This results in a build-to-order production process of cars, maintaining a guaranteed outflow [38]. To align mass production as closely as possible with specific customer preferences, car manufacturers collaborate with import companies, to easily adapt to local market trends [47]. In the Netherlands, the five largest car importers are responsible for 63% of the country's car imports, receiving vehicles at their central hub, followed by the distribution to local car dealers [84] [13].

To avoid supply chain accumulation, the distribution of cars is crucial. Various modes of transport are used, with the majority being transported by truck due to the flexibility in routes, lower costs, and reliably predictable delivery times. It is stated by the Netherlands' largest car import company Pon Automotive, that 46% of cars are imported by truck, and all domestic transportation is distributed by truck.

From environmental point of view, trucks and busses are responsible for about 28% of the direct CO_2 emissions from road transport in the EU, accounting for only 2% of the vehicles on the road [72]. Hence, the European Union is mandating the reduction of direct CO_2 emissions in the transport sector to achieve the climate goals set for 2050 [75]. Without intervention, the number of trucks in the EU would have increased by 9% compared to 2010 by the year 2030 [37]. Therefore, in 2019, the European Commission published a CO_2 emission reduction target plan for the entire heavy-duty vehicle fleet in Europe [72]. This starts with an required emission reduction of 15% for heavy weight trucks by 2025 compared with 2019. In addition, companies are required to develop improvement plans by 2025 to reduce future direct emissions. Companies failing to report and comply to the prescribed standards will incur emission penalties [37].

Despite the environmental legislation, the environmental awareness among customers has heightened [25]. A growing segment of consumers now considers the environmental impact of their purchases, including the carbon footprint associated with the manufacturing and distribution processes [70] [45]. In recent years, shifts in consumer behavior towards environmentally sustainable practices have exerted additional pressure on the automotive industry to innovate distribution processes [70]. This change in consumer priorities has started a re-evaluation of traditional distribution models, with a stronger focus on reducing CO_2 emissions throughout the supply chain. According to the Sustainability Report 2022 of the Volkswagen Group, measures are taken to achieve future carbon-neutral logistics, with a priority of moving car shipments from road to rail [5]. Also, measures have already been implemented within the Dutch supply chain of the Volkswagen Group to achieve environmental reductions, such as using bio-diesel instead of regular diesel, practicing full truckload shipments, and limiting deliveries to a maximum of 2 locations per truck. These measures are necessary given the trend of an increasing number of vehicles to be transported [83].

The interplay between the tightening of environmental regulations and consumer expectations in sustainability highlights the urgent need for the automotive industry to adopt more sustainable distribution practices. This context sets the foundation for this research, which aims to explore innovative strategies for redesigning truck-based car distribution processes including perspectives of main stakeholders to align with short term environmental goals. By addressing and investigating distribution process bottlenecks, this research seeks to contribute insights into how these processes can be adapted to navigate the challenges of sustainability on the short term, leading to a reduction in direct CO_2 emissions.

1.2. Problem definition

In this research, two types of problem definitions can be defined: scientific research gaps and practical implications.

1.2.1. Scientific problem definition

In this research, two scientific research gaps are discussed.

1. **Short-term direct CO_2 emission measures**: First, this research provides a holistic approach where actor requirements of the main stakeholders in the distribution process are combined to propose short term improvements in the car distribution process with the aim to reduce direct CO_2 emissions. The need for these improvements is emphasized by the the short-term targets of the European Commission [72], but scarce emphasizes is provided on short-term alternatives in truck-based distribution processes of cars in literature. While numerous studies have proposed long-term technological solutions to reduce automotive CO_2 emissions, there is a gap in understanding the short-term environmental impacts within the specific context of car distribution. Efficient vehicle routing is recognized as a potentially effective strategy on the short term [24], but its application and effectiveness in the context of automobile distribution have not been sufficiently explored. Especially, research is done from specific perspectives of stakeholders, but a holistic approach lacks. This gap is particularly critical in light of the need to develop improvement plans by 2025 to reduce future direct emissions [72]. Therefore, this research contributes with the identification of bottlenecks in the context of direct CO_2 emissions of trucks in the car distribution process. This is done by an extensive research from system perspective. This enables to provide adjustments that improves the system, and are not bounded by stakeholder specific perspectives.
2. **Lack of model designs to measure car distribution procedures**: In literature, a Capacitated Vehicle Routing Problem (CVRP) is recognized as suitable and powerful approach to optimize Vehicle Routing Problems. However, due to the complexity and size of these problems, modeling

real world situations is complex. On the one hand, exact methods aim to find optimal solutions, but are not applicable on large scale due to the problem complexity. On the other hand, meta-heuristics aim to find near-optimal solutions in a reasonable time, but uncertainty of the solution holds. In literature, state-of-the-art meta-heuristics are suitable for large CVRP problems, but not directly applicable for car distribution processes due to the limited capacity of transportation vehicles compared to high demand of car dealers [90]. The ability to serve car dealers with multiple vehicles is called split delivery and very scarce described in literature [24] [27]. Therefore, this research aims to add knowledge to the scientific literature on CVRP applications in the car distribution industry, with an application of a state-of-the-art meta-heuristic including split delivery function on large scale. This application is verified by an exact method on small scale. This enables the evaluation of proposed short term improvement of in the truck based car distribution.

1.2.2. Practical implications

In this research, four practical implications are discussed. Together, they form the practical research gap:

- **Overall efficiency**: By adopting a holistic approach to vehicle routing and distribution, companies can significantly improve the efficiency of their distribution networks. This can lead to improved routing, reduced travel distances, and potentially lower operational costs. In practice, this could mean fewer trucks on the road, shorter delivery times, and increased overall productivity.
- **Reduced CO_2 emissions**: A more efficient routing system directly contributes to a decrease in CO_2 emissions. This is especially important in the context of the automotive industry, which is under increasing pressure to reduce its environmental footprint. Practical implications include not only meeting but potentially exceeding regulatory targets for emission reductions, contributing to environmental sustainability goals.
- **Competitive Advantage**: Companies that successfully implement more efficient car distribution strategies may gain a competitive advantage. By reducing emissions and improving efficiency, these companies can market themselves as both environmentally responsible and cost-effective, appealing to both environmentally conscious consumers and stakeholders looking for operational efficiencies.
- **Stakeholder engagement and collaboration**: Addressing these gaps requires collaboration across various stakeholders in the supply chain, including a central distribution center, a transportation company and car dealers. This collaborative approach not only improves the distribution process but also strengthens stakeholder relationships, leading to more integrated and cohesive distribution practices.

Therefore this research will fill the following practical research gap:
This research identifies a critical practical gap in the understanding and implementation of system-wide efficient car distribution strategies from distribution hubs to car dealers. The gap highlights a lack of collaborative efforts among key stakeholders in the car distribution chain – the car import company, truck transportation companies and car dealers. This absence of coordinated action leads to inefficiencies in vehicle routing, distribution processes, and ultimately results in higher direct CO_2 emissions.

1.3. Research scope

In this section, the scope of the research is discussed. First the system boundaries are elaborated followed by practical limitations. After that, an overview of the research is visualized.

1.3.1. System boundaries

This research focused on the national truck-based car distribution processes of new cars from a central distribution hub to dealerships. The scope of this, which is visualized in 1.1 in red, includes three stakeholders: central distribution hub, truck transportation companies and car dealers, including the external parking (EP) of a car dealer. These stakeholders interacts to determine the car delivery processes. Based on this interaction choices are made, resulting in distribution processes.

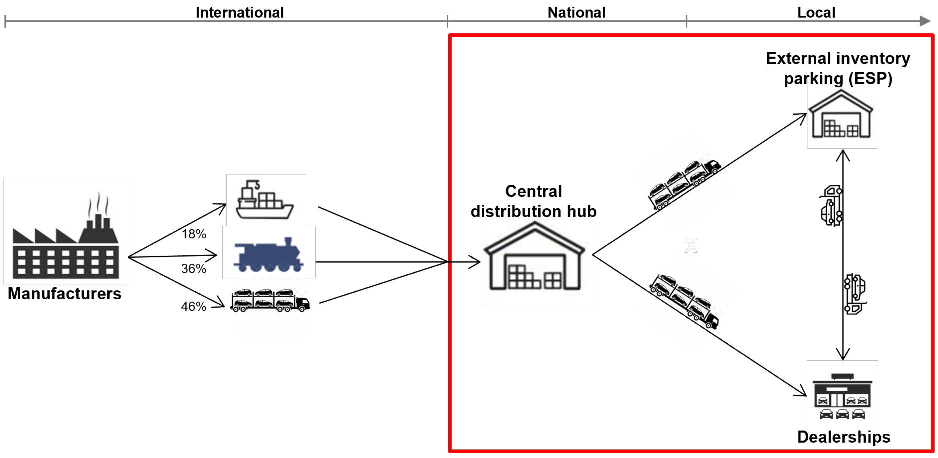

Figure 1.1: Car distribution from distribution hub to car dealer, source (Author)

Total distances of the routes of transportation vehicles are calculated, as trucks are the main cause of the direct CO_2 emissions. Different processes strongly influence these trips. In this research, the distribution processes of the three main stakeholders are analyses. Based on that, bottlenecks are identified and improvements are proposed. Other processes, influencing the direct CO_2 emissions are excluded from this research. Focusing on direct truck emissions is significant as direct CO_2 emissions from trucks are the by far main contributor. Here, the total emissions are recalculated by using a CO_2 equivalent.

1.3.2. Practical limitations

This research concentrates on the distribution of passenger cars and company vans in the Netherlands. Special transport for luxury brands is not included, as it is conducted through different transport channels. Also, dealer holdings represent multiple brands across multiple car dealers. In some cases, one dealer holding consists multiple car dealers per brand. For practical reasons, the scope is narrowed to one brand per car dealer. The car dealer with the highest sales volume is selected. Sales from the smaller car dealers are summed and added to the sales volume of the representative car dealer. This limitation impacts the model outcome, as the situation is simplified to a reduced number of car dealers. This might lead to a reduced visible impact of multiple car dealers within a small region. This limitation can be mitigated by focusing on performance differences in areas with different dealer densities. However, the majority of the car dealers, including all different car dealer types and sizes, is included.

The CO_2 emissions are calculated based on the kilometers traveled by a truck, per sub-route, taking into account the load factor. However, specific time windows of dealers were not considered. Time windows ensures that all trucks can be loaded without capacity constraints. Since exogenous trip data are used based on daily demand of car in 2022 that were actually carried out, it is assumed that these trips can still be conducted in the same manner. Moreover, the average fuel consumption was used, based on the trucks utilized in the Netherlands. This calculation did not account for extra fuel consumption due to making multiple stops, focusing solely on the distance that needs to be covered. The assumption to consider the actual distance as opposed to the absolute distance is based on a detour index, verified for the Netherlands. This detour index is a generalization and applicable for high road density regions. The applicability in other regions or countries requires a reconsideration of the detour index.

1.4. Research objective

The objective of this research is twofold, and comes from the reviewed literature and defined problem statements. First, this study aims to understand the car distribution processes, focused on how direct CO_2 emissions can be reduced. With this knowledge, car distribution processes can be reconsidered to better align the processes, to make improvements or to adapt current policies. Also, insights are provided by allocating cars to specific locations to reduce trips performed by car dealers to an external

parking and reducing its environmental impact.
Second, developing a solution approach to model truck-based car distribution processes, with the focus on taking into account system and actor requirements of the main actors and considering transport motions on large scale. The outcome is a new, easy to implement methodology to evaluate car distribution processes which is applicable for general car distribution processes.

The following research statement is defined:
To design and implement a comprehensive methodology to assess and optimize car distribution processes for reducing direct CO_2 emissions. By understanding and reevaluating the current car distribution processes, the study seeks to devise a solution approach that not only considers the direct environmental impact of truck-based car distribution but also incorporates the system and actor requirements essential for sustainable operations.

1.5. Research questions

The objective function is formulated as:

"To what extent can redesigning car distribution processes reduce direct CO_2 emissions emitted by transportation vehicles?"

The following sub-questions are formulated

1. What are key characteristics of the car distribution of new cars?
2. Which methods and determinants can be used to analyze and evaluate the direct CO_2 emissions in the distribution process of new cars?
3. How can the car distribution process for new cars be evaluated?
4. What are bottlenecks in the current car distribution system?
5. How is the car distribution system modeled?
6. What is the impact of redesigning car distribution procedures?
   - 6a. How do new policies affect the current state of car distribution processes?
   - 6b. What is the impact of external factors the redesign?

1.6. Research design

This research uses a specific and structured set-up. This is described first, followed by the presentation of the research outline. Lastly, the data sources used in this research is described

1.6.1. Research set-up

The foundation of this research is inspired by the System Engineering (SE) framework of Dym, Brown, and Little [34]. This approach contributes to the understanding of individual interactions within the system. In the literature review, the characteristics of automotive distribution process for new cars are explored. In addition, it reviews modeling approaches, evaluation methods and determinants for identifying bottlenecks in truck-based car distribution systems. Within a three-stage framework, several methods, procedures and rules are used to design, conduct and analyze the research. First, the **Problem Identification** is used in the context of the current state of the system. Here, the current state is mapped out and interpreted to identify bottlenecks and to formulate potential improvements. Second, a **Solution Approach** is developed, based on the current distribution processes, with the aim to develop an representative model of the system. This model is verified on small scale by comparing the performance with a benchmark, a CVRP model using an exact method. After that, the proposed improvements of the problem identification can be evaluated by applying the solution approach in a real-life situation, by using a case study at Pon Automotive. To evaluate the **Future Designs**, the model is validated by scenario experiments. In the concluding phase of this research, the main findings are presented together with a discussion of limitations and recommendations for further research.

1.6.2. Research outline

An illustration of the research design is presented in figure 1.2.

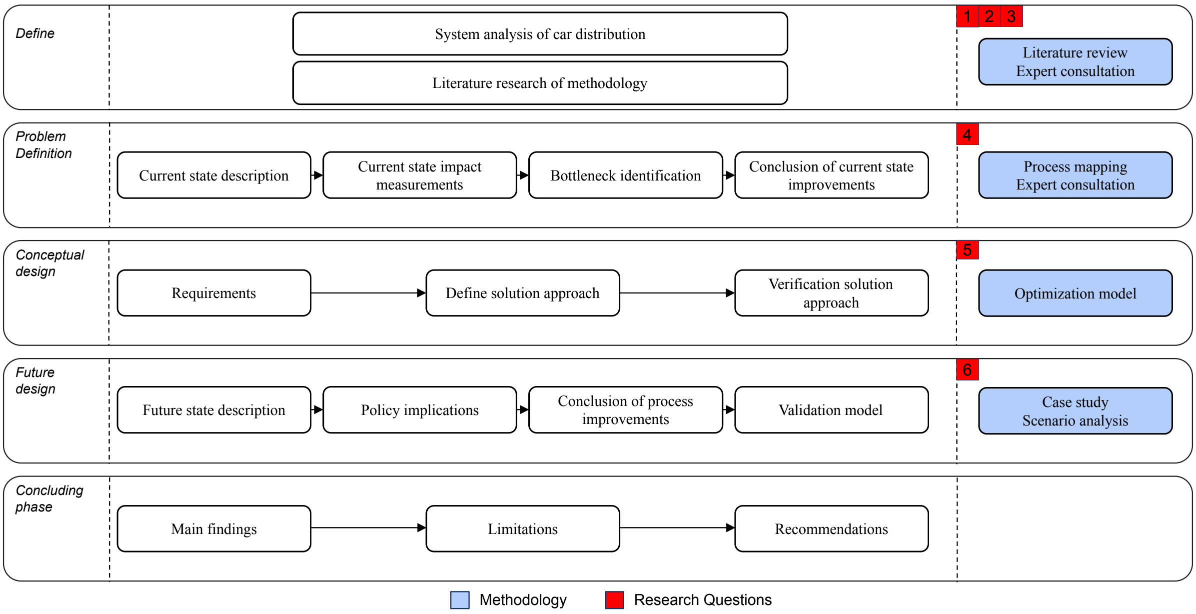

Figure 1.2: Research Design, adapted from Dym, Brown, and Little [34]

1.6.3. Data sources

In this research, quantitative and qualitative data is used. Literature is used for the problem understanding, method selection and the different supply chain strategies. The main source of the process specific knowledge is gained at Pon Automotive, the largest car import company of the Netherlands. This research includes a case study with two functions. First, to understand the current state of the car distribution processes. Second, to use the data for the performance evaluation of the Solution Approach in a real world situation. Besides the various expert interviews with Pon Automotive professionals to gain information about the supply chain, the following experts are interviewed:

- Four interviews from specific selected car dealer holdings, varying in size and market focus to understand incentives between car dealers.
- An expert interview with the main representative of Koopman, responsible for procurement and contracts.
- Several visits at Pon Logistics, interviews with responsibles and workers to gain information of the allocation process.
- Expert contact with the developer of the Hybrid Genetic Search algorithm (HGS-CVRP), T. Vidal.
- Expert interviews with brands of the Volkswagen Group for brand specific considerations.
- An expert interview with the second largest car import company, to verify the new prioritization strategy.

The Solution Approach is implemented using Python. For the implementation of the HGS-CVRP metaheuristic, the Hygese package is used. For the creation of a benchmark, the Gurobi 11.0 solver is applied in a mathematical model with CVRP constraints, adapted to ensure the split delivery function.

2
Literature review

This literature research examines two research fields subjected to the automotive industry. First, it explores the characteristics of the current automotive distribution process for new cars, discussed in section 'System Analysis'. Second, it reviews modeling approaches, evaluation methods and determinants for identifying bottlenecks in truck-based car distribution systems, addressed in section 'Distribution Process Assessment Review'. Accordingly, this literature review aims to answer the first and second sub-research questions.

- *What are key characteristics of the car distribution process of new cars?*
- *Which methods and determinants can be used to analyze and evaluate the direct CO_2 emissions in the distribution process of new cars?*

2.1. System Analysis

In this section, the discussion begins with an outline of the car distribution process. This is followed by an examination of the importance of reducing direct environmental emissions. The review then addresses the challenges associated with incorporating sustainability goals into these processes. Lastly, it evaluates the differences in main car allocation strategies.

2.1.1. How the car distribution process works

The automotive sector is characterized as a global industry due to the involvement of various regional and international actors, coupled with dependence on numerous global trends. The distribution process of new cars after production is considered as a highly complex procedure due to many influences [38]. The supply chain from the factory to the consumer is viewed as highly unpredictable, never in balance, and influenced by numerous factors such as material shortage, staff absence and technological improvements [36] [38]. Additionally, national and regional government policies vary significantly, leading to substantial differences in consumer preferences between regions and over time. Examples of trends influenced by governments include incentives for green vehicles, safety regulations, and taxation policies [72] [62].

Despite these uncertainties, many processes are automated [38]. Given the substantial demand per country to receive cars, the supply chain is designed to produce cars on a large scale per country [56]. Therefore, the automotive production approach incorporates methods, processes, and techniques to achieve mass production. Mass production involves manufacturing large quantities of standardized items or very similar items in large volumes, ensuring consistent quality and specifications. To allocate this mass production to customers, production volumes per country are determined by the factory based on historical data and forecasts [56]. Each country can fill these production volumes with specific customer orders or inventory cars. The challenges for the factory include maintaining inventories to enable timely production differentiation. Stock sourcing for car production is trend-sensitive and, in practice, it often happens that certain parts of the car are not available. Also, the number of changing components can vary from one car to another [38]. Exclusive brands such as Audi and BMW can be customized in numerous ways to suit customer preferences. BMW, for example, allows modifications up to seven days before production and their models can be configured in more than 1,000 ways [18].

This results in build-to-order production process of cars, maintaining a guaranteed outflow at the factory. This guaranteed outflow is necessary because of the limited flexibility of a factory. Sudden changes cannot be quickly accommodated by the factory.

The distribution of new cars to countries is mainly determined by production levels of the factory, which can vary significantly due to the uncertainties mentioned previously. Manufacturers are therefore encouraged to cooperate with large importing companies. The two main advantages for the factory in this arrangement are the alleviation of supply responsibilities and the ability to easily adapt to local market trends [47]. In the Netherlands, the five largest car importers together account for 63% of car imports [84] [13]. These companies receive vehicles at their central hub, where the cars are temporarily stored before being transported by car transporters to local car dealers.
To prevent congestion, the distribution of vehicles is very important. The popularity of a mode of transport is influenced by several factors, the most important of which are flexibility, speed and cost [6]. Flexibility is relatively high in truck transport compared to train transport because trucks allow door-to-door deliveries, flexibility in route planning and adjustments, quick responses to changes and access to locations inaccessible to trains. The second factor contributing to the preference for truck transport in freight transport is the generally higher speed of truck transport, especially for shorter distances. Especially for just-in-time deliveries and quick responses to market demand, truck transport can have an advantage over rail transport. This competition exerts downward pressure on prices, making it economically attractive to use freight transport by truck [6].

Due to limited vehicle capacity and to be flexible to receive different distribution flows at dealer locations, every dealer holding uses a an External Parking (EP) for temporary storage. Thus, there are three main actors involved in the distribution of cars from the central hub to car dealers: the importing company, the car transport company and the car dealers. This is visualized in figure 2.1. These three actors are separate companies that enter into contractual agreements with each other and each pursues its own objectives.

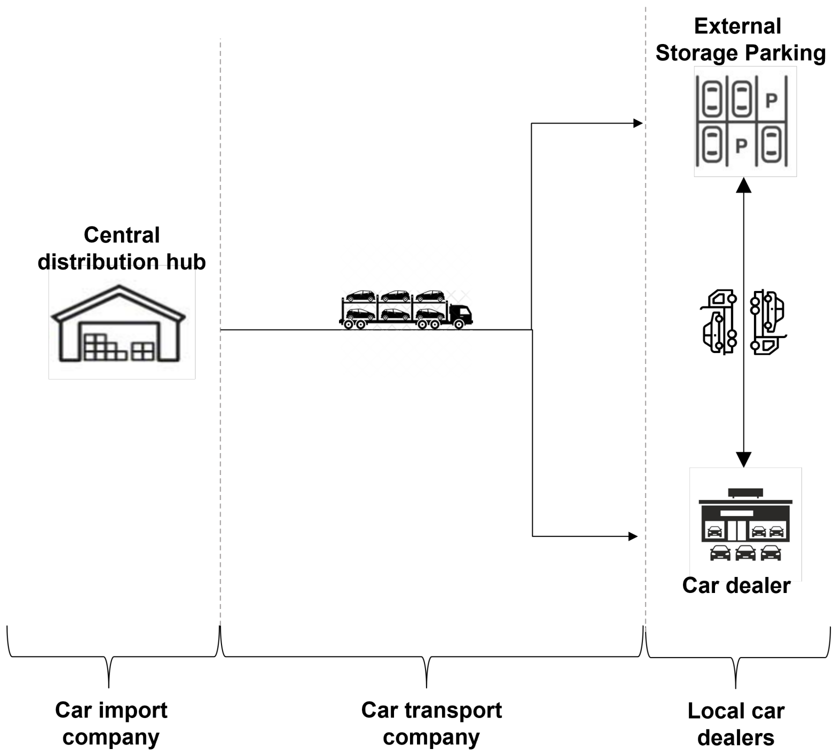

Figure 2.1: Dutch car distribution process, source (Author)

2.1.2. Importance of reducing direct environmental emissions

In Europe, 28% of the total CO_2 emissions is produced by road transport [72]. Despite the fact that less than 2,5% of the road users is a heavy-duty truck, heavy-duty vehicles such as trucks and busses account for 6% of total CO_2 emissions in the European Union [73]. This underlines the significant contribution of the impact of transport by trucks and buses. The reason for this contribution lies in the relatively high CO_2 emissions associated with heavy goods transport via trucks, which are mainly diesel-powered.

Despite the relatively high environmental impact of truck transport, it remains by far the most popular form of goods transport by land in the EU [72], as stated above. Therefore, In 2019, the European Council set a target of 30% GHG emission reductions by 2030 compared to 2005 levels for non-ETS sectors, including the road transport sector, which accounts for a significant share of total emissions [37]. Also, it is found that without further measures, the share of CO_2 emissions from heavy duty trucks is expected to increase by 9% between 2010 and 2030 [37]. Currently, there are no specific CO_2 emission reduction requirements for heavy-duty vehicles in the European Union. Therefore, specific measures are considered necessary for these vehicles, and these have been defined. These measures require companies to set emission reduction levels for the entire fleet in both the short and long term, starting from 2025 [37]. This forces companies to implement emission reduction measures in the distribution of goods, on the short term. The implementation of these measures serves to stimulate technological development to achieve the transportation of heavy goods by alternative means of transport.

In the context of the increasing urgency from the European Commission to mitigate direct CO_2 emissions from car distribution, companies are required to develop improvement plans by 2025 to reduce future direct emissions [72]. The European Union has introduced the Corporate Sustainability Reporting Directive (CSRD) in 2024, mandating certain companies to integrate CSRD into their annual reports [72]. The CSRD demands comprehensive sustainability reporting from businesses, including environmental, social, and governance (ESG) dimensions, with the goal of creating transparency and providing stakeholders with a detailed account of a company's sustainability performance [39].

Under the CSRD, companies must report on Scope 1, Scope 2, and Scope 3 emissions, as classified by the Greenhouse Gas Protocol (GHG Protocol) [42]:

- **Scope 1:** emissions are direct emissions from sources that are owned or controlled by the company. This includes emissions from combustion in operations such as company vehicles or furnaces.
- **Scope 2:** emissions pertain to indirect emissions from the generation of purchased energy consumed by the company, such as electricity or heating [50].
- **Scope 3:** emissions represent all other indirect emissions that occur within a company's value chain, both upstream and downstream. These are not directly controlled by the company but are a consequence of the company's operations, such as the manufacturing of purchased goods or the use of sold products and services.

Partly due to this new legislation and the incentives to analyze a company's sustainable impact of customers, companies realize the need to address their sustainability impact. According to the Volkswagen Group's Sustainability Report 2022, both short-term and long-term measures are being taken to reduce direct CO_2 emissions [5]. Currently, the Volkswagen Group imports 46% of its cars to the Netherlands by trucks and 36% by train [14], and all domestic transportation is carried out by truck. On the long term, the Volkswagen Group wants to replace road transport with rail transport using green energy [5]. This transition is expected to make a positive contribution to its carbon footprint. However, achieving this goal in the short term seems too optimistic due to factors such as flexibility, capacity and speed. On the short term, the Volkswagen Group has set specific targets to train staff, for example through the Drive Sustainability Programme, to minimize the impact. This includes training sessions and e-courses. In addition, the company says it is working with external transport companies that specialize in offering sustainable transport. No other concrete measures are known, including from other major car companies such as BMW and Toyota. [22] [87]. The European Commission suggests a shift from road transport to other more sustainable forms of transport to reduce direct environmental impact [72].

Second, the optimization of the efficiency of current routes used by trucks. Efficiency in route planning can be achieved in several ways, such as minimizing urban driving, avoiding hilly terrain and ensuring direct routes to targeted locations. In addition, Okyere, Yang, and Adams [65] shows that optimizing current truck routes can lead to significant improvements in CO_2 emissions. Also, Çınar, Gakis, and Pardalos [31] concludes that direct CO_2 emissions can be reduced, by allowing more stops and limited duration.

2.1.3. Challenges of reducing direct emissions in the distribution process

It is asserted that the distribution process of goods represents a relatively significant CO_2 emission factor, but implementing measures to make the distribution process less polluting in the short term is a challenge. This literature gives several reasons for this difficulty. As mentioned earlier, the flexibility and speed of goods distribution play a crucial role. Moreover, dependence on transport is high and contractual changes cannot easily be realized in the short term. In addition, production and systems are often built around supply chain activities, leading to practical inefficiencies in companies. It is concluded that significant modifications to the transport fleet are considered unfeasible in the short term for reducing direct emissions without significant practical and economic consequences.

The total performance from system-approach can be misaligned with the performance of individual actors. Misalignment between actors leads to inefficiencies in overall performance [94]. For example, he performance of individual actors may be high but the overall system performance may not be optimal. The misalignment between individual goals and the system leads to sub optimal system performance [17]. The main reason for this misalignment is the difference in goals. For example, a factory may have the goal of transporting goods at minimum cost, while a distributor's goal is to deliver goods as quickly as possible. These goals may occur at a much more detailed level in the supply chain, making it less obvious that the misalignment lies there. Another major reason for misalignment of performance is information asymmetry. Incomplete or delayed information causes misalignment of demand fluctuations, inventory levels or production schedules. This is called the ”Bullwhip effect”. This phenomenon occurs in supply chains and is characterized by the amplification of demand fluctuations as information is communicated from low-level to high-level [71] [29]. For example, a minor fluctuation in customer patterns can result in significant and impactful variations in production quantities and strategic decisions, such as inventory levels. This can have substantial implications for the total costs incurred by multiple actors [29]. By applying collaborative plannings, the bullwhip effect is mitigated. As multiple actors can review the data, communicate, and discuss changes in figures, assessing consequences becomes more manageable [56]. Reducing the bullwhip effect also facilitates the implementation of inventory management strategies, such as just-in-time (JIT) inventory systems [94].

As a conclusion, on the short term, environmental gains can be obtained by the alignment of individual objectives with the system objectives. For distribution processes, this can be translated into the alignment between demand and supply between actors to reduce transport motions. Also, in the automotive sector, strategy differences between car dealers are mostly related to the served market and the size of the car dealer. It has been concluded that the adaption of the fleet configuration is not realistic on short term, as sunk costs are high, contracts with partners cannot be adjusted quickly and practical issues occur when alternatives are chosen. However, communication and information exchange can potentially create environmental impact, such as more efficient routing and planning to reduce redundant trips. Efficient vehicle routing could have a significant improvement in direct environmental impact. Despite risks of bullwhip effects, the system performance can be higher when using an integral distribution process, instead of striving to individual performances.

2.1.4. Strategies to better align the distribution process

In this section, several reasons for the sub-optimal performance of supply chain systems are identified. In the literature in 2.1.1, it suggests that enhancing collaboration among participants in the supply chain could lead to improved system efficiency. Within supply chain management, various allocation strategies are described in the literature. The two extremes in allocation strategies are the push allocation and the pull allocation strategy. In the middle, a lot versions are known, and has its own advantages and disadvantages. Below, both allocation strategies are further explained.

Push-allocation

Pushed based allocation of goods to retailers is a fundamental aspect in supply chain management, involving the distribution of goods proactively. This allocation philosophy plays a crucial role in ensuring product availability, the fulfillment of demand and serving customers [58]. The essence is of push based allocation of goods is forecasting the demand and pushing goods without waiting for specific customer orders [48]. In general, the application of a push-based supply chain is preferable in instances where a high demand for mass products, in combination with avoidance of inventory at high-level in the supply chain.

The advantage of push allocation lies in the ability to generate demand by proactively pushing products to market. Offering large quantities of products can result in lower prices, mainly due to possible reductions in bulk shipping costs [48]. This approach creates a larger target market for the products. From a process perspective, the advantage of push allocation, as described in the literature, is its recognition as a simple and understandable method for product movement [58]. With clear agreements in place, production processes can be automated more easily. Adjustments are less likely, a feature valued within the Six Sigma methodology for organizing a process efficiently. In practice, this allocation strategy is used in large-scale mass production facilities where holding stocks of finished goods is undesirable. Well-defined agreements with the distributing party allow the plant to produce precisely at a certain capacity to minimize over- or under-capacity [58]. The push allocation method is most common in industries characterized by high product demand, minimal requirements for personal preferences and difficult or non-existent communication between parties.

The lack of effective communication is as a significant issue in many supply chains, primarily due to the constant need for adjustments in production and demand [98]. This challenge is particularly significant in systems employing push allocation strategies, leading to sub optimal overall performance. The primary issues stemming from inadequate communication in a supply chain that uses a push strategy include stockpiling and a lack of real-time insight into market trends and consumer preferences [98]. Such communication gaps can have severe implications, both economically and environmentally, as well as on inter-party cooperation, in both the short and long term [58].

In the immediate term, storage spaces become excessively filled, which results in high inventory costs and less operational efficiency. To manage the surplus, additional storage facilities may be utilized, which, with the growing volume of products, escalates the likelihood of longer delivery times and increased labor expenses [58]. From an environmental perspective, this scenario necessitates that products be rerouted within the supply chain due to the saturation of storage capacities or the use of alternate sites [89]. Established distribution processes are not easily modified, forcing ad-hoc decisions about redirecting goods. Such adjustments directly results in extra transportation motions.

An options for manufacturers to engage a third party, the so called Vendor-managed Inventory (VMI) [19]. This is done to share risk in the supply and storage of products, often in industries where push strategies are used. There are several ways to engage a third party: By buying over a product completely from the supplier, so to speak, or by having the supplier pay a rent to store goods. For vendors, it is beneficial to control more goods in order to improve demand forecasts and to reduce holding costs [61]. For retailers, risks are being reduced and specific knowledge can be outsourced, creating more space for other tasks. A vendor will contain regional knowledge that the factory does not have and does not have time to find out [19]. This results in optimal stock levels, ensuring that products are available when customers need them. By using regional, and smaller-scale knowledge, unnecessary inventories can be avoided, which is cost-saving. In addition, applying VMI will reduce bullwhip effects, as more reliable estimates of production and demand can be made [71]. A major challenge has to do with granting data rights and trust in collaborations. The application of VMI relies heavily on accurate and timely exchange of data between vendors and consumers. The moment a plant engages a vendor, personal information must be granted and the delivery of the data must be managed in a fast and well-organized manner. Integrated IT services and data consistency can thus lead are necessary for good cooperation.

Pull-allocation

An opposing perspective to using demand forecasts to align demand and supply is the utilization of so-called pull systems. In a pull system, production and replenishment processes are initiated by the customer rather than being guided by forecasts predicting schedules. Analyzing supply chain mechanisms based on customer behavior is presumed in the literature to contribute to achieving lean manufacturing. Lean manufacturing is a production and management methodology focused on creating and delivering value to consumers while minimizing waste in all areas [96]. This literature explicitly states that inventory represents a form of waste because it incurs significant costs. Pull systems have a mitigating effect on inventory since production can rapidly adjust to actual demand through direct orders [26] As pull systems communicate the actual demand, they help prevent overproduction and unnecessary storage [96].

A key aspect in pull systems is efficient order prioritization to ensure the desired allocation of goods and to guarantee timely deliveries. A often used methodology in inventory management and queuing systems is the ”First-in, First-out” principle (FIFO), used where items need to be processed in the same order as they arrived. This method reduces the risks outdated products by ensuring that older items are processed before newer items [67]. Secondly, this principle is straightforward to implement and it does not require complex software. However, FIFO is suitable for a perishable goods and it may be not effective in situations of non-perishable goods, where the impact of the usability does not change over time. This is tested by Ching and Wu [28] using System Dynamics which reveals that FIFO performances, such as the quality of long term predictions and cost reductions, decreases significantly when non-perishable goods are used, compared to other inventory methodologies.

Moreover, a widely discussed prioritization principle is the just-in-time (JIT) principle, which aims to deliver goods at the right moment to reduce excess inventory. The goal is to operate the supply chain without long-time inventory utilization [32]. This is achieved through a demand-driven approach that aligns production and delivery based on actual customer demand rather than forecasts. To implement the JIT system, a continuous flow with minimal interruptions or delays is established. Close communication is required, and literature emphasizes that prior communication about scenarios and trend changes is essential [55]. This allows stakeholders to anticipate adjustments and ensures a reduction in waste. Additionally, the just-in-time approach is often complemented by a key principle of the Kanban method: visualization. The widely used Kanban method emphasizes visualizing workflows and schemes to create clarity regarding prioritization and responsibilities [93]. A critical performance metric is ”takt time,” which represents the rate at which production and demand must be aligned. A higher takt time allows for more precise supply delivery and better adaptation to fluctuations. In the context of the automotive industry, ensuring compliance is highlighted as a crucial aspect and challenge for JIT-systems, as certain standards for vehicle safety must be maintained at all times. Criticism of the just-in-time approach is based on the practical difficulty of delivering every product exactly just in time in a supply chain with a large number of goods[55].

Many solutions within the just-in-time principle address this challenge by prioritizing groups of products rather than individual products. A systematically focused method for achieving this is the ABC analysis. An essential requirement for these methods is that the data used to differentiate between items is complete for each individual item [78]. Metrics are then employed to classify products and make differences measurable. Commonly used metrics include ”Annual Usage Value” or ”Percentage of Total Inventory Value”, and ”lead time averages” [16]. The values for each product are classified into three groups: Group A (most valued products), Group B (moderately valued), and Group C (least valued), which determine the priority. In many applications of this method, batch delivery can be implemented per class. This means that batch priority is applied instead of individual priority[78].

Focusing on the environmental impact of the distribution, a pull strategy generally has a more accurate production schedule. Given this accurate production schedule, the impact if it is not adhered to is relatively large. Thus, the focus to adhere to this production schedule is relatively high, which can keep the probability of fluctuations in production schedule relatively low, provided no unforeseen circumstances arise. This leads to a reducing influence on the probability that excessive transportation capacity is required. As a result, the number of unforeseen transport movements in a pull system will be relatively low. Communication here should be current and punctual. Another added value of pull strategies is that distribution routes can be optimized based on real-time demand, reducing the total distance traveled within the system to transport the products for the same quantity of products. This reduces direct CO_2 emissions, which will provide a lower direct environmental impact per product unit. The flexibility of both distributing and producing parties is required. It must be feasible for these parties to cope with last-minute adaptations. For producing parties this may cause delays, but practice has proven that it is feasible. For instance, BMW allows modifications up to seven days before production, and their models can be configured in more than 1000 ways [18]. Based on market demand and market dynamics, the ways in which pull should be designed and the characteristics of the pull system should be considered. Even within a supply chain system, this can vary per actor.

Emergence of the need to use the Push pull combination

The previous sections described the advantages and disadvantages of goods allocation based on push and pull strategies, highlighting potential instabilities in the supply chain. Customer demand due to pulling and supply chain instabilities due to pushing goods have been discussed separately, despite the interconnections of these approaches. In fact, these two approaches can be used simultaneously, as stated by Afshari, Searcy, and Jaber [4]. Push allocation is a method aimed at ensuring minimum flow of goods in the supply chain [48]. This is further explained using the three main actors in a supply chain: the producing entity, the transportation party and the retailer. In most mass production industries, the producing entity aims to operates at maximum production capacity [58]. These production quantities are predetermined because of the need for sunk costs in the form of materials, equipment and personnel [33]. Specific products are made based on the product differentiation desired by the retailer [74]. After production, the products are immediately handed over to the transportation party to avoid bottlenecks, a requirement for the producing entity because otherwise excess storage space would be created. The distributing party transports the goods to the central distribution point in a country [74]. Here the products are temporarily stored with the aim of minimizing storage time. A push strategy is also preferred at this stage. Next, the retailer receives the goods from storage, but only if the products can be accommodated. This depends on capacity and connection to the end user. If supply and delivery to the end consumer are not synchronized, products become unwanted. In this context, a clear preference for pull principles dominates.

The preference for push or pull strategies is influenced by cost-saving considerations for different parties involved in the supply chain. For one party, such as a manufacturer, push is desirable because it helps save costs, while for another party pull is preferred because of cost efficiency [58]. This can be explained by focusing on the goods being distributed [46]. In many cases, a manufactured good for a factory or a distribution entity differs little from other goods. Once goods are produced, there is almost no distinction in their transportation - they must arrive at the delivery location as quickly as possible, shifting the risk to the other party [74]. This also applies to an intermediate location such as a distribution hub. Incoming goods are calculated based on forecasts to ensure that they can be transported quickly to the next station. For products with specifications, distinctions are made. For example, a perishable product requires the use of a ”push” system with a maximum lead time to prevent spoilage [46]. By maintaining a certain outflow, inventory problems are less likely to occur and push allocation is used. However, the third main party, the retailer, prefers a pull allocation system based on specific order details to align processes with customer preferences. This is because at the end of the supply chain, inventory accumulates, partly because outflow cannot be stored at the retailer. The choice between a push and pull system is based on the relationship between production and inventory in the supply chain [58]. The level of detail of a product becomes increasingly critical as a product moves further down the supply chain, matching the supply of products as closely as possible to the outflow to the end consumer. Failure leads to inefficiencies, especially in the form of accumulation of inventories.

Mass production at the beginning of the supply chain transforms to the issue of personal and specific goods when moving further down the supply chain. The added value of the push-pull hybrid combination in distribution integrates both push and pull elements to provide flexibility in the distribution network [58] [98]. For example, part of production can be driven by push standards, while another part can be driven by actual demand. This makes it possible to optimize production quantities and distribution of goods over time, taking into account the needs of other actors [46]. Being aware of distribution activities makes it possible to make adjustments in schedules at receiving parties. The literature suggests that unnecessary transport movements can be minimized by including actors' preferences in current distribution programs [46]. The risk lies in the potentially large consequences of miscommunication, highlighting the need for clear and transparent agreements on responsibilities. Push allocation from the factory is necessary to some extent to remain profitable. However, pull aspects can also be integrated. Preferences of parties at the bottom of the supply chain can be taken into account without necessarily affecting the production process of the producing entity, thus improving the performance of the system. However, this requires punctual and up-to-date communication between the parties.

2.2. Distribution Process Assessment Review

First, evaluation domains will be described. Second, different process mapping tools are elaborated. Third, methods to analyze and design vehicle routing problems are described.

2.2.1. Process Evaluation Domains

Performance analyses of distribution processes often considers three main domains: Environmental performance, Operational performance and Financial performance [34]. Environmental performance assesses the sustainability of supply chain activities, focusing on the environmental footprint. Key metrics include direct CO_2 emissions, waste management, energy consumption and overall impact on natural resources [59]. Environmental efficiency is becoming increasingly important and reflects a commitment to corporate social responsibility and compliance with legal standards [73] [72]. Operational efficiency measures how effectively the supply chain uses its resources to meet business objectives. This includes metrics such as total amount of trips, order processing accuracy and speed, idle time of products and average distances per transport motion. High operational efficiency usually translates into improved customer satisfaction and competitiveness. Financial metrics provide a quantifiable measure of the supply chain's economic impact. This includes cost analysis, profitability, return on investment, and overall financial health of the supply chain operations. Financial performance indicators are often critical for assessing the bottom-line effectiveness of distribution strategies [59].

Environmental Performance

Measuring direct environmental system performance is extensively discussed in the literature. The primary purpose of measuring current environmental loads is twofold [34]. First, bottlenecks can be identified by assessing the current state. Second, measurements of the current state can be compared with outcomes of potential future states to measure the impact of differences. Therefore, it is crucial to choose a method that can be applied consistently in both current and future states. To evaluate the direct CO_2 impacts, specifically focusing on greenhouse gas emissions, during the transportation motions from distribution centers to automobile dealerships, several methods are described: life cycle analysis (LCA), the greenhouse gas protocol, and environmental impact assessment (EIA), found in existing literature [42] [63] [79].

A Life Cycle Assessment (LCA) is a comprehensive tool used to measure the environmental impact of a transportation system throughout its life cycle. This analysis not only assesses direct emissions, but also looks at the processes from resource extraction to production, use and disposal [79]. The purpose of this analysis is to provide a complete picture of environmental impact in various categories, such as global warming potential, acid potential and greenhouse gas emissions. Within scientific research, this tool is considered valuable for understanding the environmental impact of products and processes, enabling more sustainable decision-making. In addition, the GHG Protocol is a widely used accounting tool for understanding and quantifying greenhouse gas emissions in processes. The advantage of this tool lies in the use of standardized measurement methods validated by official bodies such as the World Resource Institute, ensuring consistent measurements. The European Union also recognizes this tool as a measurement tool [63]. A fundamental part of the GHG Protocol is the use of emission factors (EF). An EF represents the amount of greenhouse gas emissions per unit of a process, expressed in CO_2 equivalents. Organizations use these standardized emission factors in combination with their activity data to calculate their greenhouse gas emissions. Environmental Impact Assessment (EIA) is a widely used method to calculate the environmental impacts of a process, focusing on the balance between development goals and environmental conservation. It involves a comprehensive analysis that integrates environmental considerations into the decision-making process. The main advantage of this method is that it takes into account different perspectives, which requires multidisciplinary expertise. Another aspect of EIA is the consideration of public feedback in the review process.

To calculate CO_2 emissions using the EF used in the GHG Protocol, two main methods are typically used: the activity-based approach (ABA) and the energy-based approach (EBA) [95] [2]. The choice between these methods depends heavily on the specific context and data availability. Both approaches have their own advantages and limitations. The EBA calculates CO_2 emissions based on energy consumption. In cases where specific energy or fuel consumption data are not available, such as when transportation is outsourced to another party or when transparency is lacking, activity-based estimation is recommended [2]. This method approximates CO_2 emissions by determining an average value per transportation activity and multiplying it by the amount of transportation activity and distance. For transportation companies, the simplest and most accurate method to calculate transportation emissions is to track fuel consumption per time period [95]. This fuel consumption can be used in conjunction with standardized emission factors to convert energy values into CO_2 emissions. On the other hand, the ABA focuses on the activities within the process that are responsible for greenhouse gas emissions, such as transportation motions or industrial production. In many cases, fuel consumption per month is not accurately tracked or not transparent. Therefore, the ABA is used in most of the cases in literature. When the ABA is used, trip data accuracy becomes crucial.

Operational performance

Operational performance is a complex domain, involving a range of aspects from logistics to inventory management. The choice of indicators to measure the operational performance, is strongly dependent on the objective. According to the literature, there are several key indicators that reflect the operational efficiency of the distribution process where costs are minimized.

- **Amount of Transportation Trips**: This measures the frequency of trips made by each type of vehicle. Often, the number of vehicles is a hard constraint. Thus, to efficiently satisfy the demand with minimum vehicle usage, this indicator is desired to be minimized. The number of trips is often related to the trip lenght, to find an optimal consideration between trip length and amount of trips.
- **Idle time of goods**: In distribution processes, often the lead time of product streams is an indicator to assess efficiency. Here, a shorter lead time is desired. When products are not involved in sub-processes, it is called idle time. Often, this is minimized, as temporal storage is seen as waste in processes [96]. However, in the context of the car distribution processes, very short idle time at a location, indicates different transport motions. Different transportation motions are not desired and may results in inefficiencies. Therefore, the usage of idle time indicators needs careful interpretations and is dependent on the purpose and characteristics of the aim.
- **Load density**: This is the ratio between the load and capacity per vehicle, to assesses the efficiency of load. This ratio is often desired to be 1, where the maximum capacity is used efficiently.

Financial performance

Financial performance in distribution processes is a critical indicator for stakeholders, as the main purpose of almost every instance is related to financial purposes [56]. Focusing on how financial performance can be used in distribution processes, costs are divided into two groups: variable costs and the fixed costs [56]. Variable costs fluctuate with the level of operations, whereas fixed costs remain unchanged regardless of operational activities. Fuel, staff wages, and vehicle maintenance expenses are examples of variable costs due to their direct correlation with operations. In contrast, fixed expenses include the purchase of trucks and the costs of infrastructure. A common phenomenon is that implementations to improve environmental impact, are contradict to the costs. With the current of environmental awareness by companies and customers, the trade-off between costs and environmental impact is more focused to the environmental impact. Companies have to invest in environmental implementations to meet the European targets, set by the European Commission [72].

2.2.2. Process mapping

Process mapping is an essential step in optimizing operational systems and provides clarity and insight into the complexity of organizational workflows. In the context of car distribution processes, it becomes a crucial tool for understanding and improving sub-processes. In literature process mapping tools are elaborated. Also, the Theory of Constraints has a strong function in process mapping.

Methods outline

This research emphasizes the importance of understanding the current state of car distribution processes, as highlighted by Biazzo [21]. Within the literature, three process mapping tools are discussed for detailing the car distribution processes. Firstly, the Integration DEFinition for Function Modeling (IDEF-0) methodology stands out for its systematic approach to analyzing sub-processes and relationships. This method highlights detailed insights into the flow of information and actions, as well as clarifying the roles and responsibilities of different stakeholders [21]. The hierarchical structure of IDEF-0 allows for a comprehensive examination and understanding of processes, necessary for improving these processes. However, while IDEF-0 is effective for functional analysis, it may simplify stakeholder roles, focusing on process complexity potentially at the expense of considering the human aspects and individual responsibilities within the system.

Furthermore, Swimlane diagrams focus on functions provided by IDEF-0 by clearly showing responsibilities of stakeholders within the process flow [10]. By allocating tasks to specific lanes linked to key stakeholders, these diagrams accurately depict the connection between tasks and the stakeholders in charge. Swimlane diagrams are particularly good at showing the order of processes and are helpful in spotting areas where teamwork is either strong or weak. However, Swimlane diagrams fall short in capturing the timing of tasks, which is something the IDEF-0 method does better [10]. When looking into car distribution processes, the goal is to precisely describe the current way things operate, detailing functions and assigning responsibilities. A IDEF-0 diagram lays the groundwork for analyzing functions, whereas Swimlane diagrams add value by outlining who is responsible for what, and pointing out potential issues in how work flows [15]. While Unified Modeling Language (UML) diagrams have mainly been used for technical details, their value increases when paired with software tools that aid in analysis and documentation. For car distribution, the IDEF-0 model focuses on the functional side of actions, which is then enriched by Swimlane diagrams that assign responsibilities [57]. This combined method identifies key issues and patterns in behavior throughout the system, offering a detailed overview that is beneficial for improving the process.

In addition, Swimlane diagrams complement the functional focus of IDEF-0 by explicitly mapping responsibilities into the process flow. By assigning tasks within lanes coupled to the main stakeholders, these diagrams capture the relation between activities and the stakeholders responsible for them as precise as possible [15]. Swimlane diagrams excel at outlining process sequences and are particularly useful in identifying areas where collaboration is robust or lacking. However, a limitation of Swimlane diagrams is their inability to effectively capture the temporal aspects of tasks, an area where the IDEF-0 method provides more clarity. When analyzing car distribution processes, the aim is to accurately capture the current operational state, describing functions in detail and assigning responsibilities. An IDEF-0 diagram provides the foundation for functional analysis, while Swimlane diagrams build on this by mapping the responsibilities of actors and revealing potential problems within the workflow [15]. Although UML diagrams have traditionally focused on technical descriptions, their usefulness is enhanced when used in conjunction with software tools that promote analysis and documentation. For the car distribution process, the IDEF-0 model provides essential insights into functional aspects, which are then complemented by the assignment of responsibilities by Swimlane diagrams. This dual approach highlights critical bottlenecks and behavioral patterns within the system, providing a comprehensive understanding useful for process improvement. [10]

Theory of constraints

The strength of the Theory of Constraints (TOC) lies in its capability to highlight existing limitations and offer understanding into the restrictive elements within the system, by looking just to the system and not the stakeholder preferences [80]. The TOC is grounded in scientific concepts and has found widespread application across different sectors, also in distribution processes. TOC revolves around five fundamental principles that are essential. These are as follows:

1. **Identification of constraints:** The first step is to spot bottlenecks within the system that hinder achieving the objectives. These bottlenecks, or constraints, usually fall into two categories: physical constraints (like the maximum capacity) and policy constraints (such as safety regulations limiting speed).
2. **Exploitation of constraints:** After identifying the constraints, the aim is to optimize the process within these limits. This means making the best use of the constraints by focusing all efforts to support reaching the maximum potential, ensuring a comprehensive approach without favoring certain parts of the process over others [80].
3. **Subordination of other processes:** Processes that are not directly related to the constraint are adjusted to support the constraint its performance. This involves aligning resource distribution and decisions to back up the constraint, ensuring it operates as effectively as possible.

4. **Elevation of constraints:** When it becomes clear that a constraint cannot be fully leveraged, measures are implemented to either eliminate or relax the constraint. Such measures may involve the reallocation of resources, the introduction of technological advancements, or modifications to the procedural framework.
5. **Continuous improvement:** The strength of this theory is the iterative nature. After addressing a constraint, the attention moves to other constraints to ensure a comprehensive perspective. The aim of this theory is to continuously improve the system's overall performance [76].

Despite its popularity and widespread use in many industries, the TOC has faced several criticisms, including misunderstandings and perceived shortcomings. [80] points out that TOC mainly focuses on shortening process times, but it misses out on other important factors that could improve performance. According to [76], this narrow focus might unintentionally harm other vital aspects, such as how satisfied customers are or the workplace culture. Regaliza et al. [76] also mentions effects of removing a constraint, suggesting that TOC's basic assumptions might not fully consider how complex the interactions between multiple constraints can be, affecting how well a system performs. Regaliza et al. [76] argues that what seems like a single bottleneck might actually be influenced by several other constraints, which could block attempts to make things better. Therefore, [80] recommends carefully studying the effects of removing constraints to get a better overall picture of their impact on the system.

2.2.3. Capacitated Vehicle Routing Problem

The Travel Salesman Problem (TSP) in operational research is a many used method where the goal is to find the shortest path that visits each node once and returns to the origin. This concept lays the groundwork for more complex logistic equations such as the Vehicle Routing Problem (VRP) [86]. The VRP expands upon the TSP by incorporating a fleet of vehicles originating from a depot to deliver goods to several locations. The goal is typically to minimize the total distance traveled, the total cost, or to maximize some measure of efficiency, while considering a variety of constraints [3]. There are several variations of the VRP, each addressing different real-world complexities. The Capacitated Vehicle Routing Problem (CVRP) is a fundamental combinatorial optimization problem and well-studied variant of the VRP [86]. In the CVRP, the primary objective is to design the optimal set of routes for a fleet of vehicles to deliver goods to various customers, subject to certain constraints. Besides the academic relevance, CVRP models are widely used in practical logistics and distribution problems, such as delivery services (e.g. parcel delivery, food delivery), waste collection and management and distribution of goods from warehouses to retail stores [69].

Key characteristics CVRP

The traditional CVRP starts with a central depot where a fleet of vehicles is stationed. There are multiple customers, each with a known demand that must be satisfied [86]. The demand usually represents the quantity of goods to be delivered. Each vehicle in the fleet has a limited carrying capacity. The total demand of the customers assigned to a vehicle cannot exceed this capacity. The primary goal is to minimize the total distance traveled or the total cost of the routes, while ensuring that each customer is visited exactly once and the vehicle capacity is not exceeded [3]. After delivering the demand, each vehicles ends at the depot. When these constraints are met, it can be concluded that this is a CVRP.

Main challenges

The CVRP problem has various applications in literature, all to increase the design of variants of real-world problems [69]. This is done by adjusting and adding constraints. After that, algorithms are used to solve these problems. CVRP is a generalization of the Traveling Salesman Problem, which is a well-known NP-hard problem [90]. TSP involves finding the shortest possible route that visits a set of cities and returns to the origin city. Since CVRP includes additional constraints like vehicle capacity, it inherits the complexity of TSP and extends it further [92]. In addition, the number of possible routes increases exponentially as more customers are added, due to the increase of route combinations. This is because each customer can be visited in many different sequences, and each sequence can be served by different vehicles [91]. Therefore, the NP-hard nature of CVRP and the exponential growth of the solution space due to improving the model to real world situations are fundamental challenges that necessitate the use of sophisticated and specialized computational methods to find feasible solutions within a practical time-frame. In addition, when selecting an appropriate method for solving the CVRP, several critical factors must be considered [86]. The size and complexity of the problem have a major influence on the choice; smaller, less complex problems can be effectively addressed by exact methods such as Integer Linear Programming, while larger, more complex problems often require heuristic or meta-heuristic approaches due to computational constraints [9]. The specific constraints and variants of CVRP, such as time windows or multiple locations, have a significant impact on method selection, as some algorithms are better equipped for certain constraints [19]. In addition, the adaptability and flexibility of the algorithm in dynamic environments and the solver's familiarity and expertise with specific methods all play a crucial role in determining the most appropriate approach for solving CVRP [86].

Exact methods

The use of exact methods to solve the CVRP involves algorithms that are designed to find the optimal solution [43]. These methods include Mixed Integer Linear Programming (MILP), Branch-and-Bound algorithms, and Branch-and-Cut algorithms [52]. MILP formulates the CVRP as a set of linear equations with integer or continuous constraints. Branch-and-Bound is a systematic method of exploring the solution space, and Branch-and-Cut improves this process by adding cutting planes to reduce the feasible region and accelerate convergence to the optimal solution [52]. This is visualized in figure 2.2.

Branch-and-Bound systematically explores the solution space by dividing it into smaller sub-problems (branching) and evaluating their bounds. If the bound of a sub-problem is worse than the current best solution, it is removed, optimizing the search process. Branch-and-Cut improves the Branch-and-Bound method by adding cutting edges. These are additional constraints (cuts) that eliminate parts of the search space that do not contain the optimal solution [82]. By reducing the size of the search space, the Branch-and-Bound algorithm can find the optimal solution more efficiently, especially in problems where the solution space is large. While exact methods guarantee an optimal solution, their major drawback is computational intensity, especially for larger problem instances where the solution space grows exponentially, leading to increased computation time and resource usage. Several solvers that are categorized as exact algorithms can be used to solve the Capacitated Vehicle Routing Problem (CVRP), such as CPLEX, Gurobi and COIN-OR [7] [53]. Gurobi is seen as a state-of-the-art solver, including advantages in efficiency and speed and combined with free excess for academic usage [82]. To enhance solution times and manage large-scale problems using exact methods in the context of the Capacitated Vehicle Routing Problem (CVRP), in literature two strategies are described:

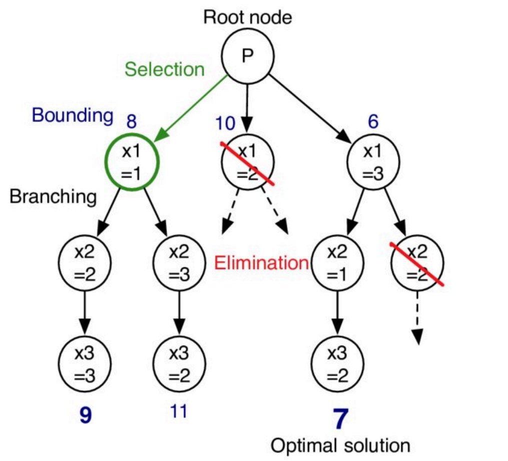

Figure 2.2: Branch and Cut method, source (Hölzer, Knerr, and Rupp [52])

- Implementing time windows in CVRP models can significantly streamline the resolution process. By introducing specific time frames within which deliveries or collections should take place, the number of feasible routes is reduced [53]. This constraint not only reflects real-world scenarios more accurately, but also limits the solution space that exact methods have to explore, potentially leading to faster solutions. However, when time-windows are not representing real-world characteristics, the solution space is not realistic, resulting in sub-optimal solutions [82].
- Addressing smaller-scale problems can be a strategic approach to understanding and solving larger CVRP problems. By solving these smaller cases, patterns or strategies can emerge that are scalable or applicable to larger problems [86]. This method involves analyzing smaller datasets to develop insights or rules that can be extrapolated or applied to larger datasets, which helps manage the complexity and computational power of large-scale problems [53]. But, a major drawback is that inter-dependencies cannot be integrated while implementing extrapolation strategies.

Combining these strategies can lead to more effective and efficient solutions for large-scale CVRP problems, where a trade-off is made between the need for accuracy with computational feasibility [2].

Meta-heuristics for CVRP

Meta-heuristic algorithms are computational intelligence paradigms mainly used for sophisticated solving of optimization problems [1]. Meta-heuristics are used because of the effectively for solving complex optimization problems that are difficult or impossible to solve by exact methods. Meta-heuristics can handle large, complicated search spaces and find good solutions in a reasonable time, even when the optimal solution is difficult to determine [90] [2].

CVRP often involves many variables and constraints, making it challenging to find the optimal solution using exact methods. Meta-heuristics can effectively approximate near-optimal solutions for CVRP, even in cases with many vehicles, routes, and delivery points [2]. Their capability to escape local optima and explore various solution possibilities makes them highly suitable for the diverse and dynamic scenarios encountered in CVRP. Several heuristics are described in literature to minimize total route distance. Knowledge Guided Local Search (KGLS) is a meta-heuristic that integrates domain-specific knowledge into the search process, improving efficiency and effectiveness, particularly in clear problem areas, such as the CVRP [11]. Slack Induction by String Removals (SISR) is a novel approach in VRP, focusing on dynamically removing and reintroducing sequences of customer visits to optimize routes [30]. The Hybrid Iterated Local Search (HILS) combines local search with other heuristic strategies. This hybrid method aims to leverage the strengths of both heuristic and exact solution strategies [85]. Also, ILS-SP addresses some of the limitations of applying either heuristic or exact methods alone, particularly in terms of scalability and solution quality [85]. The KH-3 heuristic improves on its predecessors through advanced techniques such as k-opt moves, replacing 'k' edges in a tour to find shorter routes [51]. This algorithm performs well on large-scale problems, making it suitable for complex routing challenges such as CVRP [51]. The Fast Iterative Localized Optimization (FILO) algorithm, designed for large-scale Capacitated Vehicle Routing Problems, uses Simulated Annealing-based criteria for diverse yet controlled exploration of the search space [3]. However, it uses various strategies to find a solution, which may lead to increased algorithmic complexity [3] [90].

Lastly, as an extension of the Hybrid Genetic Search (HGS) in 2012 Vidal et al. [92], the hybrid genetic search HGS-CVRP is introduced in 2022 [90]. This algorithm uses the SWAP* neighbourhood, an innovative feature that improves route optimization by allowing the exchange of two clients between different routes without immediate re-insertion [90]. In his paper Vidal [90], a wide diversity of algorithms implementations are analyzed, by performing experiments on 100 classical benchmark instances of Uchôa et al. [88], to cover a divers amount of characteristics. Here, the solution quality is calculated per heuristic, given a maximum computation time. In figure **??**, the results are presented.

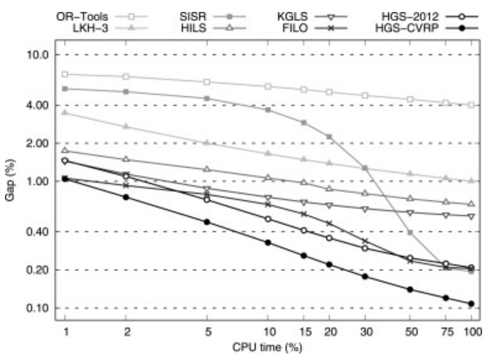

Figure 2.3: Meta-heuristic comparison, source: Vidal [90]

The experimental outcomes and SWAP* neighborhood function sensitivity analysis indicate that HGS-CVRP is a leading meta-heuristic in terms of solution quality and convergence speed [90]. A limitation of HGS-CVRP, however, is its inability to perform split deliveries, meaning each location must be fully served by a single vehicle. In the 100 experiments of Uchôa et al. [88] executed by Vidal [90], vehicle capacities always met or exceeded individual location demands. Nonetheless, in real-world scenarios like car distribution, where truck capacity is relatively low compared to the location demand, HGS-CVRP's current model fails to address situations where demand is larger than the vehicle capacity.

Split delivery for Vehicle Routing Problem

The Split Delivery Vehicle Routing Problem (SDCVRP) improves the traditional CVRP framework by allowing the distribution of a single customer's demand across multiple vehicles. This adaption of constraints is intended to increase distribution efficiency. In the SDCVRP, it has been shown that there is a potential to reduce the efficiency by at most 50% by using split delivery [9]. This improvement is due to a better capacity usage and more efficient route possibilities. Despite the potential for a leaner fleet and higher adaptability, the complexity of the SDCVRP creates significant computational challenges in exact methods and heuristics. Except for some special cases, the SDCVRP is NP- hard in general [9]. In addition, due to its difficulties to implement, it is not straightforward. It would require introducing new local search operators, adapt the crossover, as well as delivery quantity information in the solution representation of the HGS-CVRP.

However, Chen et al. [27] proposes a novel, efficient and easily implemented approach to solve the SDCVRP using an *a priori* split strategy. This a priori approach for the SDCVRP aims to split the demand in moderate demand sets, including the addition of dummy locations when the demand is split. In Chen et al. [27], the initial demand of 76 is split by using the 20/10/5/1 or 25/10/5/1 rule. By using the 20/10/5/1 rule, the following procedure is used to make the groups:

- $m_{20} = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.20Qm \leq D_i\}$,
- $m_{10} = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.10Qm \leq D_i - 0.20Qm_{20}\}$,
- $m_5 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.05Qm \leq D_i - 0.20Qm_{20} - 0.10Qm_{10}\}$,
- $m_1 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.01Qm \leq D_i - 0.20Qm_{20} - 0.10Qm_{10} - 0.05Qm_5\}$.

Here, Q represents the maximum capacity of a truck and D_i is the demand of node $i \in N$. It has been discussed that there are many different ways to split the demand, but that a reasonable trade-off between running time and the quality of solutions have to be made [27]. Therefore, moderate sized groups and small demand groups are chosen. This approach, enables large scale usage of meta-heuristics including split delivery of goods.

2.3. Conclusion

In this chapter, the following sub-research questions are answered:

- *What are key characteristics of the car distribution of new cars?*
- *Which methods and determinants can be used to analyze and evaluate the direct CO_2 emissions in the distribution process of new cars?*

The system analysis highlights the complexities and challenges of reducing direct CO_2 emissions in the automotive distribution process. It emphasizes the importance of aligning individual objectives with system-wide goals to achieve environmental gains. With the direct CO_2 emission targets of the European Commission on the short term, distribution processes by trucks must become more environmental friendly. However, large adjustments in distribution processes of cars is not realistic on the short term, due to a lack of alternative transport modes, high costs and reduced operational performances. Alternatives such as improved route planning and the implementation of push-pull allocation strategies could help in avoiding redundant trips, which offer potential improvements in reducing direct CO_2 emissions.

An essential and important initial step in this approach is a detailed process mapping of distribution activities from stakeholders to identify the sources and contexts of direct CO_2 emissions. This includes direct CO_2 emissions, but also indicators in the operational and financial domains. The Swimlane analysis and IDEF-0 diagrams provides a complementary value in the process mapping of supply chain processes. By including a system requirement analysis, proposed improvements are obtained. By doing this, it becomes possible to analyze the emissions impact of these policies and adjust strategies systematically of the current state. The CVRP is recognized in literature as a suitable quantitative approach for modeling vehicle routing problems. By doing this, the current state can be modeled and proposed improvements can be analyzed. Among many methodological options, exact methods are known for their easy applicability, but often struggle with the computational challenges inherent in NP-hard problems. Therefore, most of the CVRP applications with exact methods are performed on small scale. On the other hand, state-of-the-art meta-heuristics are suitable for large CVRP problems, but often encountering obstacles in adapting to the unique requirements. In the car distribution process, split delivery requirements are needed to model the problem as the capacity of trucks is relatively small to the demand of dealer locations. Thus, requirement adjustments are needed to enable large scale CVRP calculations with split delivery.

In Appendix C, the research gap tables are presented.

3 Methodology

In this chapter, the used methods of this research is elaborated. In this research, the overarching methodology of System Engineering is applied, described in section 3.1. This methodology consists three main stages: Problem Identification, Solution Approach and Future Design. First, the Problem Identification phase is elaborated in section 3.2. Second, the Solution Approach is developed. Third, the Future Design is designed in section 3.3. Therefore, sub-question 3 of this research will be answered: *How can the car distribution process for new cars be evaluated?*

3.1. Overarching Methodology

In this research a System Engineering (SE) approach, based on Dym, Brown, and Little [34], is used as holistic framework. The focus of SE lies in the interdisciplinary field of engineering and engineering management where the process analysis, process design and process integration are important aspects [34]. The main characteristic of this approach, is the consideration of a system as a whole rather than a collection of individual components. Therefore, the understanding of the individual interactions within the system between actors and the environment will be involved in this analysis to come up with an integrated solution. A systematic approach is defined by David Dym and Dean Little [34], who reached an important scientific contribution to System Engineering. The approach encourages a system thinking perspective, considering the interconnection between components within a system.

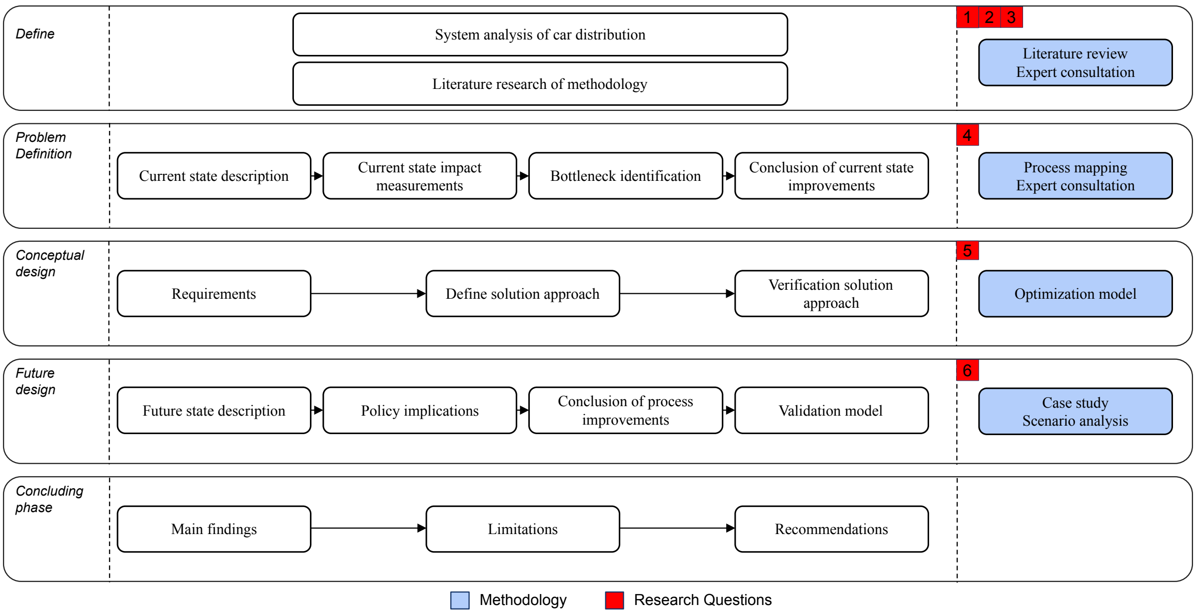

Figure 3.1: Research Design, adapted from Dym, Brown, and Little [34]

This overarching approach recognizes the importance of not only numerical metrics, but also the contextual and qualitative nuances that shape the complexity of process dependencies. Within a three-stage framework, several methods, procedures and rules are used to design, conduct and analyze the research.

- First, the **Problem Identification** is used in the context of the current state of the system. Analyzing processes from systems thinking provides an understanding of how different elements depend on and influence each other. This systems perspective is crucial for adding performance to systems as a whole, based on the current state analysis, system requirements, and including a collaborative perspective of the main actors. This results in proposed policies.
- Second, a **Solution Approach** is developed of the distribution process on large scale, serving as a solution approach. Based on validated assumptions and process characteristics the Solution Approach functions as the representation of the current state. By doing this, proposed policies can be tested
- Third, **Future Designs** are made. The policies concluded in the problem identification of the current state can be applied on the Solution Approach of the system. Here, differences between the current state can be concluded and analyses. In addition, potential scenarios can be tested.

For this research, a Case study is conducted. The use of a Case study in scientific research is a methodological approach that allows researchers to go deep into a specific phenomenon, such as certain processes, in a real-life context [40]. A case study is used to make a situation measurable, and therefore can be used to quantitatively analyze processes [32]. Besides matching the research aim to the case study, it is crucial to carefully choose the case selection based on the aim of conducting a representative and generalized study [41]. Therefore, it is essential that the data collection is reliable, comprehensive and valid. In this research a case study is conducted at the largest car importing company in the Netherlands: Pon Automotive, responsible for importing 22% of all cars in the Netherlands in 2022 [14]. By analyzing processes of a year at the largest car import company, a generalized case study is used. The aim of the case study usage is twofold. First, the current processes are analyzed in order to identify current bottlenecks in the distribution process of new cars. These bottlenecks can trigger policy improvements that potentially contributes to reducing the direct CO_2 emissions of trucks. Second, the data of Pon Automotive is used to evaluate proposed policies compared to the current processes.

3.2. Problem Identification

The problem identification phase of the current state is a pre-processing stage which is the groundwork for the other stages in the Systems Engineering approach [34]. A clear process outline and a understanding of the stakeholder needs are critical. The objective is to understand the current distribution processes, described in 2.1, from different perspectives and to identify current bottlenecks in the distribution process. Therefore, the current car distribution process is mapped out and analyzed.

First the car distribution processes are mapped out by using process mapping methods [34] [21]. Process mapping is a systematic method to obtain a step-for-step overview of current systems. By doing this, it becomes clear to identify redundancies, bottlenecks, unnecessary steps, or complexities that could be simplified, which could lead to increased efficiency. This has been done by using Swimlane diagrams and IDEF-0 diagrams to clarify individual processes and make the process measurable. A Swimlane analysis provides a systematic way to visually represent complex processes [10]. By allocating process steps to lanes, representing different actors, it provides a clear overview of how different actors interact and contribute to the overall process. The needs of actors becomes clear and can be compared with the actual information flow. This clarifies dependencies and responsibilities between actors[15]. In addition, to provide a more detailed overview of individual processes, an IDEF-0 diagram can be used to focus on the various processes that occur in a sequential manner. Here, a comprehensive overview can be obtained of each process stage.
For a deeper understanding, certain processes are quantitatively analyzed by using Key Performance Indicators (KPIs). KPIs provide measurements that reflect the critical aspects of processes to identify bottlenecks [59]. By doing this, influences of individual actors and process characteristics can be analyzed [62]. As described in 2.2.1, the system can be analyzed on different domains. The related KPIs for this research are presented in table 5.1.

Table 3.1: Global Key Performance Indicators

Domain	Key Performance Indicator	Measure Unit
Environmental Performance	Direct CO_2 Emissions	CO_2 eq emissions per day
Operational Performance	Number of Trucks	Units needed per day
Operational Performance	Load Density	Load-capacity ratio per truck
Operational Performance	Average Idle Time	Idle time per location
Operational Performance	Average Distance	Distance per truck
Financial Performance	Average Transportation Costs	Daily costs

The choice of KPIs in this research relies on three evaluation domains mentioned in literature, as described in 2.2.1. Also, during the process mapping stage, process specific KPIs are obtained. In this research, interviews are hold with supply chain specialists of Pon Automotive, external supply chain analysts, transportation companies and 4 different dealer holdings. In combination with a complete overview of 2022 of the distribution operations of Pon, the foundation of the problem definition of the car distribution is set.

Besides the objectives set by each actor, and the system as a whole, various constraints arise from the process and the actors themselves. These constraints can be contractual, practical or external factors. By analyzing these constraints and approaching them from a systemic perspective, considerations can be made about their necessity and feasibility. As described in section 2.2.2, not every constraint is absolute and emphasis should be placed on those constraints that are integral or add significant value. These goals and constraints can be translated into functions of the system, revealing the requirements that the system must meet to ensure these functions. As a conclusion of the problem definition, bottlenecks of the current processes are identified. Related to these bottlenecks, policies are proposed to improve the current processes.

3.3. Solution Approach

The first design phase of the System Engineering is the development of the Solution Approach. Solution approaches serve as a high-level representation of the process [34]. With the process understanding the objective is to develop an approach that outlines the structure, operations, and relationships within a process. As described in 2.2.3, the CVRP is a classic issue in the field of logistics and operations research that focuses on finding the most efficient (optimal) route to deliver goods to various destinations using a fleet of trucks with fixed capacity [86]. The foundation of a CVRP can be visualized as figure 3.2. Here, in node set $n \in N$, distances are calculated between starting points $i \in N$ and endpoint $j \in N$ by vehicle $v \in V$.

The primary goal of the CVRP is to minimize the total costs, in this research expressed in total traveled distance, while ensuring that each customer's demand is met without exceeding the capacity of any vehicle [86]. CVRP models provide the flexibility to add details as needed to create a detailed model for the specific situation [8]. In this research, the objective is to minimize the CO2 emissions by optimizing the total distance traveled in the distribution process of new cars. As described in 2.2.3, the CVRP is highly relevant to optimizing the car distribution process because it offers a systematic approach to reducing travel distance, while considering detailed constraints, such as vehicle capacity [92]. By applying CVRP, the requirements of the three main stakeholders

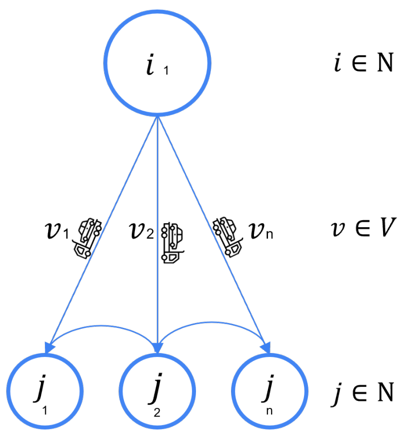

Figure 3.2: Foundation of distribution process, source (Author)

in this research can be merged in a measurable
model, ensuring that the right vehicles are delivered per day, while minimizing the total distance. CVRP models enable the comparison of current state procedures with new designs. These new designs consist different or adjusted constraints and assumptions.

Exact methods versus Meta-heuristic

As elaborated in section 2.2.3, different CVRP algorithms are described in literature for developing efficient logistics strategies that minimize environmental impact, divided in exact methods and meta-heuristics. Exact methods aim to find the optimal solution to the CVRP by exploring all possible combinations of routes that meet the problem's constraints. Using methods, such as Branch and Bound, Branch Cut, in a Mixed Integer Linear Programming Problem guarantee finding the optimal solution, given enough computational time and resources [86] [43]. Since exact solutions are computationally intensive, their practical application is limited to smaller instances where the exhaustive exploration of the solution space is feasible. For larger problem instances, where exact methods become infeasible due to computational constraints, meta-heuristics offer a viable alternative [90]. Meta-heuristics are approximate algorithms designed to find "good-enough" solutions within a reasonable time frame, where a trade-off is made between optimality and computational efficiency [2]. In this research, the state-of-the-art meta-heuristic "HGS-CVRP" is used calculate the different routes while minimizing the total traveled distance [90]. However, as described in 2.2.3, the HGS-CVRP is not directly suitable, as a hard requirement of the meta-heuristic is that all customers are visited once by a vehicle [90]. This implies that a single customer is served by maximum one vehicle. Thus, focusing on the car distribution process, the maximum demand of dealer locations cannot be larger than the maximum capacity of the a transportation vehicle. This phenomenon is very common, as car dealers receives a large amount of cars per week and the capacity of a single car carrier is relatively small. Therefore, the solution approach is introduced to enable the possibility of the so-called Split Delivery function on large scale problems.

Here, Chen et al. [27] proposes a proven efficient and easily implemented approach to solve the SD-CVRP using an *a priori split strategy*. This a priori approach for the SDCVRP aims to split the demand in small and moderate demand sets. As there are numerous ways to split demand, Chase, Jacobs, and Shankar [26] researched the impact of the group sizes, based on performance comparisons with leading CVRP heuristics, leading to model improvements.

This enables HGS-CVRP to split delivery and makes it a suitable method for problems where the demand of end-location is higher than the vehicle capacity. Exact methods and heuristics complement each other in this research. Exact methods offers a benchmark and insights into the problem structure on small scale, while heuristics offer practical, large scale solutions for real-world application, to verify the performance. Also, the behavior of the HGS-CVRP and exact algorithm are verified. By doing this, the results of the HGS-CVRP in different experiments are compared with an optimal solution. This enables the determination of the input variables, maximum number of vehicles and maximum group size of the demand set, of the HGS-CVRP for usage on large scales.

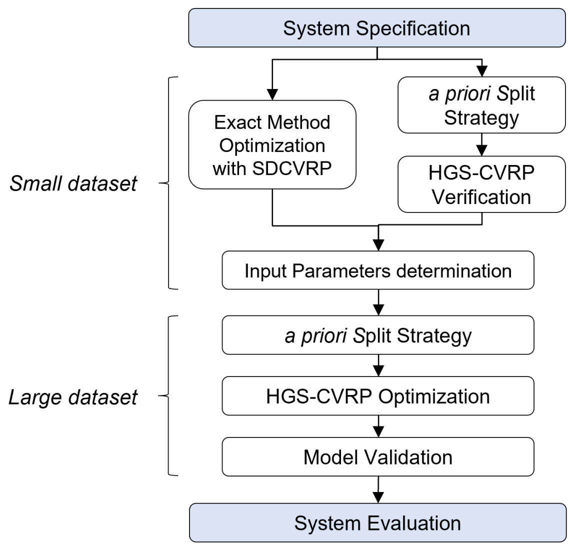

Figure 3.3: Outline Solution Approach, source (Author)

3.4. Future Design

After the verification of the solution approach, benchmarks are used to evaluate the performance of the model when the proposed policies are implemented. The performance indicators are presented in table **??**. The outcomes of the performance of the HGS-CVRP on is compared to the benchmark performance, the performance of the model with rule of the current state. Benchmarking is a commonly used methodology in scientific research to define the input parameter settings, and to compare solutions [88]. In this research, two types of benchmarks are used. First, experiments are performed with for the determination of the input parameters of the HGS-CVRP. Second, the current state is used as benchmark to evaluate the performance of the model after policy implementations. Here, the relative performance (RP) is calculated, as the ratio of the HGS-CVRP performance P_a and as the ratio of each benchmark P_b. Equation 3.1, describes the relative performance calculation [12].

$$RP = \frac{P_a}{P_b} \cdot 100\% \tag{3.1}$$

By measuring performance gap, new insights can be obtained [88]. This study uses the Key Performance Indicators of 5.1 to compare results.

3.5. Conclusion

This chapter aimed to answer the following sub-question:

How can the car distribution process for new cars be evaluated?

In this research a System Engineering approach, based on Dym, Brown, and Little [34], is used as holistic framework. The problem is defined as a result of the current state analysis, consisting two process mapping frameworks: a Swimlane analysis and IDEF-O diagrams. These methods complement each other and provide the capability to map the process from holistic perspective. Also, through selected Key Performance Indicators, sub-processes can be measured to identify bottlenecks. Furthermore, there remains an opportunity to employ process-specific KPIs identified during the current state analysis, through reverse engineering. Next, the Solution Approach contains the Hybrid Genetic Search algorithm for Capacitated Vehicle Routing Problems (HGS-CVRP) meta-heuristic of Vidal [90] for route calculations as it represents as the state-of-the-art method for solving large scale CVRP problems. To integrate this into the car distribution processes, a priori split demand strategy of Chen et al. [27] is added, enabling the use of the split delivery function. Given that this combination has not previously been documented in the literature, its performance is verified on a small scale using an exact method. After this, the solution approach is applied on large scale instances of Pon Automotive, to evaluate the policy adjustments gained from the current state analysis. Furthermore, scenarios are set-up to examine the effects of external factors and the potential impacts on the distribution process.

4 Current State Analysis

In this chapter, the current distribution process of new cars is analyzed. Given the new targets of the the European Union to come up with short-term measures to reduce direct CO_2 emissions in the distribution process, the situation in the Netherlands is analyzed through a case study at Pon Automotive. First, the case study is introduced. Then, distribution process is mapped out, followed by performing measurements of the Key Performance Indicators to analyze the processes. The aim of the Current State Analysis is to identify bottlenecks of the current car distribution processes. Therefore, the following research question will be answered: *What are bottlenecks in the current car distribution system?*

4. *What are bottlenecks in the current car distribution system?*

4.1. Case Study introduction: Pon Automotive

In 2022, Approximately 320 thousand new passenger vehicles were imported and registered with Dutch license plates in 2022, with the majority 63% being imported by the five largest import companies [13]. Pon Automotive, the official distributor for the Volkswagen Group in the Netherlands, stands as the largest importer with a 22% market share and has imported 70.440 cars in 2022 in the Netherlands. Cars imported by Pon Automotive arrives at the central distribution hub in Leusden. This hub, with a storage capacity for 7,000 cars, served as the temporary holding area for the vehicles for an average of eight days per car in 2022. Here, the cars are sorted and prepared for delivery to various local dealer holdings. Sometimes, cars are modified in Leusden. The transportation to these dealerships has been contracted to Koopman, a large transportation company, which is responsible for the delivery of vehicles via trucks. Koopman is is responsible for the routing decisions, optimizing the routes to the dealerships for efficiency. The dealerships, which are part of 21 partner car dealer holdings associated with the Volkswagen group, often operate multiple locations within the Netherlands. At these dealerships the cars are delivered to the end consumer.
For Pon Automotive, the year 2022 represented a recovery after the COVID-19 period. This was evident from the reactivation of production flows from the production factories, which significantly increased pressure on the throughput. Consequently, at Pon Automotive, buffer capacity was maximized, requiring a sudden increase in manpower to process vehicles at the central distribution center. As the year progressed, factories reached their maximum production capacity, which led them to handle relatively older orders and overloaded dealer locations. In response, car dealers rented or bought additional external car parks to handle the influx of vehicles.

4.1.1. Stakeholder outline

To identify and understand the multiple involved stakeholders, a Power-Interest Grid can be used. This tool has the aim to compare the interest of each stakeholder with its power to make changes. By doing this, it helps identifying influential stakeholders in the field related to the import of new cars. The main actors in this problem are listed below, followed by the less involved stakeholders to complete the context. The visualization of the Power Interest diagram is presented in 4.2.

In the Power Interest Grid the main stakeholders are presented:

1. **Car dealers - Volkswagen Group dealers** Dealers have a significant interest in maintaining their contractual agreements with Pon Automotive regarding sales volumes. This is because these

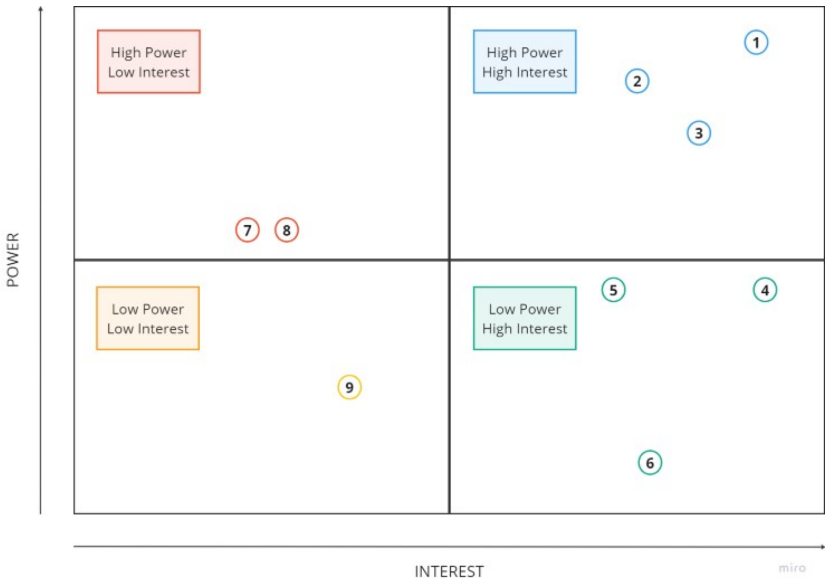

Figure 4.1: Power Interest Grid, Source (Author)

contracts are financially attractive. Adhering to these contracts allows them to receive bonuses from Pon Automotive when monthly objectives are achieved. and enables them to sell as many cars as possible. Furthermore, dealers are highly motivated to keep their customers satisfied and loyalty to customers is very important. Dealers achieve this by honoring agreements with customers, maintaining transparency, and making strategic decisions about the types of vehicles they order. Therefore, dealers have a strong interest in ensuring a cost-effective supply chain. Failing to achieve this efficiency could potentially lead dealers to reconsider their partnership with Pon Automotive. In terms of direct influence, their ability to impact supply chain operations is moderate, as they may not have direct control over these processes. However, when car dealers are not satisfied, contracts will be broken, resulting in large influences in the supply chain of new cars.

2. **Transportation company - Koopman** All cars that have arrived in the Netherlands at the hub must be transported to specific car dealers. This is carried out by a contracted partner. The contract specifies which cars need to be transported and within what time frame these cars must be delivered. It is the responsibility of the transportation company to deliver the cars within these conditions to be eligible for bonuses. Koopman, the contracted partner of Pon Automotive for transporting cars from the unloading points in Leusden or Rotterdam to the partner dealers, uses a fleet of trucks for this purpose. Pon Logistics compiles a daily pool of cars (the "Expedition Pool"), from which Koopman selects vehicles for transportation. The contractual agreement with Pon Automotive stipulates that 95% of the cars in this pool must be delivered to the dealers within 3 days. Koopman has a strong incentive to meet these delivery timelines, given that they are responsible for the transportation of cars to the dealers. This characterizes them with considerable influence in ensuring an efficient supply chain. Their interest is also substantial, as they are required to guarantee the 95% delivery reliability.
3. **Distribution company: Pon Automotive** The distribution company has the final responsibility for the whole supply chain and represents for all the imported car brands. The strategic considerations in the supply chain are taken into account. Their main tasks is the smooth distribution of cars from the manufacturer to the dealers, by working together with many partners. Their interest is very high, to fulfill the desires of the manufacturers, the dealers and the transportation parties. Also their power is very high, because of the final responsibility and control of the car distribution of all the cars. At the distribution company, imported cars are received from the manufacturer by the railway transportation partners, by boat transportation partners or by truck delivery partners. At the distribution hubs, the cars are temporarily stored before being transported to the partner dealers. The transportation partner selects the cars out of this pool to load on trucks. The distri-

bution plays an important role in making crucial decisions regarding the transportation strategy of cars, which gives them significant influence in the supply chain. In addition, the distribution company has the power to adapt the supply chain, which results in a high degree of power.

4. **Manufacturers - Volkswagen Group** The manufacturers of the cars are informed by Pon about the proposed production to serve the Netherlands and other countries with new cars. Based on forecasts and historical data, materials are bought for the production of the cars. The supply chain is the backbone for the delivery of cars to customers, so the interest is very high. Because the responsibility is given to Pon Automotive, the direct power is medium. But some power can be used, because of the contractual corporation with Pon Automotive.
5. **End-consumer** The end consumer is an individual or a business that purchases cars from the dealer. It is the desire of the end consumer to receive the car at the right time, often on an agreed-upon date based on the delivery time and the minimum date when the customer wants to start using the car. A car is ordered based on the customer's preference, following arrangements with the dealer, which underscores the high interest of the customer in having an efficient supply chain. However, the customer's influence or power over the supply chain is low, as they cannot directly contribute to its improvement.
6. **Railway transportation parties** Several railway transportation parties, such as HSL Logistik, are involved in the transportation of new cars from the manufacturer to Leusden. In Leusden, a special railway is been build for the car delivery on location. These parties are contracted by Pon and also the costs are for Pon if any disruptions will occur. The periodic deliveries are scheduled, with three trains arriving in Leusden each week, each carrying approximately 70 cars per train. The power of railway transportation parties is high in the supply chain, because all parties further in the supply chain are dependent on the delivery of cars. The interest is medium, as they are not further involved in the supply chain and get contractually paid by Pon Automotive.
7. **Boat transportation parties** Some manufacturers are easier to reach by boat, because of the fact that some specific models in the Pon Automotive portfolio are produced in other continents. These boat transportation parties are contracted by Pon Automobile and are essential for the delivery of specific models in the Netherlands. They have a high impact and medium interest, as they are not further involved in the supply chain process.

4.1.2. Environmental Policy and Objectives

This section outlines the proactive steps Pon Automotive is taking to address its carbon footprint and to comply with the upcoming CSRD regulations. As described in 2.1.2, the European Commission has introduced the Corporate Sustainability Reporting Directive (CSRD) in 2024, mandating certain companies to integrate CSRD into their annual reports. Given the complexity of the new car supply chain, which comprises various companies each with their own environmental policies and objectives, every stakeholder is individually required to incorporate the CSRD in their annual reports. In this research, Pon Automotive is the problem owner, and the environmental policy and objectives are described from Pon Automotive's perspective. Pon Automotive is also obligated to include a CSRD in its annual report, resulting that every form of emission must be categorized according to the Greenhouse Gas Protocol's Scope 1, 2, and 3 emissions framework. The following goals have set:

- **Scope 1 Emissions:** Pon Automotive has set targets to achieve CO_2 Net Zero in its operations by 2030, compared to the baseline year of 2022. This includes emissions from any transport assets they own or control directly.
- **Scope 2 emissions:** These emissions are indirectly associated with Pon Automotive's purchased energy. The goal is aligned with Scope 1 targets for operational emissions neutrality by 2030.
- **Scope 3 emissions:** These indirect emissions are not under the direct control of Pon Automotive but are influenced by the company through its value chain activities. Pon Automotive has set ambitious goals to reduce these emissions by 50% by 2033 and to achieve Net Zero by 2038, again using 2022 as the baseline year.

As an importer, the truck transport hired by Pon Automotive falls under Scope 3 emissions. Since freight transport constitutes a significant portion of the controllable emissions, measures are taken. Pon Automotive has contracted with transportation company Koopman to use Hydrotreated Vegetable Oil (HVO) as a cleaner alternative to diesel, in 30% of the truck fuel. The future expansion of HVO usage desired but depends on the availability and demand. Over the past two years, HVO has been on average 17.7% more expensive than regular diesel, and this cost differential is expected to increase. In addition, one electric truck pilot is also underway, but is not yet used in the daily transportation trips. For dealer holdings operating their own fleets, freight transport falls under Scope 1 emissions. Pon Automotive is encouraging these dealer holdings to also transition to HVO and electric trucks in the near future, although the exact timeline for this shift is not yet established.

4.2. Process Mapping

As the case study is clear, a detailed overview has been obtained of the current distribution process of new cars in the Netherlands, performed by Pon. This overview is generated by using a Swimlane Analysis and a IDEF-0 diagram and a Swimlane analysis. As described in section, A Swimlane analysis visualizes complex processes by mapping out each step within designated lanes for different actors, simplifying the understanding of interactions and contributions within the process. In addition, To provide a more detailed overview of individual processes, an IDEF-0 diagram can be used to focus on the various processes that occur in a sequential manner. This methods enables the identification and resolution of bottlenecks by clearly illustrating the needs of each stakeholder and the existing information flows.

4.2.1. Swimlane

As the processes are described, the interaction between actors can be obtained. This interaction contains informational interaction via communication resources, and the actual interaction in goods in the supply chain. This interaction combines the actor specific processes to each other, to create an collaborative view of the distribution process. As a result, inefficiencies can be obtained on a detailed level. A Swimlane analysis provides a systematic way to visually represent complex processes. By allocating process steps to lanes, representing different actors, it provides a clear overview of how different actors interact and contribute to the overall process. The needs of actors becomes clear and can be compared with the actual information flow. This enlightened dependencies and responsibilities between actors. In the diagram shown in figure **??**, three lanes are presented. Each lane represents an actor, indicating that the actions in each lane are executed by this actor. The diagram is read from left to right and presents a chronological sequence of steps taken to transport cars from the distribution hub to car dealers. It is important to note that the lanes do not represent the different locations where the car is transported but rather the responsible party. For each responsible party, the process and information flow in the current state are described below. Figure **??** represents the Swimlane diagram applied to Pon Automotive's distribution process within the scope of this research.

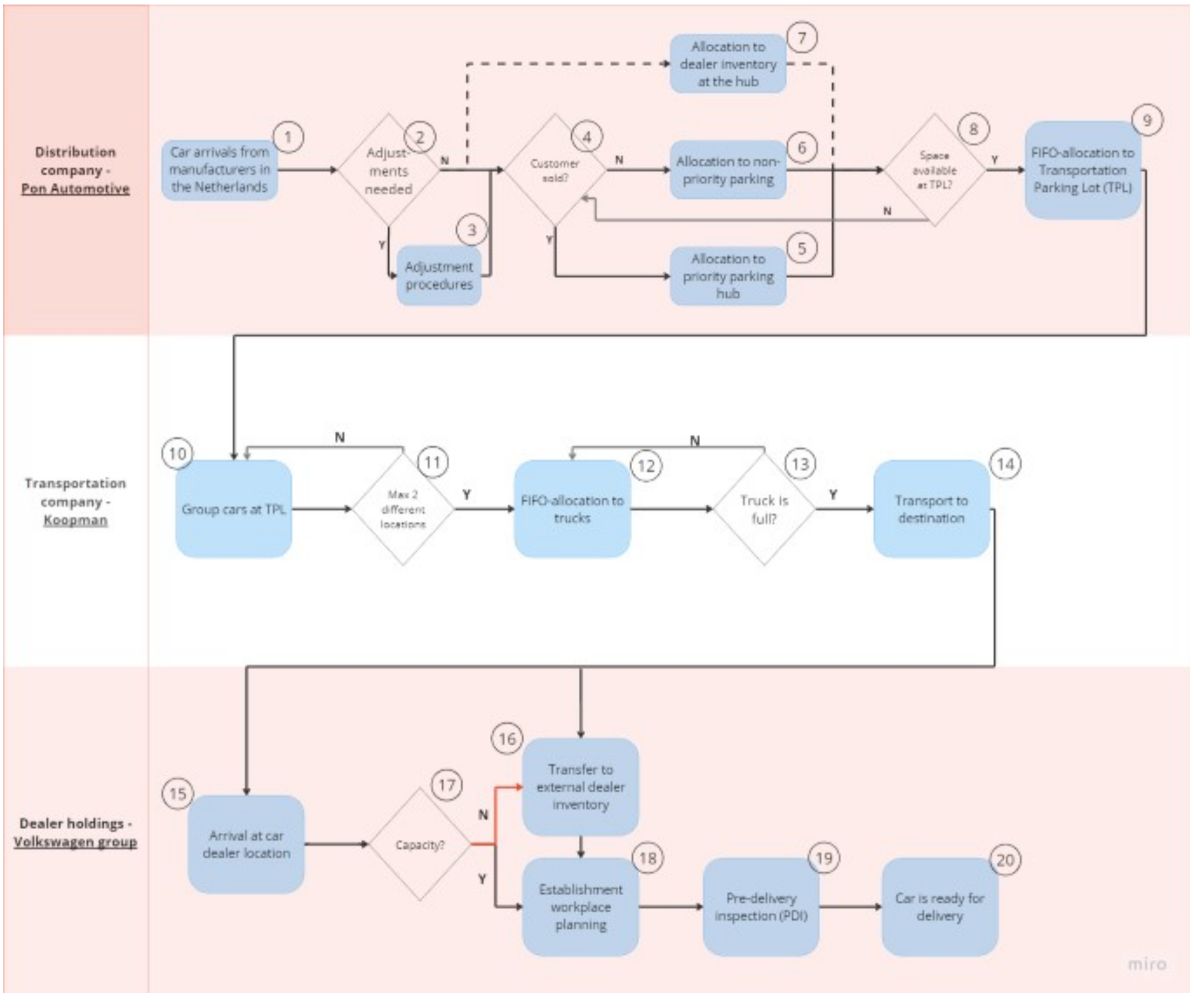

Figure 4.2: Swimlane analysis, source (Author)

When cars arrive from manufacturers in the Netherlands (1), they are transported to Pon Automotive, the central distribution hub in Leusden. Until arrival, it is not specified which specific cars are transported via train. Upon arrival, the cars are unloaded either by the train staff or by the truck driver. Once in Leusden, a comprehensive inspection is carried out to assess any damage, coupled with a systematic scanning process via QR codes. The QR code scan is crucial to determine the need for any additional modifications (2), such as interior upgrades or load space changes, to meet specific customer preferences. As described in section 4.2.4, about 30% of vehicles are modified in Leusden (3). If no additional adjustments are needed, the car order details are checked (4). If the car was ordered by customers, it is placed in a priority zone(5), as dealers prefer to receive cars ordered by customers rather than stock cars. If the car is not connected to a customer, it is parked in a non-priority area (6). Some car dealers have separately rented inventory areas where cars from specific dealers are stored separately (7), as indicated by the dotted line in figure **??**.

The connection between the distribution hubs and the transporters is facilitated by the Transportation Parking Lot (TPL) (9). This field includes the cars that can be transported from the distribution hubs to the car dealers. Filling this area is done systematically (8). Initially, the priority area is used to fill the TPL area. The remaining spaces are filled with cars from the non-priority area. In addition, cars from the dealer inventory are placed in the TPL area at the same time as the priority area, at the request of the dealers. Cars are transported from all areas based on the first-in-first-out (FIFO) principle. This ensures a low average processing time of a car within the distribution hubs.

Everyday new cars are placed in the TPL. First, the distribution company, Koopman, groups the cars at TPL based on the destination of the vehicles (10). This information is provided by the QR code on each car, and required a maximum of two different locations per trip (11). With the application of a load factor for each truck, optimal groups can be made. When a group is configured, a truck is coupled to the trip (12). Based on the contracts between Koopman and Pon Automotve, it is determined that in 95% of the cars in the TPL is transported to their destination within 48 hours. The destinations include dealer premises or external storage facilities (14). These destinations are pre-defined by the dealers and are often set as defaults. Consequently, all cars are transported to specific destinations, without individual distinctions made at the level of each car. Manual adjustments at the car level are seldom made by the dealers. In cases where adjustments are required, dealers communicate such changes to Pon Automotive through telephone correspondence.

Ideally, cars are transported from Leusden directly to dealer locations (15). However, due to lack of capacity at dealer locations, dealers are forced to use external dealer storage fields (16). These storage fields serve as intermediate locations before the cars are transported to the dealer. There are thus two types of destinations from Leusden: directly to the dealer location or to an external dealer depot. The car transport destination is determined at the time of ordering. Moreover, until the car arrives in Leusden, dealer locations have the flexibility to change the unloading location. This is not done for each car individually, but dealer locations specify whether the entire flow of cars should be transported to dealer locations or to an external dealer inventory.

When cars are transported directly to a dealer location, inefficiencies occur as indicated by the red arrow in the Swimlane diagram. Upon arrival at dealer locations, cars cannot always be accommodated at the facility itself due to capacity constraints (17). Consequently, some cars have to be unexpectedly transported to a dealer's external storage facility. These transports are considered inefficiencies: extra miles have to be traveled to move cars and employees have to assist in this process. As a result, employees are forced to help in the car distribution process, leaving other tasks and potential sales opportunities.

Once the right cars are at the dealership, workplace planning is established (18). In practice, this planning is not done in advance because dealerships perceive the reliability of deliveries from the carrier to be too low. It is challenging to estimate when a car will arrive at a dealership, leading to significant extra costs if planning does take place beforehand. In the workplace, cars are prepared for delivery through the Pre-Delivery Inspection (PDI) (19). This inspection takes about 2 hours and includes the final steps to prepare the car for delivery according to quality and safety standards. Once the PDI is completed, the car can be delivered to the customer (20).

4.2.2. Conclusion

The Swimlane Analysis has detailed the car distribution process for each main stakeholder. It reveals that Pon Automotive decides the distribution of cars, allocating them to the Transportation Parking Lot (TPL) based on a prioritization score influenced by time and whether the car is already sold to a customer. Consequently, cars sold to customers are prioritized for transportation to the TPL, followed by cars that have spent a significant amount of time at the distribution hub.
Koopman receives daily updates of the logistics within the TPL, receiving daily updates on the car inventory, including the delivery locations. This information is used to organize the load of the trucks, ensuring they are loaded efficiently and routes are planned effectively. Koopman, bound by a delivery schedule agreement with Pon Automotive, adheres to a sustainability-driven policy limiting trucks to a maximum of two stops.
Car dealers are informed when their cars arrive in Leusden. Up until the cars reach the TPL, their final destinations can be switched. However, once a car is stationed at the TPL, its destination is fixed. Dealers receive notifications when their cars are at the TPL, indicating delivery is expected within one to three days under optimal conditions.

4.2.3. IDEF-0

As described in section 4.2, the IDEF (Integrated Definition for Function) is a graphical process modeling language in the field of system engineering. By using these approach, textual and graphical representations of the system can be made in a detailed, hierarchical view.

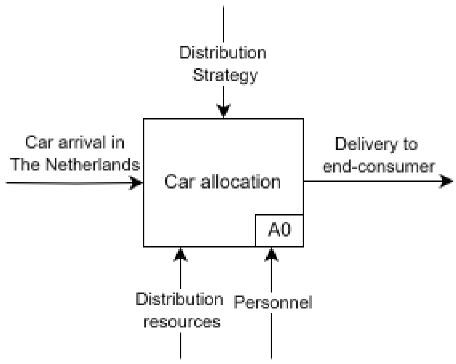

Figure 4.3: IDEF-A0 diagram, source (Author)

To provide a more detailed overview of the process, an IDEF-0 diagram can be used to focus on the various processes that occur in a sequential manner. The IDEF-0 diagram of the system is shown in Figure 4.3, outlining the entire process from car manufacturing to customer delivery. The red outline delineates the scope of this research. For a deeper analysis of each process step, an IDEF-0 diagram can be created for each sub-process. The first sub-process is the allocation of incoming cars to car dealers. This procedure applies to every car that arrives in Leusden. The distribution process from the distribution hub to car dealers can be divided into 3 sub-processes. These sub-processes are depicted of the main processes: Car allocation at the hub, Transport to the dealer, and Processing at car dealers. First, a general description of the process is provided, followed by an exploration of how each sub-process takes place.

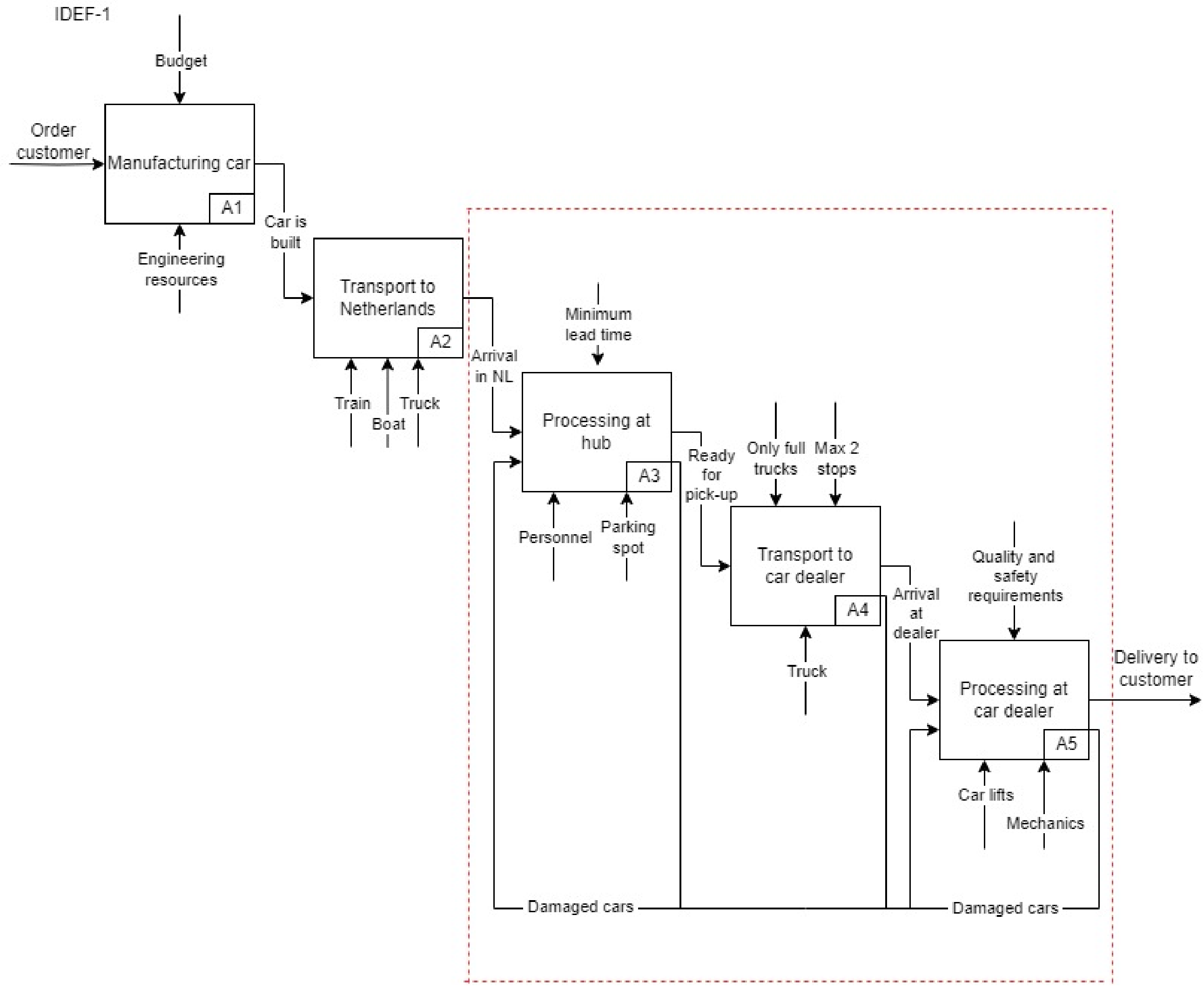

Figure 4.4: IDEF-A1 diagram, source (Author)

Once the car arrives in the Netherlands, it is received at the Leusden hub. This is a centrally located distribution hub where cars are received and then transported to the car dealers. In addition to distribution, modifications are made to approximately 30% of the cars. These modifications include procedures such as reupholstering the car or converting cargo space according to customer preferences, for example, in the case of a delivery van. When the car is ready for transport to the dealer, it is given a ”Ready For Pick-up” (RFP) status. Based on the FIFO principle, cars are offered to the transport service. The transport service selects the cars it wants to transport and assigns a truck to the transport task. Two important requirements of the transport service are specified. Firstly, only fully loaded trucks are used to transport the cars, increasing efficiency and minimizing the number of trucks needed. Secondly, a transport task is only carried out with cars from a maximum of two different locations. This is because unloading vehicles takes relatively much time. Additionally, the travel distance becomes significantly longer if the truck visits multiple locations, resulting in higher CO_2 emissions per transported car. A common extension to transporting cars to the car dealer is the interim storage of cars at an external storage facility (EP). Auto dealers have purchased these storage facilities to increase capacity for storing cars. Currently, every car dealer which works with Pon Automotive operates one or more external storage fields (EP). Cars are temporarily stored here, and when the car is requested by the dealer, it is called and transported to the dealer. The third process takes place at the car dealer, the final station before the car is delivered to the customer. Upon arrival, the car is prepared for delivery according to a schedule. This involves testing the car for quality and safety requirements so that the car can be delivered in good condition. This is done through a Pre-Delivery Inspection (PDI). The execution of the test requires a car lift and mechanics capable of conducting such a test. Once the test is completed, the car is handed over to the customer.

4.2.4. IDEF-A3

At the ”Losplaats”, cars arrive in Leusden either by truck or train. After the cars are unloaded, they are manually scanned to identify each vehicle. Following the scanning procedure, it is determined whether the car is customer-sold or if it is a stock model. Stock cars and customer sold cars are separated into different compartments based on the FIFO approach. Subsequently, cars from the various compartments are moved to the Expedition Field (EF). This field has a capacity of 1000 cars, and the transporter can choose cars from those present in this field. The transporter first groups cars based on the delivery location, with priority given to the cars that have been in the EF compartment the longest. When creating a group, consideration is given to the requirement that the truck must be fully loaded. A fully loaded truck depends on the truck's capacity and the size and height of the load. For example, up to 8 small cars can be transported on one truck, but a maximum of 4 delivery vans can be loaded on one shipment. A load factor is used to ensure that a composite load fits on one truck. Once a trip is planned, a truck is assigned to it.

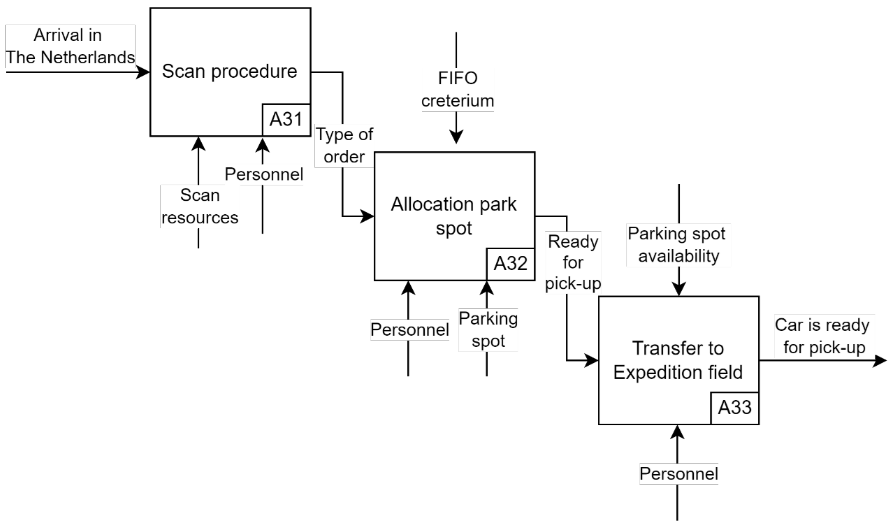

Figure 4.5: IDEF-A3 diagram, source (Author)

4.2.5. IDEF-A4

Once the truck is attached, the driver loads the cars onto the truck. A requirement of the truck is that it will make stops at a maximum of 2 locations. These locations can be a car dealer location or an External Storage Parking (EP). When a car is taken to an EP, the car is temporarily stored there because the parking capacity at a car dealer is insufficient. The decision of whether a car is temporarily taken to an EP is based on the dealer's preference. The dealer informs Pon whether cars should be taken to the dealer location or delivered to an external storage. If nothing is specified, the car will be taken to the location of the order. The dealer sometimes makes precise changes to the destination for each car, but this occurs infrequently.

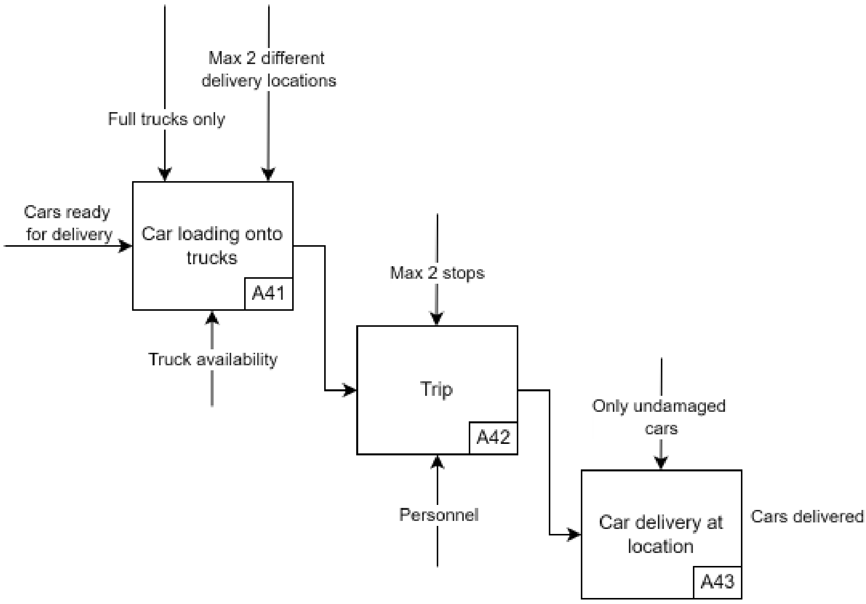

Figure 4.6: IDEF-A4 diagram, source (Author)

4.2.6. IDEF-A5

Upon arrival at the dealer location, the car is parked. Now that the car is physically present, workplace planning is determined. Conversations with dealers reveal that this planning is not made earlier because dealers do not want to plan based on the transport company's schedule. Based on past experiences, this schedule is often inaccurate, leading the dealer to incur additional personnel costs when the schedule does not align. To retain control, dealers distribute the planning based on the available cars. If it turns out that the dealer's parking capacity is insufficient, the car dealer transports the car to an external storage themselves. In practice, this occurs frequently. A common reason is that the influx of cars is higher than the outflow at a dealer location. Additionally, dealers receive cars they would prefer not to have. Some customer-sold cars have a "Not-Ride-Before" (NRB) period, during which they are not allowed to be driven on the road. In 2022, 29% of the imported cars had an NRB period. As a result, cars with a significant NRB period are transported to EPs to ensure enough capacity for cars without an NRB period. When a car can be delivered to a customer, a "Pre-delivery inspection" (PDI) is performed. During this three-hour inspection, the car is prepared for delivery by ensuring safety and quality requirements. This is a crucial inspection that cannot be fully executed at other locations because it involves the transition from "transportation mode" to normal. In transportation mode, the car cannot drive faster than 25 kilometers per hour, the suspension is fixed at the maximum height, and some parts are covered to prevent damage. After the PDI, the car can be delivered to the customer.

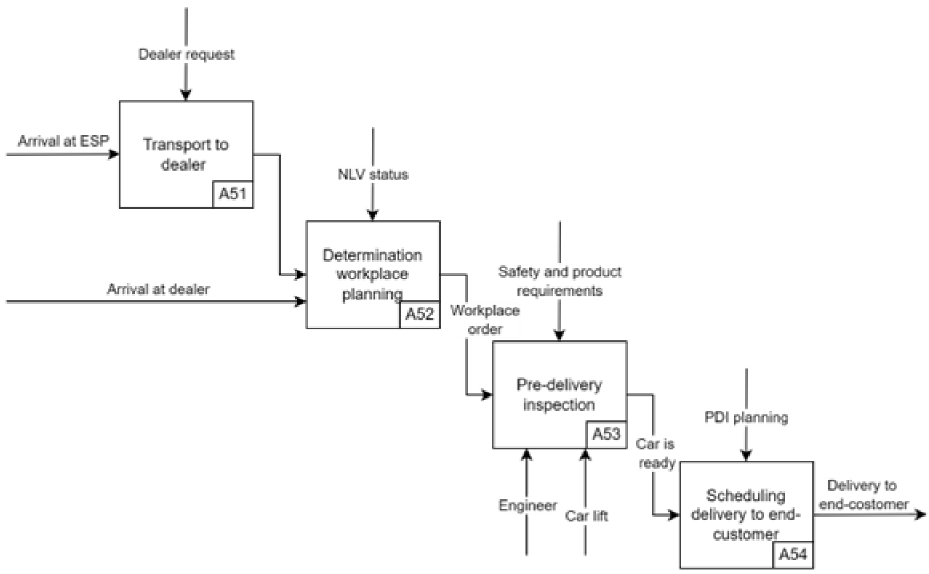

Figure 4.7: IDEF-A5 diagram, source (Author)

4.2.7. Conclusion

The analysis of IDEF-0 diagrams indicates that car dealers are experiencing issues with long delivery times. After being informed about shipments, dealers often wait additional days, which disrupts their workshop schedules. Also, it is common for dealers to receive undesired vehicles with long waiting times, due to customers preferences. This forces car dealers to move these vehicles to external storage due to limit capacity. A remarkable contractual detail between Pon Automotive and Koopman limits transport stops to a maximum of two to minimize route lengths and reduce costs. Furthermore, although purchase information is fully known at the time of sale, this detailed data is not accessible to staff on the distribution site, with the Not-Ride-Before period being critically important. As a result, Pon Automotive does not include these details in their operational procedures, and consequently, neither does Koopman. This situation results in dealers getting vehicles they did not anticipate and having to move these vehicles to external storage on their own. This is deemed highly inefficient because it diverts workforce efforts from their primary tasks in workshop maintenance or sales operations to logistical challenges.

4.3. KPI measurements

In this section, the outcomes of the process mapping are quantitative evaluated utilizing Key Performance Indicators (KPIs). The objective of these measurements is to identify inefficiencies and to quantitatively substantiate the insights derived from the Swimlane analysis and the IDEF-0 diagrams. To this end, several glob KPIs, introduced in 2 and refined based on the findings from the process mapping analysis, are employed. As described in the literature review, inefficient trips are part of unnecessary operations, disrupt the distribution flow or fail to contribute value. Examples include unnecessary movements or trips characterized by sub-optimal stop configurations. As concluded from the Swimlane Analysis and IDEF-0 Diagrams, two primary types of inefficiencies were identified:

- Inefficient trips: routes where cars are transported from the dealer to the EP, carried out by using the dealer's own transportation vans.
- Limited-stop truck trips: Trucks are constrained to a maximum of two stops, resulting in the usage of additional trucks to service other locations.

The emphasis, therefore, is on identifying the volume of inefficient trips and understanding how inefficient trips occur.

4.3.1. Approach

To identify the inefficient trips, and to understand why these trips occur, the following KPIs are used to evaluate the performance of the distribution. These KPIs are based on the global KPIs mentioned in methodology and concluded out of the findings of the process mapping. As it is concluded that redundant trips can be seen as the trips from dealers to EPs, this analysis will answer how many inefficient trips are made and why these trips occur. To compare the KPIs, the cars are separated based on their final location. The following groups are made:

- **Group Dealer:** Cars directly to the car dealer
- **Group EP(1):** Cars directly to an external parking
- **Group EP(2):** Cars indirectly transported to an external parking via car dealer

As described in 4.1, a total of 70,560 vehicles were imported in the year 2022. Of this amount, 72% were transported directly from Leusden to car dealers. The remaining vehicles were transported via Koopman trucks to an external parking facility (EP). To identify inefficiencies in these transports, an additional classification was created, referred to as Group EP(2). Vehicles in this category are first sent to a dealer before being taken to their final destination in the EP. The performance of these different groups of vehicles is evaluated using Key Performance Indicators (KPIs) to assess the efficiency of their transport routes.

Idle time at dealer location

To analyze the inefficiencies in vehicle transportation, the focus is placed on the lead time from the initial arrival of vehicles at car dealer locations. Literature suggests that in supply chain management, maintaining a low lead time is crucial for ensuring an efficient flow of goods. However, in this context, while it's important to keep the lead time short to ensure efficiency, an excessively short throughput time may indicate unnecessary additional transportation movements.
For vehicles that are directly transported to dealers:

$$LT_{dlr} = (D_a - D_{dlr}) - T_{ep} \tag{4.1}$$

Where:

- LT_{dlr} represents the Lead Time at the dealer location, measured in days.
- D_a denotes the Date of car ascription.
- D_{dlr} is the Date of transport from the Distribution Hub to the dealer.
- T_{ep} stands for the Time the vehicle spends at the External Parking.

For vehicles undergoing two stages of transport, including a transfer to the External Parking before reaching the dealer:

$$LT_{dlr} = D_{ep} - D_{dlr} \tag{4.2}$$

Where:

- D_{ep} is the Date of arrival at the External Parking.
- D_{dlr} represents the Date of arrival at the dealer.

These equations serve to quantify the lead time associated with each vehicle's transit, providing a metric to identify and assess the efficiency of transport routes and operations.

Sales to Stock Ratio

Within Pon Automotive's prioritization methods, an analysis is conducted to determine the distribution of vehicles either to car dealerships or to External Parking (EP) facilities. The preference for customer-sold cars by car dealerships stems from the potential for these vehicles to exhibit relatively short lead times at the dealership. This allows the cars to be swiftly prepared for delivery to the end consumer, facilitating their expedited removal from the system. Furthermore, during periods of limited capacity space, dealerships prefer not to have stock cars on-site, making it practical for these stock cars to be initially sent to an EP.

The Sold-to-Stock Ratio (SSR) is calculated as the proportion of sold cars to the total inventory of cars, represented by the equation:

$$SSR = \frac{\text{Number of Sold Cars}}{\text{Total Number of Cars}} \quad (4.3)$$

This metric assists in understanding the distribution and prioritization of car deliveries, emphasizing the efficiency of moving customer-sold cars quickly through the system and managing space constraints at dealerships.

"Not-Ride-Before" period

Based on the expert interviews provided by car dealerships for transporting cars to External Parking (EP) facilities, it is evaluated whether the Not-Ride-Before (NRB) period of cars transported from the dealership to the EP is relatively high. The NRB-period is defined as the time-frame during which a car is not allowed to be driven and, consequently, cannot be delivered to the end consumer. At the time of purchase, this date may be specified and added to the order. Post-purchase, the NRB date can be added or adjusted in exceptional cases, though this is rare. In 2022, 29% of purchases included an NRB period, with an average of 30 days. The reasons for setting an NRB date vary greatly but are always according to customer preferences. Common examples include the expiration of lease contracts and vacations. Dealerships indicate that, even though the vehicles are sold to customers, they are not desired at the dealership location due to these constraints. Therefore, it is assessed whether the group of cars transported from dealerships to EPs also exhibits a high incidence of NRB periods.

4.3.2. Dealer segmentation

To identify inefficient transportation routes, an analysis of car dealerships is undertaken. The literature review categorizes dealership motivations according to market demand and dealership size. This classification aids in selecting a representative sample for analysis, providing a clearer understanding of the driving forces behind dealership behaviors and the systemic challenges they face. By focusing on the size of the dealership and its primary market, we can more accurately assess how these factors influence dealership operations and strategic decisions. This methodical approach allows for a comprehensive examination of the distribution process, taking into account the diverse motivations and behaviors within the dealership network. Consequently, dealership holdings are classified according to two criteria, as delineated in Table 4.2.

Table 4.1: Dealer Segmentation

Groups	GSS-size	Market focus
1	Small	Direct-to-Customer Sales (B2C)
2	Large	Direct-to-Customer Sales (B2C)
3	Small	Sales to other businesses (B2B)
4	Large	Sales to other businesses (B2B)

The groups are based on relative small or large Gross Sales Size (GSS). The GSS is expressed in a relative percentage of the amount of sales per year. The second criterion is the market focus, which can be a focus on direct-to-customer or a focus on the lease market. The full list of the dealer segmentation is described in Appendix X. These dealers are analyzed to measure the KPIs.

4.3.3. KPI outcome hypothesis

It is hypothesized that the ”Group Dealer” will exhibit a relatively long lead time at dealership locations due to temporary storage and the execution of delivery processes to the end consumer at these sites. In contrast, ”Group EP(1)” is anticipated to have a shorter lead time at car dealerships, as vehicles in this group will only be present at dealerships when delivery processes such as license plate allocation, Pre-Delivery Inspection (PDI), and registration commence.

”Group EP(2)” is expected to have a very short lead time due to the additional transport of vehicles from the dealership to the External Parking (EP). When comparing different dealer types, no significant differences are anticipated because of a uniform approach to the types of cars preferred at each location.

As derived from the Swimlane analysis, cars that are not desired at dealership locations are typically customer-sold vehicles with a relatively high Not-Ride-Before (NRB) date. Pon Automotive prioritizes vehicles based on order details, leading to the hypothesis that ”Group Dealer” will have a relatively high Sales-to-Stock Ratio, as customer-sold cars are preferred by dealerships. ”Group EP(1)” is expected to have a lower ratio since vehicles must be stored before being sold or becoming desirable. Conversely, ”Group EP(2)” is hypothesized to have a high ratio due to the transportation of customer-sold cars that are not initially desired at the dealership.
The analysis also suggests that the NRB period might contribute to redundant transportation. Hence, in ”Group Dealer,” the NRB period is expected to be relatively low, facilitating quick delivery to customers. For ”Group EP(1)”, the NRB period is predicted to be high because vehicles are stored initially. Similarly, ”Group EP(2)” is anticipated to have a high NRB period as these vehicles are not immediately desired by customers. Among different dealer types, it is hypothesized that dealers focusing on the lease market will exhibit a higher NRB period. This is particularly true for Volkswagen Bedrijfswagens, often sold to companies with a preference for vehicles that can undergo specific adjustments. Consequently, dealerships specializing in Volkswagen Bedrijfswagens are likely to experience longer NRB periods.

4.3.4. Outcomes

This analysis aimed to pinpoint inefficient transportation routes and understand the reasons behind their occurrence. Initially, a definition of what constitutes an inefficient trip was established. Drawing from the IDEF-0 analysis, it was determined that trucks are limited to a maximum of two stops. This limitation impedes the ability to conduct efficient trips, necessitating additional journeys to meet demand. Furthermore, it was observed that some trips involve transportation from dealerships to External Parking (EP) facilities using small vans with trailers owned by the dealerships. According to the literature, such trips are considered redundant; they represent a regression in the supply chain that could have been avoided. Consequently, the study quantified the volume of inefficient trips and explored the underlying causes.
To conduct this examination, specific dealer holdings were selected that correspond with the segmentation of four distinct dealer groups. The chosen dealer holdings are associated with Pon Automotive, as detailed in Table 4.2.

Table 4.2: Dealer Holding Selection

Dealer number	Dealer	B2C-GSS (%)	B2B-GSS (%)	Total GSS(%)
481	De Waal Autogroep B.V.	3.84%	2.61%	3.41%
493	Broekhuis Alkmaar B.V.	7.82%	6.75%	7.19%
241	Auto Muntstad B.V.	4.18%	5.18%	4.65%
404	Ames Autobedrijf B.V.	4.53%	10.06%	8.03%

The analysis focuses on dealer holdings selected from each dealer group, based on the characteristics detailed in 4.2. This examination employs interviews and transportation data from the dealers, with figures derived from the Gross Sales Size in 2022, as documented in Appendix D. The discrepancy between these figures and the total counts mentioned in the case study arises because exceptional orders—those for internal use or with a special status necessitating alternative distribution approaches—are excluded from this analysis. In 2022, a total of 16,434 new cars were delivered to these four dealer holdings, representing 23% of the total cars transported that year.
Initially, it was postulated that the lead time for cars arriving at a dealership for the first time within the ”Group Dealer” would be comparatively lengthy. The findings from this analysis validate this hypothesis, with cars in the ”Group Dealer” exhibiting the longest lead times across all four dealer holdings. This outcome is expected, as these vehicles are temporarily stored and prepared for delivery to the end consumer, as noted in [Interview Dealers]. However, notable variations exist between different dealer groups; dealers focused on the B2C market exhibit shorter lead times compared to those serving the B2B market. Auto Muntstad B.V. noted that many B2B vehicles are vans requiring modifications. Similarly, Ames Autobedrijf B.V. mentioned their practice of purchasing cars in advance, given the predictability of lease companies purchasing large batches of identical vehicles, thereby minimizing risk.
As anticipated, ”Group EP(2)” demonstrated a significantly shorter lead time. The impetus for moving

cars from the EP to the dealership is to expedite delivery to the customer. Following ascription and the Pre-Delivery Inspection (PDI), the average lead time recorded was 18.3 days. Notably, all car dealerships experienced instances where vehicles were initially delivered to them before being moved to an EP, corroborating the hypothesis of random trips occurring. Documentation from specific dealers revealed that 21% of incoming cars at De Waal B.V. were subsequently transported to an EP. Similarly, 16% of vehicles at Broekhuis Alkmaar B.V. were moved to an EP after dealer arrival. While Auto Muntstad B.V. and Ames Autobedrijf B.V. did not provide detailed transport records, they indicated that vehicles with extensive NRB periods are generally unwelcome at dealership locations. [sources]

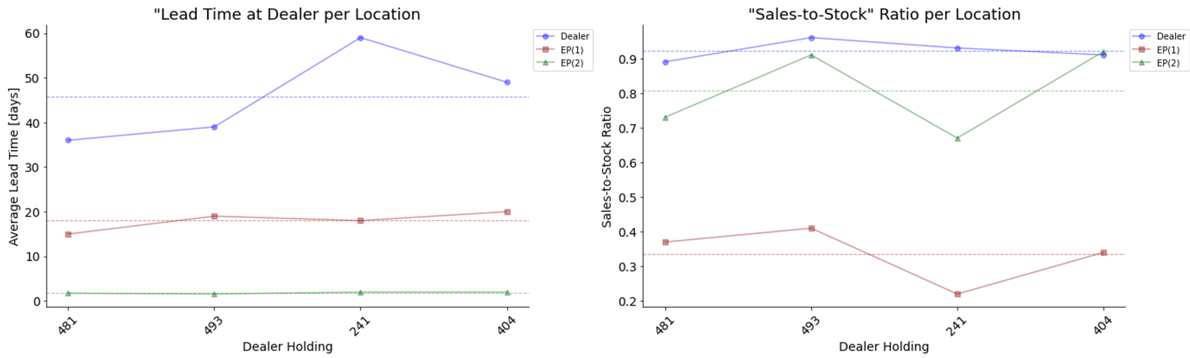

Figure 4.8: Car dealer differences, source (Author)

The second Key Performance Indicator (KPI) supports the explanations provided by the car dealers and confirms the hypothesis. The ”Group Dealer” exhibits a relatively high Sold-to-Stock Ratio (SSR), as dealers prioritize receiving cars sold to customers. The differences in SSR between dealers are not significant, which aligns with expectations since all dealers prefer customer-sold cars over stock cars. Auto Muntstad B.V. notes that stock cars are often sent to External Parking (EP) facilities to optimize the limited capacity available at dealership locations. This is illustrated in the analysis of ”Group EP(1)”, where the SSR is notably lower than that of the ”Group Dealer”. For ”Group EP(2)”, which includes cars moved from the dealership to an EP, the SSR is significantly higher, indicating that even customer-sold cars deemed undesirable by dealerships are sent to EPs. However, the SSR for ”Group EP(2)” is still lower than that of the ”Group Dealer”. Auto Muntstad B.V. further clarifies that demo or stock cars are also directed to EPs. Additionally, some EPs are not accessible by Koopman due to the absence of a contractual agreement, necessitating Muntstad to undertake these transports independently.

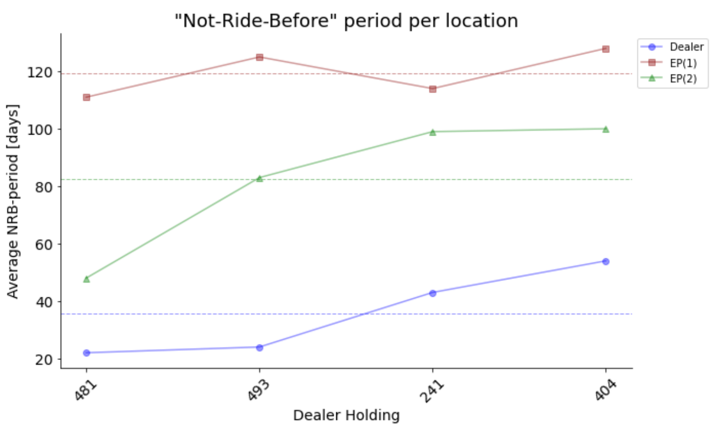

Figure 4.9: Not Ride Before difference of different dealer types, source (Author)

The third Key Performance Indicator (KPI), focusing on the Not-Ride-Before (NRB) period for customer-sold cars, by dealers it is suggested as a contributing factor to inefficient transportation routes. This hypothesis has been confirmed through analysis. As depicted in figure 4.9, vehicles within the ”Group Dealer” category exhibit a relatively short NRB period, underscoring a preference for cars that can be swiftly prepared and delivered to the customer. Conversely, vehicles with a longer NRB period

are typically assigned to an External Parking (EP) facility, as demonstrated in the analysis of ”Group EP(1)”. Such vehicles are generally not preferred at dealership locations due to their delayed readiness for customer delivery. The analysis of ”Group EP(2)” reveals that these cars also have a notably long NRB period, suggesting that the duration before a car is permitted to be driven significantly influences the necessity for additional transportation movements. This indicates that the NRB period is a major determinant of inefficient trips.
The measurement of variations across different dealer holdings, distinct patterns emerge. Dealerships with a focus on the Business-to-Business (B2B) segment have vehicles with a longer NRB period compared to those concentrating on the Business-to-Consumer (B2C) market. Ames Autobedrijf B.V. acknowledges the aim to reduce transportation to EPs. However, this is sometimes inevitable due to unpredictable vehicle deliveries. Under these circumstances, priority is given to transporting cars with the longest NRB periods. This could result in the transport of cars with a high NRB-period. In addition, De Waal B.V. points out the severe capacity constraints at dealership locations, necessitating the frequent relocation of vehicles to EPs to manage space effectively.

4.4. Requirement Analysis

Establishing comprehensive system requirements for the car distribution process is crucial for designing an efficient and customer-focused logistics system. These requirement can be obtained by combining actor requirements. These actor requirements are concluded out of the process mapping, in 4.2, As described in 3, the methodology for translating actor requirements into system requirements consists of several steps. First, each requirement is examined for its underlying functional and non-functional implications for the system. On the one hand, functional implications refer to the specific behaviors, actions, or functions the system must perform and are directly related to business operations. On the other hand, Non-functional requirements define the system’s operational attributes and constraints, such as performance and reliability. After that, these implications are mapped to specific system properties, taking into account the potential constraints. This process ensures that each requirement is represented in the design and capabilities of the system.

4.4.1. Actor requirements

As described in section 4.2, the distribution process of Pon Automotive reveals key operational insights and inefficiencies. By analyzing Key Performance Indicators (KPIs) and evaluating dealer group dynamics and logistics, the need for transparency, logistics efficiency and strategic vehicle allocation within the distribution chain became clear. Consequently, a set of requirements is determined per main actor Pon Automotive (p), Koopman (k), and Dealer holdings (d). These requirements per actor form the basis to establish the system requirements, with the aim of refining operations for Pon Automotive, Koopman and the Dealer Holdings.

These requirements for each main stakeholder are designed to address the main issues identified in the distribution network. The aim is to improve how things work, make processes clearer, and meet the needs of everyone involved. Putting these measures into place is expected to significantly enhance the distribution process, leading to better service and increased customer satisfaction.

4.4.2. System Requirements

System requirements play a crucial role in the design and operation of a car distribution system, as they translate actor requirements into concrete system functionalities. As described in 2, Actor Requirements represent the essential needs and expectations of the stakeholders. These requirements serve as the foundation for developing system functionalities that enable the effective execution of the distribution process. Functional requirements detail the specific behaviors and actions the system must perform to satisfy the stakeholders’ needs. This includes managing orders, satisfying demand, optimizing load distribution, ensuring efficient routing, and maintaining transparency throughout the distribution process. The table 4.3 describes the functional system requirements derived from the collective needs of the actors, which include Pon Automotive, the logistics partner Koopman, and the car dealerships. These requirements ensure that the system is equipped with the necessary capabilities to support the daily operational demands.
By aligning these functional requirements with the system’s capabilities, the distribution process is

p_1 **Transparency of Destination:** Ensure the clear and transparent communication of each vehicle's intended destination, a dealership or an External Parking (EP) facility.

p_2 **Detailed Order Information:** Maintain and make accessible comprehensive order details for each car, including specifications, customer-sold status, and Not-Ride-Before (NRB) periods.

p_3 **Minimum Daily Outflow:** Set and adhere to a minimum threshold for the daily outflow of vehicles from the distribution hub to facilitate consistent and efficient vehicle distribution.

k_1 **Comprehensive Transport Overview:** Require a current and transparent overview of vehicles designated for transport, inclusive of specific car details to optimize logistical planning.

k_2 **Flexible Stop Capabilities:** Enable the logistic flexibility to stop at either a dealership or an EP as dictated by transportation needs and strategic considerations.

k_3 **Destination Clarity and Distance Information:** Provide clarity on the destination of each vehicle, along with distance metrics, to support effective transport route planning and execution.

d_1 **Delivery Transparency:** Dealerships should be guaranteed transparency and accuracy in the information regarding daily car deliveries to manage inventory and prepare for customer transactions efficiently.

d_2 **Availability of Accessories for PDI:** Ensure the availability of all required accessories and tools for conducting Pre-Delivery Inspections (PDIs), critical for upholding service quality and expediting the delivery process.

Table 4.3: Functional System Requirement Specifications

Actor Requirements	System Requirements	System Application
p_1, p_2, d_2	Transparent order details	A detailed database of each car must be maintained at Pon
p_3, d_1	Full demand satisfaction	All cars with an RFP-status must be transported on a daily basis
k_1, p_2	Max load per truck	Car details must be transparent to allocate cars to trucks
k_2	Trucks leave from distribution hub	Cars must be picked up at the distribution hub
k_3	Split delivery	Demand can be delivered partly to multiple locations
p_1, k_3	Minimize amount of kilometers	Routes must be based on minimizing travel distance
d_1	Transparent delivery status	Trucks must be trackable during the route

optimized to meet the dynamic needs of the automotive supply chain, thus ensuring efficiency, transparency, and responsiveness to other stakeholders.

Non-Functional Requirements

Non-functional requirements (NFRs) are critical for the car distribution process as they define the operational qualities and constraints of the system. While functional requirements specify what the system "must have", NFRs dictate how the system "should perform" its functions. NFRs are important because of the direct impact on car dealer satisfaction satisfaction and the operational success of the distribution network. Three NFRs have been identified for the distribution process of cars. These are presented in table 4.4.

Table 4.4: Non-Functional System Requirement Specifications

Actor Requirements	System Requirements	System Application
d_1	Delivery reliability	Delivery should be accurate to prevent accumulation
p_3	Flexibility	Routes should be adjusted flexibly
k_2	Security	EPs should be safe for car storage

Delivery Reliability ensures that the delivery of vehicles is consistent and accurate, reducing the risk of delivery delays or errors that could lead to vehicle accumulation at the distribution hub or dealerships. This is done by setting a minimum outflow at Pon Automotive and the availability of dealer locations to rent or buy a External Parking (EP) to increase the capacity. Secondly, flexibility in routing and delivery is crucial to accommodate fluctuating demands and unexpected logistical challenges, such as a flat tire or to adjust on manual locations adaptions. In addition, security is important, Especially in ensuring that EPs are secure for vehicle storage, protecting against theft, damage, and unauthorized access. These non-functional aspects are part of the overall performance of the system and therefore receive a lot of attention in the design and implementation phases of the system.

4.4.3. Bottlenecks found in system

To measure the current state on the system requirements, validated by the three main actors, the bottlenecks can be obtained. Combining the process mapping results, and KPI measurements, the current state can measured on the system requirements. These scores are verified by Pon Automotive, Koopman specialists and Car Dealers, as presented in table 4.5.

Table 4.5: Current State Requirement Score

System Requirements	Type	Current State Score	Note
Transparent order details	F	*	No NRB-period details visible at allocation department
Full demand satisfaction	F	***	Contracted pick-up timeline with Koopman
Max load per truck	F	***	Usage of a loadfactor
Trucks leave from distribution hub	F	***	Start location at Distribution hub of Leusden
Split delivery	F	***	Ability to deliver partial demands
Minimize amount of kilometers	F	*	A hard constraint of maximum 2 stops per truck
Transparent delivery status	F	*	No tracking system for Koopman trucks
Delivery reliability	NF	*	Average margin of 4 days between car delivery
Flexibility	NF	***	Easy manual adjustments in transportation scheme
Security	NF	***	All locations, including EPs, are insured

It can be concluded that not all system requirements are met in the current state situation. These shortcomings can be seen as bottlenecks within the car distribution process. These bottlenecks are not only operational inefficiencies; they represent fundamental challenges that require strategic interventions and systemic improvements. Each bottleneck identified provides insights into the complexity of the distribution process and offers the possibility of the implementation of new policies

Communication Gaps

A key bottleneck is the absence of integral communication across the distribution network. The current state reveals a disconnect in the transparent exchange of vehicle information, particularly regarding the 'Not-Ride-Before' (NRB) period. The lack of visibility into these critical details at the allocation department hinders effective logistics planning, leading to inefficiencies in vehicle storage and movement.

Hard operational constraints

The constraint of a maximum of two stops per truck imposes significant limitations on routing flexibility. This restriction not only leads to sub optimal route planning but also contributes to increased CO_2 emissions as additional trips are necessitated to fulfill the transportation demand. Addressing this limitation by integrating advanced vehicle routing algorithms could yield more efficient routes and reduce the environmental impact of the distribution operations.

Redundant trips

The Swimlane analysis and the IDEF-0 diagrams have highlighted the inefficiencies of dealer trips to EPs, especially those that involve transporting vehicles that have been delivered incorrectly or whose NRB period is high. The environmental targets of Pon Automotive need a review of transport strategies to align them with sustainability goals, set by the European Commission.

Lack of efficient prioritization

The current state analysis indicates that dealer-performed trips can be inefficient, often resulting from incorrect deliveries. These inefficiencies are visible when customer-sold vehicles with high NRB periods are involved, leading to unnecessary shuttling of vehicles between locations. Furthermore, the availability of cars with low NRB-periods at external parkings suggests a misalignment in vehicle distribution priorities.

4.4.4. Proposed Policies

To overcome these bottlenecks, two policies are proposed:

- Revisiting the routing constraints to allow more route flexibility per truck.
- Implementing a strategic approach to prioritize the delivery of cars from distribution hub to car dealer and external parking.

The policies aim not only to address the operational challenges but also to lay the groundwork for a distribution system that is robust, reduces direct CO_2 emissions. The next step in this research will involve the development and evaluation of a solution approach that represents the current state. Subsequently, the implementation of these policies facilitates the restructuring of the distribution process.

4.5. Conclusion

This chapter aimed to answer the following sub-question:

What are bottlenecks in the current car distribution system?
The current state analysis of Pon Automotive's distribution process revealed key inefficiencies, particularly in communication and operational constraints. These findings are validated by stakeholders and comparable automotive companies. The lack of transparency about 'Not-Ride-Before' (NRB) periods and the two-stop maximum for trucks limits distribution efficiency and are potential reasons for CO_2 emissions. In the process mapping analysis, it has become apparent that unnecessary dealer transport occurs as a result of cars not being desired by auto dealers. It is concluded that the Not-Ride-Before (NRB) period of cars is a cause for dealer transport, a car detail currently not accounted for in the process. By initially transporting cars to their desired location, dealer transport will be reduced. Furthermore, it has been revealed that a limit of a maximum of two stops per truck imposes significant restrictions on routing flexibility. Allowing more truck stops could reduce direct CO_2 emissions, as routes could be configured more efficiently. These issues highlight the need for a more integrated communication system and new vehicle routing strategies. Therefore, two policies are proposed, based on the actor and system requirements.

1. **Policy 1:** Unlimited location stops for trucks
2. **Policy 2:** Not-Ride-Before period prioritization

The aim of the policies is to create more operational flexibility and reduce direct CO_2 emissions by minimizing inefficient trips of car dealers.The implementation of these policies is expected to create a more adaptive and efficient distribution system, directly contributing to the reduction of unnecessary trips and the optimization of transport routes. These policies are validated by the second largest car import company of the Netherlands. This approach not only addresses the immediate operational inefficiencies but also aligns with broader environmental sustainability objectives, elaborated by the European Commission.

Table 4.6: Evaluation of System Requirements Across Different Policies

System Requirements	Current State	Policy 1 NRB-Period Priority	Policy 2 Flexible Routing	Policy 1+2 Integral Process
Minimize Direct CO_2 emissions	*	**	**	* * *
Flexibility	**	**	* * *	* * *
Split delivery	**	**	* * *	* * *
Delivery reliability	*	*	**	**
Security	* * *	* * *	* * *	* * *
Full demand satisfaction	* * *	* * *	* * *	* * *
Max load per truck	* * *	* * *	* * *	* * *
Trucks leave from distribution hub	* * *	* * *	* * *	* * *
Transparent order details	*	*	*	*
Transparent delivery status	*	*	*	*

Here, the potential contributions per policy are presented in green. As concluded in the current state analysis, transparency in order details and delivery status lacks between the main stakeholders. In the further research, it is assumed that transparency of information between stakeholders is improved. This is the the foundation for the implementation of Policy 1 and Policy 2.

5 Mathematical Modeling and Solution Approach

In this chapter, the Solution Approach is developed. As the system requirement based on the three main actors is clear and the potential policies are clear, a model can be used to evaluate the implementation of policies. First, the objective and scope of the design is defined in section 5.1. This includes the definition of the mathematical model of the Capacitated Vehicle Routing Problem. Second, the application of the HGS-CVRP heuristic is described in Section 5.4. Third, the outline of the performance evaluation is explained in section 5.5. Fourth, the data collection is elaborated in section 5.6. Lastly, the verification of the model is executed in section 5.7. Therefore, sub-question 5 of this research will be answered:

- How can the car distribution system be modeled?

5.1. Optimization Model

The objective of this model is twofold. First, this model aims to design a representative model that accurately quantifies the direct CO_2 emissions arising from truck-based car distribution processes, incorporating both the system and actor requirements of the main stakeholders and taking into account the routes selected for transportation. With this knowledge, car distribution processes can be reconsidered to better align the processes, to make improvements or to adapt current policies. Also, insights are provided by allocating cars to specific locations to reduce trips performed by car dealers to an external parking and reducing its environmental impact. This can support dealers to better align preferences with other stakeholders, to improve the overall environmental impact. In addition, current contracts between transportation companies can be reconsidered, to make improve processes. It becomes clear that problem is not owned by a single actor, thus insights of this research need to be spread to all main actors.

The second objective of this optimization model is to implement a split delivery methodology to combine the state-of-the-art Hybrid Genetic Search algorithm for Capacitated Vehicle Routing Problems (HGS-CVRP) of Vidal [90] and the novel approach of $a\ priori$ split strategy of the demand proposed by Chen et al. [27]. This is done by comparing the performance of the HGS-CVRP including a priori split demand with exact methods on small scales, to verify the solution approach. As described in 2.2.3, the Capacitated Vehicle Routing Problem (CVRP) is a fundamental combinatorial optimization problem and well-studied variant of the Vehicle Routing Problem (VRP). Exact methods aim to find the optimal solution to the CVRP by exploring all possible combinations of routes that meet the problem's constraints. Also, in the mathematical formulation of a CVRP, split delivery constraints can be easily added. However, due to the NP-hard nature of CVRP and the exponential growth of the solution space by improving the model to real-world situations, large CVRP problems cannot be solved. As a result, large scale CVRP solutions can be calculated with the state-of-the-art HGS-CVRP heuristic with the aim to minimize the optimality gap.

The problem is on a complete graph $G = (N, A)$, where $N = \{0, 1, 2, ...n\}$ is the set of nodes [86]. Node 0 represents the distribution hub (DH), where a fleet of homogeneous trucks T is based. Nodes $1 \sim n$ represent the dealer locations (DL), which could be a car dealer, an external parking, or a dummy location. $A = \{i, j | i, j \in N, i \neq j\}$ is the set of arcs, the routes from point i to point j [86]. The summation of the sub-routes driven by each truck $t \in T$ is considered as a trip.

The remainder of the notions used to formulate the Capacitated Vehicle Routing Problem (CVRP), including the adaptions to ensure split delivery possibilities, is formulated as follows.

Parameters

D_i	Demand of dealer location i
N_t	Number of trucks
Q_t	Capacity of truck t
$TD_{i,j}$	Distance of the route between nodes i and j
L_t	Load of truck t at node i
FC_t	Fuel consumption of truck t
EF_t	Emission factor of truck t
FR_t	Average fuel reduction when truck t is unloaded

Variables

$x_{i,j,t}$	1: if truck t drives from node i to j 0: Otherwise
$z_{i,t}$	1: if node i can be reached by truck t 0: Otherwise
u_i	Helper variable of node j
$f_{i,j,t}$	Fraction of the demand delivered from node i to j by truck t

Minimizing the Total Travel Distance (TTD) of trips:

$$\text{Minimize TTD} = \sum_{t \in T} \sum_{i \in N} \sum_{\substack{j \in N \\ i \neq j}} TD_{ij} \cdot x_{ij}^t \tag{5.1}$$

Subject to:

$$\sum_{t=1}^{T} z_{i,t} = 1 \qquad \forall i \in N \setminus \{1 \dots n\} \tag{5.2}$$

$$\sum_{t=1}^{T} z_{0,t} = N_t \tag{5.3}$$

$$\sum_{j=1}^{N} x_{j,i}^t = \sum_{j=1}^{N} x_{i,j}^t \qquad \forall i \in N, \forall t \in T \tag{5.4}$$

$$\sum_{j=1}^{N} x_{i,j}^t = z_{i,t} \qquad \forall i \in N, \forall t \in T \tag{5.5}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} TD_i \cdot z_{i,t} \leq Q_t \qquad \forall t \in T \quad (5.6)$$

$$u_j - u_i \geq f_{i,j,t} \cdot D_j - Q_t \cdot (1 - x^t_{i,j}) \qquad \forall i \in N \setminus \{1 \dots n\}, \forall j \in N \setminus \{1 \dots n\}, \forall t \in T \quad (5.7)$$

$$u_i \geq D_i \qquad \forall i \in N \setminus \{1 \dots n\} \quad (5.8)$$

$$u_i \leq Q_t \qquad \forall i \in N \setminus \{1 \dots n\} \quad (5.9)$$

$$x^t_{i,j} \forall 0, 1 \qquad \forall i \in N \forall j \in N \forall t \in T \quad (5.10)$$

The objective function (5.1) minimizes the traveled distances of the trips. All cars are parked at the distribution hub, thus the starting point of each truck is the distribution hub(5.3). The trucks always leaves the depot and always leaves the dealer locations after satisfying the demand (5.4)(5.5). To ensure that a truck has a maximum capacity and this capacity cannot be exceeded, constraint 5.6 is implemented. However, when above constraints are taken into account, the solution can still be infeasible to the problem because of potential sub-tours. Therefore, constraint (5.7), constraint (5.8) and constraint 5.9 are added. Constraint (5.7) ensures that the next node of the trip can only be another dealer location when the fraction of the demand of node j is equal or larger then the load of location j at truck t. Here, a helper variable u_i is used to determine if visiting node j could be a dealer location, and must be equal or larger then the demand of node i to exclude the distribution hub (5.8). In addition, u_i must be equal or smaller than the capacity of truck t to ensure that the capacity is not exceeded (5.9). Lastly, the remaining constraint obligatory constraint 5.10 specify the domain of the variables. This CVRP model is known as a three-index truck flow formulation.
For the implementation of the split delivery possibility in exact methods, certain constraints of the CVRP model are adjusted and added to obtain a Split Delivery Capapcitated Vehicle Routing Problem (SD-CVRP) model. This model is used for the exact method. The objective function of the SDCVRP model remains unchanged. First, a new continuous variable is introduced, called the fraction $f_{i,j,t}$. The constraints are adjusted as follows.

$$\sum_{v=1}^{T}\sum_{i=1}^{N} f_{i,j,t} = 1 \qquad \forall j \in N \quad (5.11)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} TD_j \cdot f_{i,j,t} \leq Q_t \qquad \forall t \in T \quad (5.12)$$

$$x^t_{i,j} = \begin{cases} 0 & \text{if } i = j \\ \geq f_{i,j,t} & \text{if } i \neq j \end{cases} \qquad \forall t \in T, \forall i \in N, \forall j \in N \quad (5.13)$$

Constraint 5.2 is adjusted, as the split delivery function enables locations to receive demand from multiple trucks. Instead, constraint 5.11 is added, and makes sure that all fractions have to be 1, per truck and per node, ensuring that all demand is fulfilled. With the introduction of the fraction variable, 5.6 is adjusted. Constraint (5.12) ensures that the demand of node j can be fulfilled, only when smaller than the Q_t. This results in no sub tours, and therefore constraint (5.7), constraint (5.8) and constraint 5.9 can be released. But, to combine the variable f_i, j, t with x_i, j, t, constraints 5.13 are used. In constraint 5.13 the demand fraction of each dealer location is coupled to the decision variable of using a route or not. These two constraints ensures that no truck will leave to another dealer until all fractions are equal to zero. Therefore, all demand is fulfilled.

5.2. Initial demand determination

The demand of a location is provided as an input to the problem and remains constant. For each run, in the context of the Capacitated Vehicle Routing Problem (CVRP) applied in the automotive industry, a time frame of one day is often utilized. Daily demand is determined based on the number of cars available at the distribution hub, where each car contains a final location. The demand at a location correlates with the number of cars, but adjusted with a load factor. Assumptions regarding the specific load factor assigned to each car can be made. Through constraints 5.12 and 5.11, all demand is met, thereby the demand needs to be correlated with a freight-specific load factor. This is done by incorporating the individual load factor (ILF) of cars, with final destination i.

$$D_i = ILF \cdot Cars_i \qquad \forall i \in N \quad (5.14)$$

Typically assumptions are made based on the type of freight. In the transportation of freight, the load factor is often dependent on the dimensions and the mass of the freight. This is relevant in the distribution of cars, where the weight and size of the trucks determines the quantity that can be transported. Trucks are subjected to a maximum weight for trailers, and the size of each trailer is also restricted. In addition, when considering demand to a specific location, the demand cannot exceed the maximum capacity of dealer location. Therefore, equation 5.15 is used.

$$D_i \leq Dlr_{cap,i} \qquad \forall i \in N \quad (5.15)$$

5.3. A Priori Split Strategy

As described in 2.2.3, the HGS-CVRP heuristic is not suitable in situations where the demand of a customer is larger than the maximum capacity of the transportation truck. Many experiments of the [88] are used as validation of HGS-CVRP, where the maximum demand is always lower than the capacity because of constraint 5.2. Adaptions to a split delivery function are not straightforward, as it requires introducing new local search operators and adapt crossover [90].

Thus the a priori has two functions. Enabling split demand by using the split strategy and eliminating the nodes without demand. The a priori split delivery approach considers a complete graph $G = (N, A)$, and considers the total demand of each node. Each node without demand is eliminated, resulting in sub-graph $G' = (N', A')$, where $N' \subseteq N$ and $A' \subseteq A$. The a priori approach for the SDCVRP aims to split the demand in moderate demand sets, including the addition of dummy locations when the demand is split. In Chen et al. [27], the initial demand of 76 is split by using the 20/10/5/1 for trucks with a capacity of 40. By using the 20/10/5/1 rule, the following procedure is used to make the groups:

- $m_{20} = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.50Qm \leq D_i\}$,
- $m_{10} = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.25Qm \leq D_i - 0.50Qm_{20}\}$,
- $m_5 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.125Qm \leq D_i - 0.50Qm_{20} - 0.25Qm_{10}\}$,
- $m_1 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.025Qm \leq D_i - 0.50Qm_{20} - 0.25Qm_{10} - 0.125Qm_5\}$.

It has been discussed that there are many different ways to split the demand, but that a reasonable trade-off between running time and the quality of solutions have to be made [27]. Therefore, moderate sized groups and small demand groups are chosen. In the verification steps of the HGS-CVRP, with an Exact method as benchmark, the group sizes are chosen. When the demand is split, per demand split a dummy location is made. This dummy location is on exact the same location of the initial location and takes the split demand as demand. By doing this, the demand the constraint of 5.11 can be sustained and the split delivery can be simulated.

5.4. Hybrid Genetic Search (HGS-CVRP) algorithm

The HGS-CVRP is described by [90], and consists a meta-heuristic especially designed to solve large CVRP instances. This heuristic is based on the original method of [92], as described in 2.2.3. The general structure of the search is based on the following process, visualized in figure 5.2.

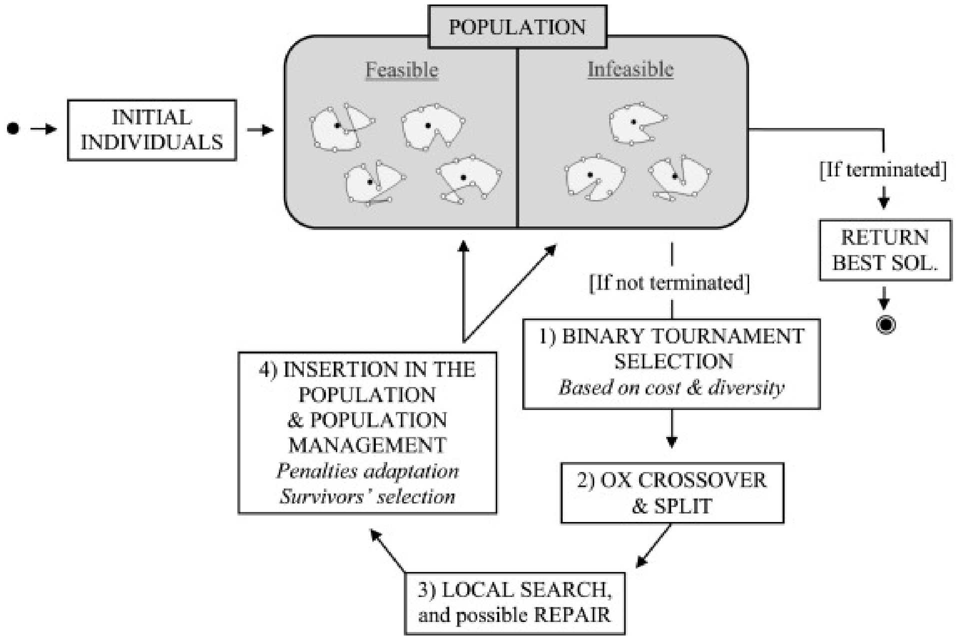

Figure 5.1: HGS-CVRP structure, retrieved from Vidal [90]

5.4.1. Parent Selection

The total populations is equal to the nodes in the complete graph $G = (N, A)$ considered. The process of selecting parents begins with a random approach known as binary tournament selection. Here, two parents (or routes) are randomly chosen with uniform probability, where the two parents are ranked based on the best fit. The fit ranking $f_{\mathcal{P}}(S)$ is based on two main factors: the objective value (the quality of the solution) $f^{\phi}_{\mathcal{P}}(S)$ and population diversity compared to other routes (contribution)$f^{\text{div}}_{\mathcal{P}}(S)$. Therefore, the following ranking formula is used [90].

$$f_{\mathcal{P}}(S) = f^{\phi}_{\mathcal{P}}(S) + \left(1 - \frac{n^{\text{Elite}}}{|\mathcal{P}|}\right) f^{\text{div}}_{\mathcal{P}}(S) \tag{5.16}$$

This equation assigns a larger emphasis on solution quality, guaranteeing that the individuals with the best performances are maintained. The ranking based on solution quality is determined by evaluating the fitness of the solutions. This is done through the model objective function associated with the routes in a solution. Then, solutions are then ranked according to their fitness values, where a lower value indicates higher quality as the objective function minimizes total travel distance. The ranking based on diversity aims to maintain a diverse selection of solutions. This is achieved by assessing the level of difference between solutions, looking at the ”average broken-pairs distance” between solutions in the sub-population. This indicates the the differences in routes between almost similar routes. This approach involves calculating the distance between solutions in the solution space, where larger ”average broken-pairs distance” indicate higher diversity. The diversity score can then be used to order the solutions, with higher scores indicating a greater contribution to the population's diversity.

5.4.2. Recombination

The HGS-CVRP applies an ordered crossover approach of two parents, by [66]. A random segment from the first parent is chosen, then the missing visits are filled in with the sequence from the second parent. This method skips visiting to the depot, thus capacity limits are not considered during the crossover. After each crossover, an efficient linear-time Split algorithm, introduced by [91], is used to calculate the rank. This ensures that the resulting solution is complete and feasible for the CVRP.
The combination of OX-crossover with the Split algorithm enables HGS-CVRP to generate solutions by combining the optimal attributes of two parental solutions, while ensuring to the capacity constraints of the problem are met.

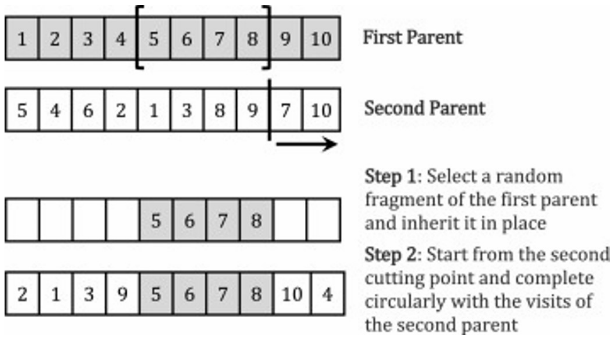

Figure 5.2: Recombination with crossovers, retrieved from Vidal [90]

5.4.3. Neighbourhood improvements with SWAP*

The local search improvements consists two stages: Route improvement and pattern improvement. This initial route improvement procedure of Vidal et al. [92] is eliminated, and included an addition neighbourhood in RI called Swap* [90].
The Swap* neighbourhood offers an approach to exchanging customers between different routes. Unlike the traditional Swap neighbourhood or [92], where two customers directly swap positions, the Swap* neighbourhood allows for the exchange of two customers between different routes without requiring a direct positional swap. This method limits the potential new insertion positions for an exchanged customer to the most promising locations, based on a preliminary evaluation. The best new positions for inserting a customer into another route are either the position of the originally removed customer or one of the three most promising positions.

The Neighbourhood Swap* moves are considered only between 2 routes that intersect within the extreme nodes. This area is determined from the depot, as illustrated in 7.2. By considering only routes whose routes crosses, the set of route pairs for Swap* move evaluations is narrowed. After this, a relocation is applied to improve the routes, only considering geographically close nodes.

5.4.4. Inserting the result in the population

Once a solution is generated, it is placed in one of the sub-populations of solutions: feasible and infeasible solutions. Each route produced during the preceding steps is immediately added into the appropriate sub-population. By defining parameters the total number of solutions is managed. The first parameter, μ, represents the minimum number of solutions in the sub-population. Also, λ is established as a predefined population size. The maximum population size is then determined as follows.

$$\text{Max sub-population size} = \mu + \lambda \tag{5.17}$$

These parameters are predetermined. Initially, 4μ, random solutions are generated in the Parent Selection. The maximum sub-population size is reached, the sub-population will be reduced. During this process, identical solutions and the worst solutions are eliminated first. The algorithm operates under a termination condition, which can be set as either a specific number of consecutive iterations without any enhancement, defaulting to 20,000 (Nit), or a maximum CPU time limit (T_max). In scenarios where the T_max criterion is applied, the algorithm undergoes a restart after every N_it iterations.

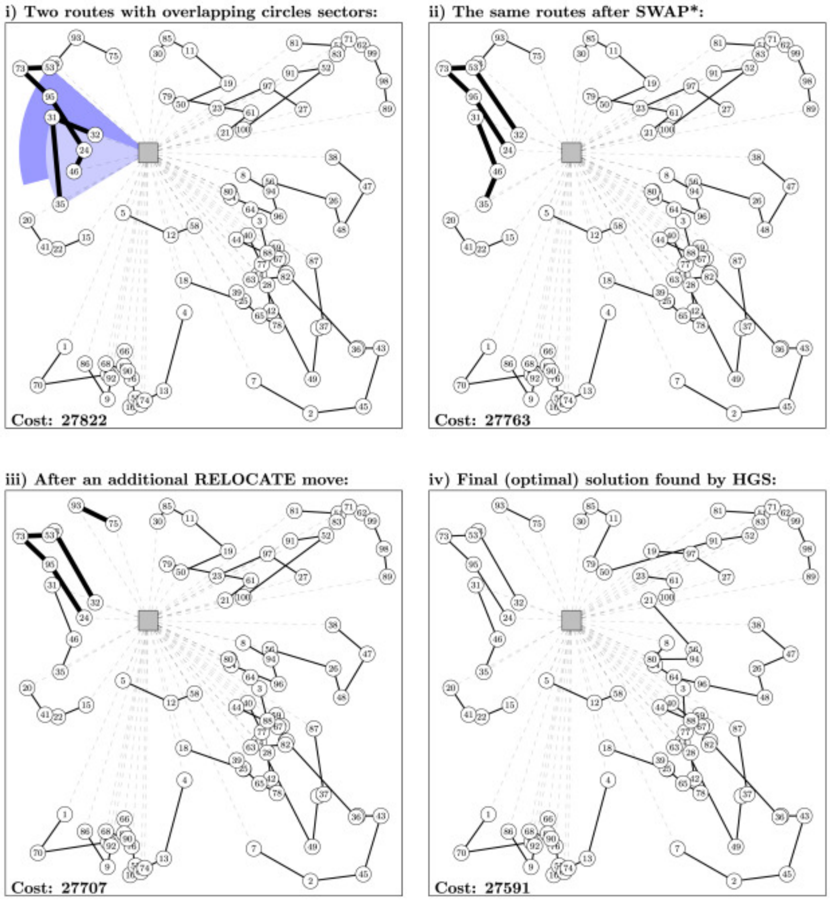

Figure 5.3: Swap* Neighbourhood illustration, retrieved from Vidal [90]

5.5. Performance Evaluation

In three main domains, Environmental Performance, Operational Performance and Financial Performance, the model is evaluated. The related Key Performance Indicators (KPI) are presented in table.

Table 5.1: Global Key Performance Indicators

Domain	Key Performance Indicator	Measure Unit
Environmental Performance	Direct CO_2 Emissions	CO_2eq emissions per day
Operational Performance	Number of Trucks	Units needed per day
Operational Performance	Load Density	Load-capacity ratio per truck
Operational Performance	Average Distance	Distance per truck
Financial Performance	Average Transportation Costs	Daily costs

In the following sections, the calculation approach of the related Key Performance Indicators (KPI) are described.

5.5.1. Direct CO_2 Emissions

In the car distribution process, trips starts from the depot and lead to various car dealer locations, which are specified by latitude and longitude coordinates. Furthermore, as determined in the analysis of the current state, car dealers also transport cars to external locations and back. From these trips, the direct CO_2 emissions can be calculated. Literature presents various methodologies for this calculation, as described in 2.2.1. The activity-based approach (ABA) is widely used and validated in the literature, and due to the availability and precision of data, ABA has been selected for this study. Implementing ABA demands precise data gathering and detailed information on each activity since it involves tracking all transportation movements. The following subsections will outline the extra details necessary to calculate the direct CO_2 emissions. The formula for this calculation is presented at the end.

Load factor influence

The ABA method can be specified in more detail by adding the load factor $Lf_{i,j,t}$ of truck t per route i, j, since the load of a truck has a significant impact on the fuel consumption [44] [54]. The load $L_{i,j,t}$ for route i, j can be determined based on the load L_t at the truck t, which is equal to the individual load factor contribution of the cars, depending on the size and weight of the car. Also the capacity Q_t is taken is considered, to determine how full the car is. Therefore, the impact of the load factor $Lf_{i,j,t}$ on fuel consumption per sub-route i, j can be calculated in the following formula:

$$Lf_{i,j,t} = \sum_{i \in N} \sum_{j \in N} \sum_{t \in T} \left(1 - FR_t + \frac{FR_t \cdot L_{i,j,t}}{Q_t} \right) \tag{5.18}$$

Where:

- FR_t = Fuel reduction percentage when truck t is unloaded
- $L_{i,j,t}$ = Load of truck t on route i, j
- Q_t = Capacity of truck t

In this equation, it is assumed that the influences of the partial load factor are linearly distributed, meaning that each change in the load factor contributes equally to the fuel consumption. By adding the load factor influence on the fuel consumption of the truck, the Direct CO_2 emissions of truck $t \in T$ of route i, j is defined as follows.

Distance determination

The Total Distance TD_i, j can be measured with the Haversine distance traveled by each truck [77]. The Haversine formula is used to calculate the distance between two points on the Earth's surface given their latitude and longitude in radians. Therefore, this is a more reliable method for calculating absolute distances between two points than the Euclidean Distance method. The Haversine distance can be calculated by using the following formula:

$$TD_{ij} = 2r \arcsin \left(\sqrt{\sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos(\phi_i) \cos(\phi_j) \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right) \tag{5.19}$$

- ϕ_i and ϕ_j are the latitudes of points 1 and 2 in radians
- λ_i and λ_j are the longitudes of points 1 and 2 in radians
- $\Delta\phi = \phi_j - \phi_i$ is the difference in latitudes
- $\Delta\lambda = \lambda_j - \lambda_i$ is the difference in longitudes
- r is the radius of the Earth (mean radius is 6,371 km)

To convert degrees to radians before applying them to the formula, use the conversion factor $\frac{\pi}{180}$.

Direct CO_2 Emission calculation

To achieve a detailed and valid calculation of the direct CO_2 emissions from a truck transporting cargo, the Activity Based Approach has been used [2] [95]. This method is supplemented with the load factor and the detour index and the Haversine distance to calculate the CO_2 emissions as accurately as possible. The following equation outlines the calculation method for the Direct CO_2 emissions produced in the distribution process.

$$\text{CO}_2 \text{ emissions (kg)} = \sum_{i \in N} \sum_{j \in N} \sum_{t \in T} \left(1 - FR_t + \frac{FR_t \cdot L_{i,j,t}}{Q_t} \right) \cdot \text{FC}_t \cdot \text{EF} \cdot \text{TD}_{i,j} \cdot \text{DI} \tag{5.20}$$

Where:

- FR_t = Fuel reduction percentage when truck t is unloaded
- $L_{i,j,t}$ = Load of truck t on route i, j
- Q_t = Capacity of truck t
- FC_t = Average fuel consumption of truck t in liter per kilometer
- EF = Emission factor in kg CO_2eq per liter
- $TD_{i,j}$ = Total Distance of route i, j in kilometers
- DI = Detour index

This average fuel consumption FC_t should reflect typical truck usage, taking into account factors such as a loaded truck consuming significantly more fuel than an unloaded truck. In addition, it is crucial to consider not only a truck's default values for determining average consumption, but also the actual fuel used. These Emission Factor EF must come from official, peer-reviewed databases. Bio-fuels, for example, have lower CO_2 emissions than fossil fuels. Since there are differences between countries in the mix of bio-diesel and regular diesel, careful consideration is needed. In addition, the Haversine formula calculates the absolute distance across the Earth [77]. Since the actual travel distance between two points does not equate to the absolute distance, a correction is necessary. Literature suggests that a commonly used correction is to apply a detour index, which must be validated and applicable to the specific country, considering its road network density.

5.5.2. Load density

The Load Density is the ratio between the total capacity and the demand. This can be calculated per truck or of the system. In equation 5.21 , the load density per truck is described.

$$LD_v = \frac{D_i}{Q_v} \tag{5.21}$$

Differences in the load density between runs suggests considerations are made between the number of trucks in the system related to the total travel distance. As is concluded that the model often uses more trucks than needed to satisfy the demand, it becomes interesting to compare the total distance with the load density.

5.5.3. Average Distance

The average distance of a truck is the ratio between the total distance and the number of trucks in the system. In equation 5.22, the average distance is described.

$$\overline{TTD} = \frac{TTD}{N_t} \tag{5.22}$$

The interpretation of the average distance per truck indicates effects in number of trucks or in the total distance traveled of the system.

5.5.4. Average transportation costs

Transportation costs are influenced by various factors. This assessment simplifies average transportation costs ($\overline{TC}$) to variable costs per day only. As outlined in 2.2.1, these costs consist of labor and operational costs. Labor costs are determined by personnel expenses, while operational costs include fuel expenses, which depend on vehicle efficiency and distance traveled. Other variable costs are not taken into account, such as maintenance costs.

$$\overline{TC} = \sum_{i\in N}\sum_{j\in N}\sum_{t\in T}\left(1 - FR_v + \frac{FR_t \cdot L_{i,j,t}}{Q_t}\right) \cdot FC_t \cdot p \cdot TD_{i,j} + N_{drivers} \cdot c \tag{5.23}$$

Where:

- FR_t = Fuel reduction percentage when truck t is unloaded

- $L_{i,j,t}$ = Load of truck t on route i, j
- Q_t = Capacity of truck t
- FC_t = Average fuel consumption of truck t in litre per kilometre
- FP = Fuel price per litre
- $TD_{i,j}$ = Total Distance of route i, j in kilometres
- $N_{drivers}$ = Number of drivers per day
- c = Daily labour costs per driver

As the daily labour costs are confidential, a constant *c*is used. Fixed costs involve acquiring new trucks and leasing or buying external parking space. Per policy implementation, an interpretation is made.

5.6. Data collection

For the usage of the solution approach, the following data is needed:

- **Demand of dealer location** [$\mathbf{D_i}$]: Has to be determined very carefully, as the demand is dependent on the amount of cars and the load factor. For the amount of cars, often this amount can easily be obtained per company. The Load factor is dependent on the size and weight of the car.
- **Number of trucks** [$\mathbf{N_t}$]: Number of trucks is the amount of trucks which are used to deliver the goods. The lower-bound of the number of trucks is the minimum amount of trucks to satisfy all demand. The upper-bound is dependent on the available trucks.
- **Capacity of trucks** [$\mathbf{Q_t}$]: The capacity of a single truck is dependent on the maximum load and dimensions of the trucks. Each truck has detailed specifications about load capacity. It is recommended to consider these detail very carefully.
- **Distance of the route** [$\mathbf{TD_{i,j}}$]: The route distance is dependent on the many factors, such as available routes and company strategies.
- **Fuel consumption of truck** [$\mathbf{FC_t}$]: the fuel consumption is dependent on truck details and geographical aspects, such as relief.
- **Emission factor of truck** [$\mathbf{EF_t}$]: Based on the chemical composition of the fuel, the CO_2 can be determined with an CO_2 equivalent factor. This is called the emission factor. The emission factor has to be peer-reviewed and a good understanding of the emission factor characteristics is needed. In literature, three types of emission factors are used: Well to Tank (WTT), Tank to Wheels and the summation of both Well to Wheels. Well to Tank (WTT) refers to emissions generated from both the production and transportation of fuel. This includes the extraction of primary materials, their refining and the subsequent distribution of the refined fuel to the point of sale. WTT calculations do not take into account emissions generated by the truck at the point of fuel consumption. Tank to Wheels (TTW) includes the emissions directly emitted by a truck when the fuel is consumed. This factor mainly considers the combustion process in the truck's engine and is often central to discussions on truck emissions. Well to Wheels (WTW) represents the total of WTT and TTW emissions and provides a holistic view of the total emissions produced during the fuel life cycle. WTW provides a thorough assessment of the environmental impact attributed to truck use and includes emissions from both fuel production and consumption.
- **Fuel reduction percentage of unloaded truck** [$\mathbf{FR_t}$]: In the equation to calculate the CO_2 emissions, a fuel consumption of a fully loaded car is taken into account. To compensate for emission reduction of partly full or empty trucks, a fuel reduction constant is used. Often, this constant is based on specification of the used trucks.
- **Latitude coordinate in radians** [$\phi_\mathbf{i}$]: can be retrieved from open source Open Streetmap. [68]
- **Longitude coordinate in radians** [$\lambda_\mathbf{i}$]: can be retrieved from open source Open Streetmap. [68]
- **Detour index** [**DI**]: Based on the landscape and road density per country, a detour can be considered. This detour index is a tool which is in several countries scientifically determined. A careful determinations is very important, due to the potentially large influence of this index.
- **Load of truck on route i, j** [$\mathbf{L_{i,j,v}}$]: The load of the truck has a large influence on the CO_2 emissions. Therefore, within each route the load between destinations has to be redefined. This can be calculated by the difference of the load compared with the initial load of the truck.

- **Dealer capacity at location** [$\mathbf{Dlr_{cap,i}}$]: the capacity of a dealer is a hard constraint in receiving cars. This capacity is dependent per location and has a large influence on trips. When the capacity of a dealer is reached, no more cars can be delivered.
- **Individual load factor of a car** [**ILF**]: Each car has an individual load factor, dependent on the size and weight of the car. This needs to be considered very careful, due to the large impact. For example electric cars can be very heavy and small cars can be loaded very efficiently, resulting in a large difference in transported cars.
- **Car with destination** i [$\mathbf{Cars_i}$]: Individual car with a specific destination. The individual load factor is multiplied by the corresponding car.
- **Fuel price** [**p**]: fuel price is fluctuating hugely. An average fuel price needs to be obtained per year.
- **Number of drivers** [$\mathbf{N_{drivers}}$]: Number of drivers per run. This is equal to the number of trucks per run.

5.7. Verification

Verification is a fundamental step in model development that helps in building confidence in the model's reliability and utility, particularly for decision-making processes and scientific research [35]. The objective of verification includes several key aspects [35]. First, the behavior of the model is verified by considering 4 aspects of the model. By doing this, the behavior of the model is analyzed systematically. Secondly, the performance of the HGS-CVRP model is verified with exact method solutions on small scale experiments. Here, the performance of an heuristic approach is compared with exact solution, with the aim to reach low performance gaps while differentiating the input parameters. These input parameters are the maximum a priori group size of split demand and the number of trucks.

5.7.1. Behavior Verification of Models

For this verification, a set of 6 random nodes is taken with a randomly chosen demand between [0-20], plus a depot with a demand of zero. Table 5.3 presents the instance definitions. The default capacity of a truck is 8. Four characteristics are verified to ensure the models behave as expected: the Number of trucks, Load Density, Split Delivery function, and the capacity per truck.

Table 5.2: Test instances for verification

Nodes	Coordinates (Lat, Lon)	Instance 1	Instance 2	Instance 3	Instance 4	Instance 5
0(depot)	52.1228635, 5.413699	0	0	0	0	0
1	53.1953205, 6.647859	4	1	11	3	11
2	51.5999488, 4.9988797	13	8	3	6	17
3	51.9264301, 5.3311303	11	2	6	11	11
4	52.3048903, 4.9327597	7	16	0	9	5
5	51.8638877, 4.4749794	2	2	19	0	8
6	52.199522, 6.5241521	16	3	7	1	9
Total demand		53	32	46	30	61

Based on the mathematical formulation and the specifications of a classic SDCVRP models, the following hypothesis are evaluated:

- **Hypothese 1:** The more trucks in the system, the smaller the load density of trucks.
- **Hypothese 2:** The load density cannot exceed the value 1.
- **Hypothesis 3:** Models including the split delivery function provides solutions with less total kilometers compared to solutions without the ability of split delivery.
- **Hypothesis 4:** An increase in capacity per truck, results in a decrease in the minimum number of trucks.

Exact Method

The exact method is performed with Gurobi 11.0 Solver. The mathematical model of the SDCVRP is used, as described in 2.2.3, including the adjusted constraint to include the Split Delivery Function. The aim is to find an optimal solution (MIPGap = 0.00 %) within the computational time constraint. Without an optimal solution, the exact method is not a valid benchmark. The computational time is set to 500 seconds. Given the relatively small experiment size, it is expected to reach optimality. In this verification, five experiments are executed. The following instances are used for the experiments.

Table 5.3: Instance Results Exact method SDCVRP

Experiment	Number of trucks	Total Traveled Distance (km)	Run time (s)	Time limit (s)
1	7	1073.14	267	500
2	4	756.63	114	500
3	6	1268.46	447	500
4	4	696.14	157	500
5	8	1411.31	467	500

Number of trucks

The experimental setup is designed with the assumption that every truck available at the depot will depart. As a result, the total distance traveled will increase with the number of trucks leaving the depot. Furthermore, the total capacity of the system (calculated as the number of trucks times the capacity of each truck) must be equal to or greater than the total demand to ensure demand satisfaction. Therefore, we can evaluate Hypothesis 1 and Hypothesis 2. For this experiment, the initial demand values from Instance 1 are utilized, incorporating the Split Delivery function.

Table 5.4: Experiment Results influence Number of trucks

Experiments	Total Demand	Total Capacity/ in system	Ratio Demand/ Capacity	Feasible Solution (y/n)	MIPGap (%)	Total Distance (km)
1	53	40	1.33	n	–	–
2	53	48	1.10	n	–	–
3	53	56	0.95	y	0.00	1073.03
4	53	64	0.83	y	0.00	1089.2
5	53	72	0.74	y	0.00	1119.32

Based on these experiments, both hypotheses are accepted. Hypotheses 1 is accepted, because, the total distance increases when the total capacity of the system increases. This is a logical observation, as the increase of the number of trucks results in a larger the total capacity. It can be concluded that when the total capacity of the trucks increases and the total demand stays the same, the trucks needs more distance to satisfy the demand. That is because the amount of trucks increases. The second hypothesis is also accepted. It can be seen that there is no feasible solution when the demand is higher than the total capacity of the trucks. Thus, it can be concluded that all demand is satisfied, otherwise the model is infeasible.

Split delivery

The split delivery function means a that the demand of a single node can be served by multiple trucks. In other words, trucks can partly satisfy the demand. With this function less trucks are necessary to fulfill the demand, which may result in routes with less kilometers. The split delivery function is presented constraints . Therefore, hypothesis 3 can be evaluated. 5 experiments are executed, per experiment a different instance of 5.3.

Table 5.5: Results of experiments with Split Delivery function

Experiments	Total Distance w/o SD (km)	No. of trucks	MIPGap (%)	Total Distance w/ SD (km)	No. of trucks	MIPGap (%)	Difference (%)
1	1455.98	9	0.00	1073.03	7	0.00	26.29
2	768.00	5	0.00	691.36	4	0.00	9.98
3	1679.14	8	0.00	1268.46	6	0.00	24.46
4	1083.78	7	0.00	696.14	4	0.00	35.77
5	1962.71	11	0.00	1411.31	8	0.00	28.09

From the results of these experiments, Hypothesis 3 is accepted. The introduction of the Split Delivery function demonstrates a reduction in the number of trucks needed to meet demand. This approach ensures that each truck's capacity is utilized more effectively. Consequently, it is evident that Split Delivery contributes to a decrease in the total distance traveled.

Capacity constraint The capacity of the truck is equal to the maximum demand a single truck can satisfy. Based on the capacity of each truck, the minimum number of trucks are determined. When the capacity increases, the less trucks are needed to satisfy the demand. Therefore, Hypothesis 4 is evaluated. To test the capacity influence, the initial demand values of experiment 1 is used with split delivery function.

Table 5.6: Capacity Results of truck Routing Experiments

Experiments	Total demand	Total capacity per truck	Feasible solution (y/n)	No. Of use trucks	MIPGap (%)
1	53	0	n	x	x
2	53	4	y	14	0.00
3	53	8	y	7	0.00
4	53	16	y	4	0.00
5	53	32	y	2	0.00

From the experiments conducted, Hypothesis 4 is confirmed. As the capacity of each truck increases, the number of trucks required to meet the demand decreases. When the capacity is insufficient, the model fails to find a solution, indicating it is not workable. Thus, it is clear that the capacity constraint, as outlined in 5.14, functions as intended.

HGS-CVRP

For the verification of the HGS-CVRP behavior, the same 5 instances are used as input to evaluate the verification experiments. The behavior of the HGS-CVRP is evaluated, on the aspects: Number of trucks, Split delivery, capacity constraints, demand satisfaction. The performance of the Split delivery is dependent on the input parameters Number of trucks and with the group size. These results are used to evaluated the behavior of the model, not to measure the performance of the HGS-CVRP model. The verification of the performance to determine these input variables, is described in section **??**. The experiments are executed, until terminated by the number of identical iterations (NbIter = 20000) or the timeLimit = 50. The experiments are executed with default parameter settings of the minimum amount of trucks per run and an a priori group size of the maximum capacity of a truck. The results of the instances calculated by the HGS-CVRP is visualized in 5.7

Table 5.7: Instance Results Exact method SDCVRP

Instance	Number of trucks	Total Traveled Distance (km)	Run time (s)	NbIter
1	7	1111.45	14	20 000
2	4	756.63	9	20 000
3	6	1298.32	13	20 000
4	4	766.14	17	20 000
5	8	1427.31	14	20 000

Number of trucks
In the HGS-CVRP, the number of trucks is an input parameter. The model iterates over different solutions, and chooses the best solution until terminated. The behavior of the model when adjusting the number of trucks is presented below. Hypothesis 1 and hypothesis 2 are tested.

Table 5.8: Experiment Results influence Number of trucks

Experiments	Total D_i	Total Capacity/ in system	Ratio Demand/ Capacity	Feasible Solution (y/n)	Runtime (s)	TTTD (km)
1	53	40	1.33	n	–	–
2	53	48	1.10	n	–	–
3	53	56	0.95	y	14	1111.21
4	53	64	0.83	y	15	1252.26
5	53	72	0.74	y	14	1111.21
6	53	80	0.66	y	16	1391.22

As a result, hypothesis 1 is accepted. When the total capacity is increased, the load density per truck decreases. However, during Experiment 5, the model presents a solution where no more trucks are added than necessary. This decision occurs because the model iterates solutions in feasible population space. Upon reaching the specified number of iterations (nbIter), the optimal solution is selected. In this case, the best solution involves using four trucks. Thus, this result is viewed as a sensible verification of the model's effectiveness.

Split delivery
The split delivery function is implemented with the a priori split approach [27]. To evaluate the impact of the split delivery function, the instances of 5.3 are used. However, these instances are not suitable for the HGS-CVRP without split demand, as the demand of individual nodes is higher than the capacity. This is presented in experiment 1-5 in 5.9. Therefore, 3 extra instances are used to verify the impact of the a priori split. The total demand of these instances are respectively: 24, 38 and 47 divided over 6 nodes. Within these instances, individual nodes have a demand between 0 and maximum 8. Therefore, there is no possibility that the demand is higher than the maximum capacity of a truck, assumed to be 8. With these experiments, Hypothesis 3 is evaluated.

Table 5.9: Results of experiments with Split Delivery function

Experiments	Total Distance w/o SD (km)	No. of trucks	Runtime (s)	Total Distance w/ SD (km)	No. of trucks	Runtime (s)	Difference (%)
1	0	0	0	1111.45	7	13	–
2	0	0	0	691.36	4	12	–
3	0	0	0	1298.32	6	11	–
4	0	0	0	766.14	4	8	–
5	0	0	0	1427.31	8	14	–
6	849.33	3	14	616.31	7	15	28.4
7	1033.91	5	10	941.53	9	19	9.9
8	1464.20	8	24	1132.67	10	28	23.7

As a result, it can be concluded that hypothesis 3 is considered as true. Based on the first 5 experiments, the model is not able to run the instances without the Split Delivery Function. In addition, with the Split Delivery function, the model is able to run the instances. Based on the results of the experiments 6 until 8, it is concluded that the when the demand is smaller than the maximum capacity, the split delivery function has a impact on the total traveled distance. However, these performance needs to be verified, as the input parameters are not verified yet. This is done in section 5.7.2.

Capacity constraint
The capacity constraint is a very important constraint in the CVRP model. To test if the capacity constraint works properly in the model, hypothesis 4 is evaluated.

Table 5.10: Capacity Results of truck Routing Experiments

Experiments	Total demand	Total capacity per truck	Feasible solution (y/n)	No. Of use trucks	Runtime (s)
1	53	0	n	–	–
2	53	4	n	–	–
3	53	8	n	–	–
4	53	16	y	4	13
5	53	32	y	2	14

As a result, the hypothesis 4 is accepted. As the capacity of the trucks is increased, the minimum number of trucks required decreases. Additionally, it is observed that when demand exceeds capacity, the model fails to operate. When within capacity limits, the model functions correctly.

Results
Based on both the behavior verification of the exact model and the HGS-CVRP, it has been determined that all hypotheses have been confirmed, indicating that both models function as expected. Also, it was found that in the HGS-CVRP model, the parameter for the number of trucks does not always match the actual number of trucks utilized in the model. This discrepancy is understandable, given that the HGS-CVRP model's solutions are derived through an iterative process. The outcomes of this verification process provide an opportunity to assess the HGS-CVRP model's results by comparing them with those obtained using the exact method.

5.7.2. HGS-CVRP verification
As it is concluded that the behavior of the two models is logical, benchmarking can be used to verify the results of the CVRP model [88]. These experiments are conducted by varying the input variables. For the a priori split delivery, the input variables are the maximum group size of the demand split and the number of trucks. As mentioned in section 5.3, Chen et al. [27] concludes that a mix of moderate and small group sizes leads to better results within a reasonable amount of time. Therefore, tests with various group sizes were carried out and compared against the exact method. To test the number of trucks, experiments are executed by varying the initial amount of trucks from the minimum to satisfy the demand. For the examination, the number of randomly selected instances was increased to 10.
To create a benchmark, the instances are calculated by using the mathematical model of the SDCVRP as described in 2.2.3. The aim is to find an optimal solution (MIPGap = 0.00 %) within the computational time constraint. Without an optimal solution, the exact method is not a valid benchmark. The computational time is set to 500 seconds. The results are described in table 5.11.

Table 5.11: Optimality gap related to Maximum Group Size

Experiment	Total Traveled Distance (km)	MIPGap(%)	Run time (s)	Time limit (s)
1	1073,14	0	267	500
2	691,36	0	114	500
3	1268,46	0	447	500
4	696,14	0	157	500
5	1411,31	0	467	500
6	1527,93	0	488	500
7	1736,72	0,96	500	500
8	936,12	0	321	500
9	735,44	0	144	500
10	1448,22	0,55	500	500

Maximum a priori group size

The outcomes from these instances by the HGS-CVRP are matched against the optimal solutions generated by the exact methods. In the research of Chen et al. [27], the a priori approach for the SDCVRP aims to split the demand in moderate and small demand sets, including the the addition of dummy locations when the demand is split. Therefore the following hypothesis is proposed:

- **Hypotesis 5:** The HGS-CVRP heuristic reaches near-optimal solution with moderate a priori group sizes.

By performing 10 experiments with 8 different with different group sizes per instance, the solutions with minimum number of trucks are evaluated. The results are presented in table 5.12. These results are visualized in figure 5.4.

Table 5.12: Performance (%) related to Maximum Group Size

Maximum a priori group size	Experiment	1	2	3	4	5	6	7	8	9	10
1	Total Distance	79,80%	91,10%	92,08%	81,29%	76,29%	78,80%	92,10%	88,08%	79,29%	78,29%
	No. Of Veh	7	4	6	4	8	8	8	5	5	8
2	Total Distance	90,01%	91,11%	96,90%	92,71%	93,11%	88,01%	88,11%	89,90%	89,71%	91,11%
	No. Of Veh	7	4	6	4	8	8	8	5	5	8
3	Total Distance	89,24%	87,85%	95,31%	91,46%	96,46%	84,24%	89,85%	93,31%	93,46%	95,46%
	No. Of Veh	8	4	7	5	9	8	9	5	5	8
4	Total Distance	97,18%	94,26%	97,74%	98,93%	99,59%	98,18%	93,26%	99,74%	94,13%	97,59%
	No. Of Veh	7	4	7	4	8	8	9	5	5	9
5	Total Distance (%)	87.43%	76.80%	91.64%	97.58%	89.10%	91.43%	78.80%	92.64%	91.58%	91.10%
	No. Of Veh	9	4	8	5	11	9	9	6	5	9
6	Total Distance (%)	96.16%	86.75%	95.31%	97.79%	89.74%	97.16%	84.75%	90.31%	94.79%	93.14%
	No. Of Veh	8	4	7	5	10	8	9	7	5	9
7	Total Distance (%)	96.16%	91.38%	95.31%	91.24%	97.48%	94.16%	93.38%	77.31%	98.24%	96.48%
	No. Of Veh	8	5	7	5	9	9	9	7	6	9
No split delivery function	Total Distance (%)	62.65%	75.62%	75.88%	74.15%	62.80%	69.65%	71.62%	68.88%	64.15%	71.80%
	No. Of Veh	11	5	10	9	16	9	10	7	6	9

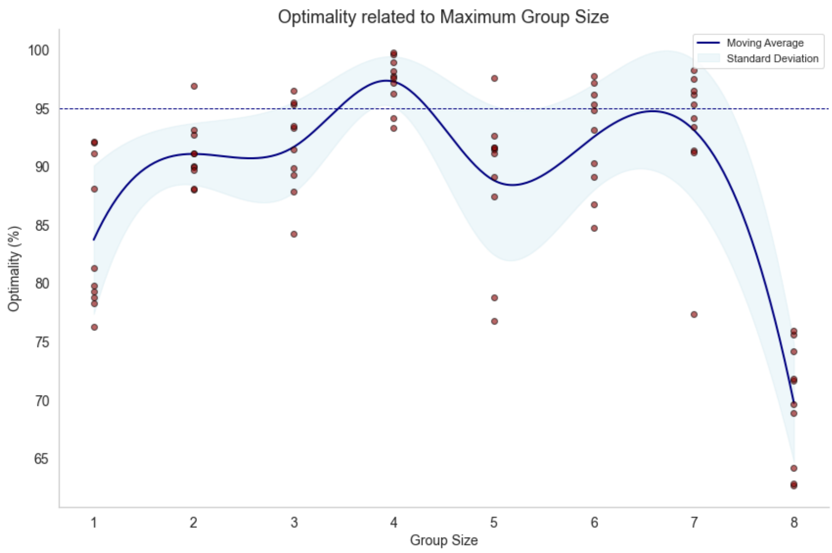

Figure 5.4: Optimality gap related to Maximum a priori group size, source (Author)

This verification finds that the initial size of groups significantly affects the model's effectiveness. Smaller groups are more adaptable but require extensive computational time. Despite running the simulations for 500 to 1000 seconds, the NbIter limit is never reached, and there is no improvement in the solutions compared to those achieved within 50 seconds. It is observed that the near-optimal outcomes are achieved when the group size does not exceed four. In 80% of tests involving groups of up to four cars, the difference between the expected and actual results is less than 5%. It is also noted that the most effective solutions are not always reached with the smallest number of trucks used. In 30% of cases, the selection of an additional truck proved better solutions. Consequently, hypothesis 5 is confirmed by these findings.

Maximum number of trucks

The second input parameter is the maximum number of trucks. As it becomes clear in verification of the behavior, the model iterates of the solutions until terminated. Also in the verification results of group size determination, it is concluded that solutions are found with more than the minimum number of trucks. In these experiments, the aim is to find solutions with minimum, optimality gap, while varying the maximum number of trucks.
Therefore, the following hypothesis is tested:

- **Hypothesis 6:** The meta-heuristic model provides near-optimal solutions compared to the exact method model.

This is tested by performing 10 experiments, varying the number of trucks used in 10 different instances. The outcomes are documented in 5.13. A visual representation of these results are is figure **??**.

Table 5.13: Optimality gap related to Number of trucks parameter, source (Author)

Experiment	Method	Minimum number of trucks	Minimum N_v +1	Minimum N_v +2	Minimum N_v +3
1	Exact method	0%	5.23%	7.43%	10.16%
	HGS-CVRP	2.82%	3.77%	7.22%	17.33%
2	Exact method	0%	6.54%	6.12%	12.44%
	HGS-CVRP	5.74%	7.23%	3.00%	21.40%
3	Exact method	5.22%	0%	5.77%	11.50%
	HGS-CVRP	7.39%	2.33%	1.99%	19.20%
4	Exact method	0%	5.23%	5.30%	5.60%
	HGS-CVRP	1.07%	2.33%	6.09%	7.30%
5	Exact method	0%	6.91%	7.41%	9.31%
	HGS-CVRP	0.41%	4.62%	9.45%	12.66%
6	Exact method	0%	3.56%	5.00%	9.11%
	HGS-CVRP	1.82%	7.32%	13.44%	16.40%
7	Exact method	0%	5.78%	7.40%	10.45%
	HGS-CVRP	6.62%	1.44%	4.31%	10.91%
8	Exact method	6.24%	0%	4.39%	9.11%
	HGS-CVRP	7.12%	0.26%	4.89%	10.80%
9	Exact method	0%	5.24%	6.20%	9.12%
	HGS-CVRP	1.76%	6.23%	9.30%	10.41%
10	Exact method	0%	5.36%	10.44%	9.61%
	HGS-CVRP	2.41%	8.24%	12.41%	17.15%

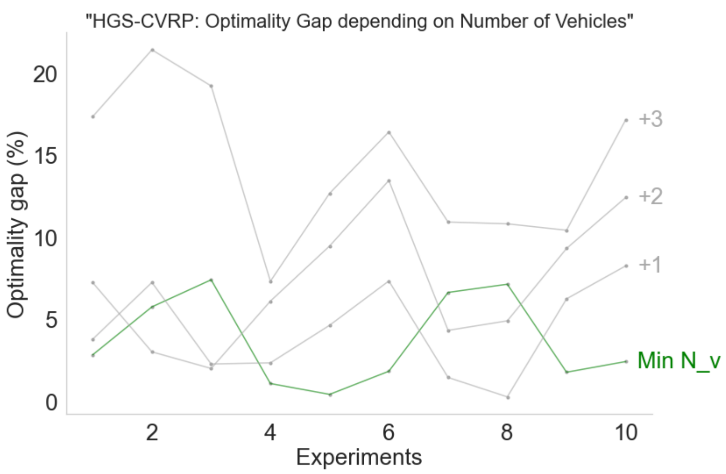

Figure 5.5: Optimality gap related to Number of trucks parameter, source (Author)

In 60% of the experiments, the best solution involves using the minimum number of trucks. However, there are experiments where solutions that include one additional truck prove to be more efficient. Also, solutions including extra trucks sometimes outperform those the solutions with minimum truck requirement. This indicates that while the minimum number of trucks often leads to the best outcomes, it's essential to explore adding more trucks to obtain better results. Specifically, in experiments where the best solution involves the minimum number of trucks, it is observed that the demands of locations located further from the depot are higher. Therefore, it is more clear for the model to choose for full trucks to the depot. The addition of an extra trucks than is not making the difference.

5.8. Conclusion

This chapter addresses the following sub-question:

- *How can the car distribution system be modeled?*

The methods used in the solution approach aim to redesign CO_2 emissions of truck-based distribution processes and to enable performance evaluations of large scale car distribution processes. This solution approach starts with a demand split strategy of Chen et al. [27] to divide initial demands of locations into moderate and small segments, allocated to dummy locations. This enables the application the HGS-CVRP heuristic including a Split Delivery function on large scale instances. By doing this, the routes of trucks to dealer locations are calculated based on minimum total travel distance. The performance of the model is evaluated by key performance indicators in three domains: Environmental Performance, Operational Performance and Financial Performance. Detailed methods for evaluating CO_2 emissions at sub-tour level is implemented, as the influence of the load can have sufficient influence. This solution approach is verified against an exact model on a small scale to ensure its functionality. After the verification with an exact method, is concluded that the behavior of the HGS-CVRP and performance is sufficient, by accepting all hypotheses. In the verification it is concluded that the *a priori* demand split strategy in combination with the HGS-CVRP reaches near-optimal solutions. However, special attention is needed for the input variable number of trucks, as the best solution is not always found with the minimum number of trucks.

6 Policy Implications

In this chapter, the Solution Approach is applied on a real life case, of Pon Automotive, to measure the impact of Policy 1 and Policy 2 on the current distribution process of new cars. Here, the current state of the distribution processes function as the benchmark of this analysis. First, the benchmark is described, representing the current state of the car distribution processes. Second, the data is prepared and the model is analyzed to measure the current state, and Policy adjustments. This section includes the model assumptions. Third, the results of the Policy implementations are evaluated by the evaluation Key Performance Indicators: Direct CO_2 emissions, Load Density, and Average Travel Distance per vehicle. Besides the conclusions, an interpretation of the results is provided. The function of benchmark is to validate the results of the Policy implementations. Therefore, the sub-question 6a: *What is the impact of redesigning car distribution procedures with new policies?* is answered.

6.1. Benchmark description

The benchmark for the Policy measurement analysis is the application of the current state of Pon Automotive on the solution approach. This is been done by using the data of 2022 of Pon Automotive. The detailed introduction of Pon Automotive is described in section 4.1. To ensure a systematic comparison of the current state of Pon Automotive and the proposed policies, the data of 2022 is used with the same order demands of the car dealers.

In 2022, 80,414 cars are imported by Pon Automotive. From these cars, 9501 cars where transported to other locations than the partner dealer locations of the connected dealer holding or to the Pon Luxury brands. In addition, 591 of the cars are demo cars, which encounter other procedures and therefore are not taken into account. This results in a total transported cars amount of 71,322 cars to the dealer locations. This could be an car dealer or external parking. In total 24 dealer holdings represents car brands which Pon Automotive imports. Each dealer holding have a minimum of 5 dealer locations, for the brands ”Audi”, ”Volkswagen”, ”Seat”, ”Skoda” and ”Volkswagen Bedrijfswagens”. Each car dealer has the ability to use an external parking for temporal storage. This external storage is in the neighborhood of each car dealer, with an average distance of 10,83 km. External parking locations have strict safety and security requirements, due to the high value. The transportation company Koopman is responsible for the car distribution from Pon Automotive to car dealers or an external parking, by using trucks. Car dealers are responsible for the transportation between car dealers and an external parking, by using own dealer transport with vans. In total, there are 144 different delivery locations and 1 central hub.

6.2. Experimental plan

The benchmark is based on the full data set, to include all yearly potential deviations within a year. As described in 4, the data is from Pon Automotive, transportation company Koopman, specific dealer holdings, internal and external expert interviews and literature. For data fitting and the calculations, data is validated by Pon Automotive or other stakeholders. The used data files are described in Appendix B.

The used data in the solution approach consists variables and assumptions. The data is specified is as follows.

- **Number of vehicles** [N_v]: This is an input parameter of the model, verified in section 5.7. Lowerbound: The minimum amount of trucks is equal to the demand of the customers. Upperbound: unlimited.
- **Capacity of vehicle** [Q_v]: The capacity of a truck, based on the maximum weight and the dimensions of the vehicle, is determined by a maximum load factor value. This is assumed to be 8, validated by Pon Automotive and Jäck, Gönsch, and Dörmann-Osuna [54]. This means that 8 normal cars can be loaded on a single vehicle, or 4 large or heavy vehicles.
- **Distance of the route** [$TD_{i,j}$]: The distance of the route is determined by the HGS-CVRP heuristic of Vidal [90] in combination with the a priori split strategy of Chen et al. [27].
- **Maximum a prior group size** [$TD_{i,j}$]: This is an input parameter of the model, verified in section 5.7. The distance of the route is determined by the HGS-CVRP heuristic of Vidal [90] in combination with the a priori split strategy of Chen et al. [27].
- **Fuel consumption of vehicle** [FC_v]: The fuel consumption is based on the averaged fuel consumption is the year 2022 of Koopman, 3,12 kilometer per liter.
- **Emission factor of vehicle** [EF_v]: In this research, the well to wheels emission factors are used of diesel and Hydrotreated Vegetable Oil. The emission factor of diesel and HVO are respectively, is 3.530 CO_{2eq} and 0.413 CO_{2eq} [42]. Based on a contractual agreement of Koopman and Pon Automotive, 30% of the used fuel must be HVO. Therefore, the emission factor used in this research is 2,59 CO_{2eq}.
- **Fuel reduction percentage of unloaded vehicle** [FR_v]: The fuel reduction percentage is the correction in fuel usage, when a vehicle is empty. It is assumed that a truck reduces 30% of the fuel when empty [54]. Also it is assumed that the the partial load factor differences has a linear influence on the fuel usage.
- **Latitude coordinate in radians** [ϕ_i]: Retrieved from OpenStreetMap [68]
- **Longitude coordinate in radians** [λ_i]: Retrieved from OpenStreetMap [68]
- **Detour index** [**DI**]: The detour index is based on a detour index research, executed in the United States. This is a correction of the Haversine distance and the actual distance. In the United States, this is assumed to be 1.4. Based on the higher road density, and easy accessible roads, the detour index of the Netherlands is assumed to be 1.2 [23].
- **Load of vehicle on route i, j** [$L_{i,j,v}$]: This is the actual load of vehicle v on route i, j. This is the difference between the initial load of the vehicle when leaving the distribution hub and the already delivered cars.
- **Dealer capacity** [$Dlr_{cap,i}$]: the dealer capacity is based on the amount of cars a car dealer could receive on a specific day. Per day, the dealer capacity is determined by taking the difference of the cars delivered by Koopman and the transportation motions of the car dealer from the dealer to the external parking. Hereby, it is prevented that car dealers become overfull.
- **Individual load factor of a car** [**ILF**]: The individual load factor of a car is a value of 1 or 2. It is assumed that normal or small cars with average weight are considered to have a load factor of 1. Large cars and heavy cars have a load factor of 2. This Load factor is carefully taken into account. In Appendix X, the detailed load factor determination is explained.
- **Car with destination** i [$Cars_i$]: This represents the group of cars to be considered for transport from the distribution hub to location i.
- **Demand of dealer location** [D_i]: The demand per dealer location is obtained by the summation of the transported car with destination i times on a specific date in 2022 times the individual load factor (LFI).

Besides these model parameters and variables, the following assumptions are made:

- All cars with an RFP (Ready-For-Pickup) status are transported on the same day. This is substantiated by the historical transport motions established in 2022.
- Unlimited trucks are available for transport needs. Koopman guarantees sufficient truck availability if communicated beforehand.

- The load factor for a van with a trailer is confirmed to be 2, as validated by dealer holdings.
- Each car has an individual load factor of 1 or 2, determined by its size and weight, as certified with Pon.
- Vans with trailers, owned by dealer holdings, are used for transportation between the dealership and external storage locations. For the calculation of CO_2 emissions of dealer transportation, this load factor is taken into account.
- It is confirmed that each car dealership has an external storage facility. The average distance to these facilities is 10.76 kilometers.
- Dealer holdings sometimes have multiple dealer locations per brand. In this analysis, it is assumed that all dealer holdings have one dealer location per brand. The summation of demand is considered for this location. The dealer location with the largest Gross Sales Size is considered as dealer location, also representing the other locations. Therefore,
- Trucks are required to return to the depot after completing the last delivery for potential new pickups.
- The Well-to-Wheel emission factor for Diesel is determined to be 3.530 kg CO_2 per liter [42].
- The Well-to-Wheel emission factor for HVO (Hydrotreated Vegetable Oil) is 0.413 kg CO_2 per liter [42].
- Fuel consumption for a fully loaded truck is 32,05 liters per 100 kilometers, and 22,43 liters per 100 kilometers when the truck is empty. [interview Head of Logistics] [54]
- Fuel consumption for a van with a loaded trailer is 20 liters per 100 kilometers, and 11.11 liters per 100 kilometers when the van is empty [interviews dealer holdings].
- Transportation motions of car dealers are mainly driven by the the NRB period of cars, as described in 4. There it is concluded that cars with a Not-Ride-Before period of 44 or higher definitely are transported to the external parking. This value is determined in collaboration with Pon Automotive and Car dealer holdings, with the following explanation: after the transportation date, it is contracted with the car brands gets a license plate registration within 15 days. From the moment of leaving the distribution center, cars must get an ascription within 30 days. These two periods could be merged. However, to add some flexibility in this assumption these periods are added. Therefore, it is concluded that cars with a NRB-period above this flexible threshold, definitely are transported to an external parking. For VW-bedrijfswagens, the same rules are applied, but the most of the vans are adjusted due to customer preferences. For the reconstruction procedures, the NRB-period threshold is extended with 30 days to 74 days in total, validated by the Dealer Holdings.
- The transportation motions from car dealer to an external parking are daily operations. The main reason is to transport cars temporarily, mainly because of a high NRB-period. However, other reasons to make these trips are assumed. Also transport motions to pick-up cars are made. Therefore, it is assumed that each car dealer location gets 0 to 2 cars per day from the External Parking (EP) to the car dealer. This is a randomly determined value, validated by car dealers.
- The Haversine distance formula is used for distance calculations, adjusted with a detour index of 1.2 [77] [23].
- A transportation time flexibility of 5 days is considered for the determination of the Not-Ride-Before Period, validated by Koopman.
- Each dealer location is assumed to have the same External Parking (EP) facility per dealer holding.
- A flat landscape is assumed for all transportation routes in the Netherlands.
- The influence of load factor on the capacity of a truck is assumed to be equivalent to the influence of the load factor on the capacity of the car dealer.

The evaluation of the assumption is further mentioned in the discussion.

6.3. Distribution model designs

In this section, first the benchmark design of the distribution processes is created using the solution approach and the Case Study data. This is done by the initial demand determination, the usage of the HGS-CVRP heuristic and the calculation of the Direct CO_2 emissions. After that, the model adjustments for the Policy implementation is described.

6.3.1. Benchmark Model Application

In 2022, cars were transported to dealer locations on a daily basis. The total number of cars transported corresponds are defined in the dataset of 2022, by specific location. By using these cars as demand, the daily demand of 2022 is satisfied. These cars, with ready for transport status, are loaded onto trucks according to their destination. The loading process takes into account the size and weight of each car, assigned a loading factor of 1 or 2, as indicated in 6.2. The destination of each vehicle influences how trucks are loaded. In the current state, the maximum amount of locations per vehicle is aimed to be two, due to sustainability purposes of Koopman.
To manage cases where demand exceeded vehicle capacity, an a priori split delivery method is used. For example, on 3 January 2022, when demand at five locations exceeded the capacity of a truck of 8, demand was split into smaller groups using the method described in 5.3 [27]. The model set the maximum group size to 4, which meant that demand for locations requiring more than four cars was split into groups of 4, 3, 2 or 1. This approach also introduces dummy locations with the corresponding demand.

- $m_4 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.5Qm \leq D_i\}$,
- $m_3 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.33Qm \leq D_i - 0.5Qm_4\}$,
- $m_2 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.25Qm \leq D_i - 0.5Qm_4 - 0.33Qm_3\}$,
- $m_1 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.125Qm \leq D_i - 0.5Qm_4 - 0.33Qm_3 - 0.25Qm_2\}$.

As described in the current status section, Koopman aims to limit the number of stops to a maximum of two for sustainability reasons. By creating a priori groups no larger than four and adjusting the number of vehicle parameter to maximize groups with group sizes of 4, most of the trucks are loaded with maximum two different destinations. This approach minimizes remaining small groups, corresponding with the current operations of Pon Automotive. Here, the aim is to visit maximum 2 dealers per vehicle, as described in section 4.2.5.

Based on the objective function, the routes are calculated with the HGS-CVRP by minimizing the total traveled distance. The input-parameter setting of the demand split is set to 4. The number of vehicles is initially determined based on minimum amount of vehicles, as most of the cases this provides the best solution. The primary objective is to ensure that routes are planned with the shortest possible travel distance. Also, the minimum number of vehicles required to transport all cars is used as default value, as minimizing vehicle use typically leads to more efficient solutions, verified in 5.7. However, to identify the most effective transportation design, the model is run with different number of trucks due to the aim to find the solution where most of the routes are made with max 2 stops. Therefore, every run the number of trucks is changed to 1,2,4 and 8 extra vehicles. The best solution is chosen. In three main domains, Environmental Performance, Operational Performance and Financial Performance, the implementation of the policies is evaluated. As described in section 5.5, the related KPIs are described.

6.3.2. Policy 1: Unlimited location stops

Policy 1 is defined as follows:

- **Unlimited location stops:** Revisiting the routing constraints to allow more route flexibility per truck.

The implementation of Policy 1, results in a flexible choice for trucks to stop at dealer locations. Compared to the benchmark, the maximum amount of stops by vehicles is considered as unlimited in stead of a maximum of 2 stops. The reason for this policy implementation is the literature of [8], where is stated that the sub-optimal routes could occur when vehicles are limited to the amount of stops. Also, route efficiency can increase with 50% when implementing split delivery [9]. At Koopman, it is confirmed that in several practical situations, the maximum number of stops is constraining the trips. In this research, the routes of the trucks by Koopman becomes more flexible, implying that the delivery can be executed by stopping at multiple locations. Compared to the benchmark, the input variable number of vehicles is based on maximum route performance, minimizing the total traveled distance. Therefore, as determined in 5.7, the first run is executed with minimum amount of vehicles to satisfy the demand, but to ensure the best solution is used, experiments with 1,2,4,8 extra vehicles are made. This increases the degrees of freedom of the model, to search for the best solution.

6.3.3. Policy 2: New prioritization strategy

Policy 2 is defined as follows:

- **Not-Ride-Before period prioritization:** Implementing a strategic approach to prioritize the delivery of cars from distribution hub to car dealer and external parking.

Policy 2 is an adaption of the current process, in terms of the implementation of NRB-period Policy in the processes of Pon Automotive. As described in the 4.2.4, the priority of cars at Pon Automotive is given to customer sold cars before stock cars and to cars without adjustment procedures at Pon Automotive. However, at car dealers, inefficient transport motions are executed based on the Not-Ride-Before period of cars from car dealers to EPs. Therefore, the destination of the cars at Leusden needs to be updated by the influence of NRB-periods of cars. In 4, it is verified by 4 different car dealers that cars with a NRB-period of 44 days or higher always are transported to External Parking when they arrived. Also, it became clear that 29% of the cars do have a NRB before period. Therefore, this Policy will align the preferences of the dealer with the priority system of Pon Automotive, to efficiently use the capacity of Koopman.

This is modeled by making adjustments in the model. The demand of dealers is determined as in the benchmark, with some adjustments. First when an individual car is customer sold and has a NRB-period of 44 or larger for normal cars, or 74 and larger for VW Bedrijfswagens, the destination at Pon is changed to an the external parking location of that dealer holding. In 4, it became clear that external parking sometimes contains cars without NRB date. An explanation of this phenomenon, is that dealer holding can only make manual adjustments, which are seldom made and not accurate. Therefore, differentiation between cars based on NRB-period at Pon, with an relatively large NRB-period of cars which are always transported to an external parking, is a suitable solution to optimize car allocation.

However, not all cars can be switched, as the capacity of dealer locations to store cars cannot be exceeded. Otherwise, still trips to an External Parking need to be made. Therefore, the maximum capacity of car dealers is taken into account. In the current process, cars with NRB-periods above the 44 days, and ”VW bedrijfswagen” cars with NRB-periods above 74 days, are definitely transported to EPs. Thus, as described in 5.15, the net dealer location capacity per day is the difference between the incoming cars by Koopman minus the outgoing cars to an external parking.

6.4. Results Policy 1

6.4.1. Direct CO_2 Emissions

The direct CO_2 emissions are measured as a result of Policy implementation. Policy 1 affects the routes of vehicles. Therefore, it's important to analyze the CO_2 emissions of vehicles, as the emissions from dealer transport remain unchanged compared to the benchmark. The performance of the direct CO_2 compared to the benchmark of the current state, is visualized in figure 6.1.

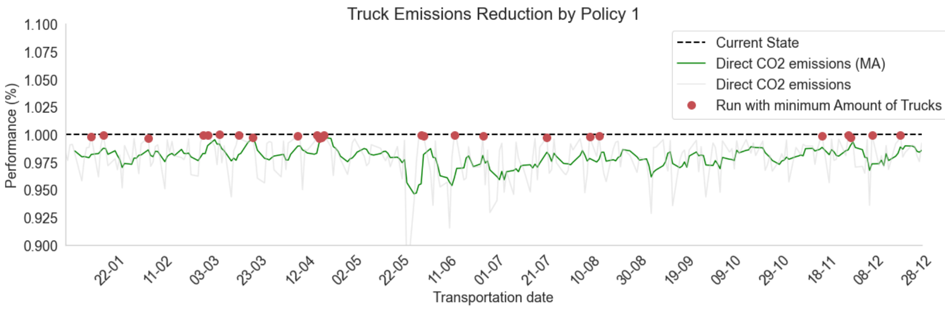

Figure 6.1: Truck emissions reduction after implementation of Policy 1, source (Author)

As a result, the direct CO_2 emissions from trucks are lower than the benchmark, resulting in reduced CO_2 emissions when Policy 1 is introduced, with an average CO_2 reduction of 2,1 %. Also, 92% of the trucks carries a group of cars with 1 or 2 destinations in the benchmark. After the implementation of Policy 1, 46% of the vehicles visits 1 or 2 locations. Focusing on the number of trucks, in 87% of the days, improved CO_2 performance is observed when more than the minimum number of trucks is utilized. This means, more trucks are used to satisfy the demand of the dealer locations. This reduction is mainly due to the flexibility to visit multiple locations with one vehicles. However, the daily CO_2 reductions can vary significantly, from 0% to more than 4%. A key conclusion is that there is not a single day where CO_2 emissions exceed the benchmark, since the model can always revert to making 2 stops per run if that selection proves to be the most efficient route.

6.4.2. Load Density

Secondly, the load density ratio is calculated. This represents the ratio of the total demand that needs to be satisfied, compared with the total capacity available of the vehicles, the sum of the number of vehicles times the maximum capacity per truck. The difference in load density after the implementation of Policy 1 compared with the benchmark is visualized in figure 6.2.

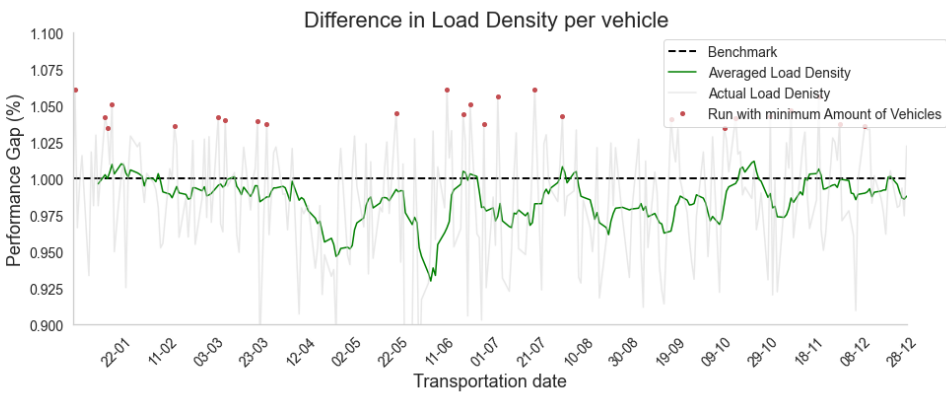

Figure 6.2: Difference in Load Density per truck, source (Author)

By implementing Policy 1, on average the load density per vehicle is 1,5% lower compared to the benchmark. However, 27% of the days, the load density is higher than the benchmark. Given the fact that the total demand per run between the benchmark and the Policy 1, is the same, the amount of used vehicles is increased in most of the cases. Zooming in in the cases where the load density is quite high, these runs are made with minimum number of vehicles. As a result, it is concluded that by implementing Policy 1, there are cases where the minimum number of vehicles results in a better solution compared to the benchmark. However, by implementing Policy 1, the load capacity decreases. Zooming in in the cases where the a lower load density results in better performance, this is the case where the more vehicles are used to satisfy the demand.

6.4.3. Average Distance per vehicle

Based on the total traveled distance per day of all vehicles, and the amount of vehicles used, the average distance per vehicle is determined. In runs, by looking at the total distance of the vehicles per day, a reduction in distance is 1,85% compared to the benchmark on average. Also, on average 6,89% more trucks are used, as the demand stays the same and the load density per vehicles is decreased on average.

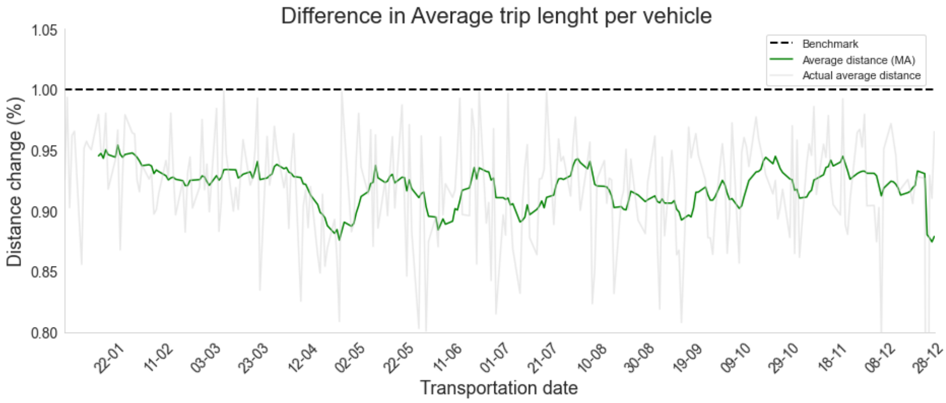

Figure 6.3: Difference in average trip length per truck, source (Author)

In figure 6.3, the average trip length is visualized. It can be concluded that the average trip length of a truck is reduced with 7,9%. In 87% of the times, more trucks are used to satisfy the demand compared to the benchmark.

6.4.4. Average Transportation costs

The average transportation costs is separated in fixed and variable costs. The variable costs can be calculated by equation 5.23, as the fuel costs and driver costs are the largest variable costs influences.

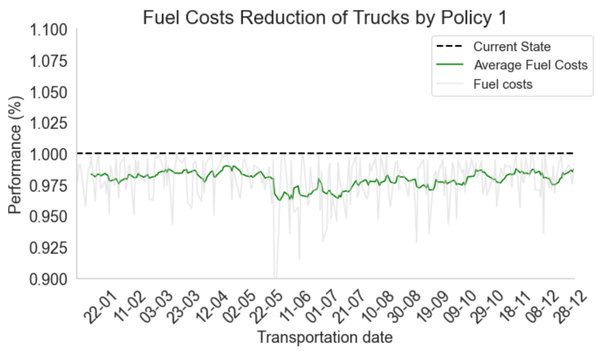

Figure 6.4: Fuel costs reduction of trucks, source (Author)

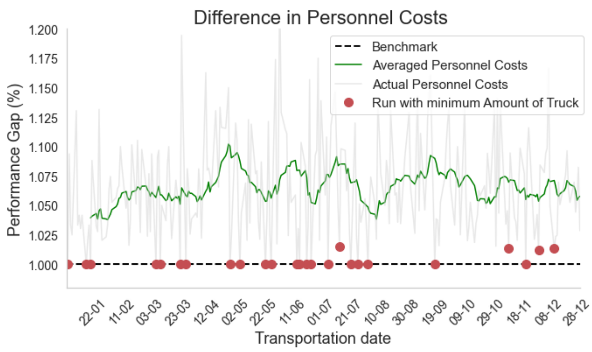

Figure 6.5: Driver costs difference, source (Author)

After the implementation of Policy 1, changes in variable costs are observed. First, as the total amount of kilometers decreases with 1,85%, the fuel usage decreases. As a result, the fuel costs decreases with 1,67% on average due to less driven kilometers. Due to a fixed percentage of 30% of HVO fuel usage, which is more expensive, the costs reduction is lower than the amount of kilometers. Secondly, the driver costs increases with 6,89% per year, as more trucks per day are used. In the runs where the minimum number of trucks are used, the extra driver costs are relatively low. The fixed costs increases, as more vehicles per day are needed. Therefore, it is concluded that the transportation costs of transportation companies increases.

6.5. Results Policy 2: New car prioritization strategy

6.5.1. Direct CO_2 emissions

The calculation of direct CO_2 emissions is the summation of the emissions from trips made by the transportation company Koopman (vehicles) and transport motions by car dealers (dealer transport). Following the adoption of Policy 2, there is, on average, a reduction in total direct CO_2 emissions by 6.4% when compared to the benchmark.

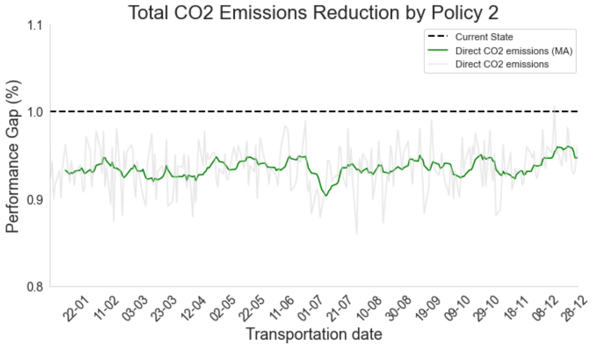

Figure 6.6: Total CO_2 emissions by implementation of Policy 2, source (Author)

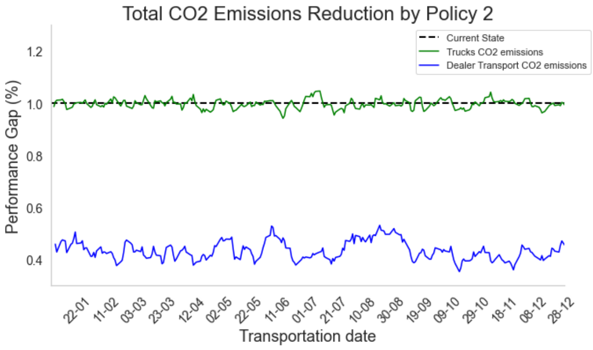

Figure 6.7: CO_2 emissions per mode, source (Author)

When looking the trips made by Koopman and comparing them to the benchmark, it's found that there's no significant difference in the total CO_2 emissions, with a slight average increase of 0.2%. This minor increase occurs because of the changed locations of trips, resulting from the reallocation of cars according to the NRB-period. However, Policy 2 significantly impacts dealer transport. Car dealers still make trips to external sites, but these are limited to collecting cars or handling special cases. As a result, the average direct CO_2 emissions caused by dealers is reduced by 56,7% compared to the baseline scenario.

6.5.2. Load Density

On average, the load density of trucks is changed with 0.1% compared with the benchmark. As described in 5.6, an external parking is on average 10,83 km away located from car dealers. Thus, the distances covered by vehicles do not significantly change with the introduction of Policy 2, but minor variations are possible. Additionally, there's a slight increase in the number of trucks per day, with a 0.06% rise observed. This indicates that Policy 2 exerts a minimal impact on Koopman's truck operations.

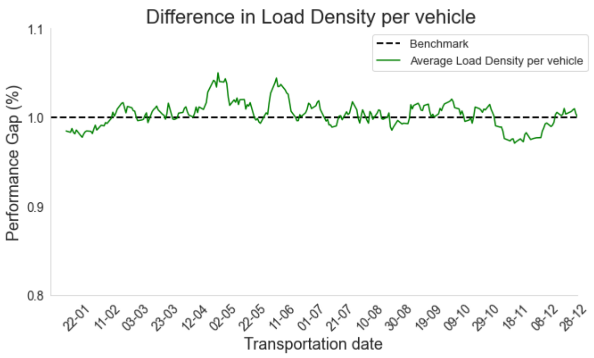

Figure 6.8: Load density under Policy 2, source (Author)

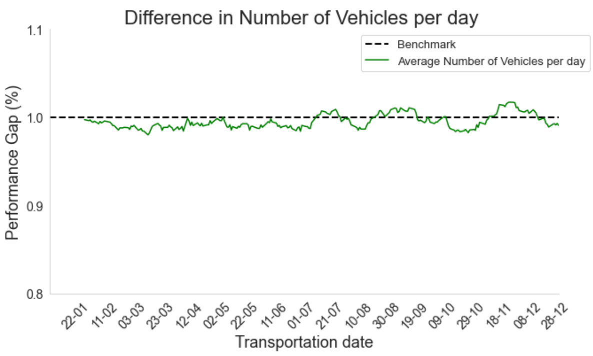

Figure 6.9: Number of vehicles under Policy 2, source (Author)

When focusing on the load density for dealer transport, fluctuations are observed. However, these variations are not considered significant because the load density is always optimized to full load. Focusing on dealer transport, minor differences are large percentage differences in load density, as the capacity of dealer transport is equal to a load factor of 2. As the dealer transport is largely influenced by the number of cars having a high NRB-period, this fluctuates. Consequently, the frequency of trips for each car dealer changes significantly. Due to this variability, it is not feasible to make conclusions regarding the load density of dealer transport.

6.5.3. Average distance per truck

The average trip length of trucks is dependent on the total distance and the number of trucks. Since the cars are prioritized based on their NRB-period, the location of cars at the distribution hub are changed. On average, per day 82 cars are switched to another location. With an average of 274 cars for transportation per day, this is 21,6% of the cars. The potential switch is higher, but the capacity of dealer locations enables it that large amount of cars are transported to the dealer locations. The switches has a significant impact on dealer transport.

The average distance that trucks travel is influenced by both the total distance covered and the number of trucks in operation. Cars are allocated in order of their NRB-period, leading to changes in the final destination at the distribution hub. On a daily basis, an average of 82 cars are relocated by implementing Policy 2. Given that about 274 cars are transported daily, this means on average 21.6% of the cars are moved to a different location. The potential for switching cars is greater, but the capacity at dealer locations constraints the phenomenon that a large number of cars can be moved to dealer locations. These changes significantly affect the transportation operations of dealers.

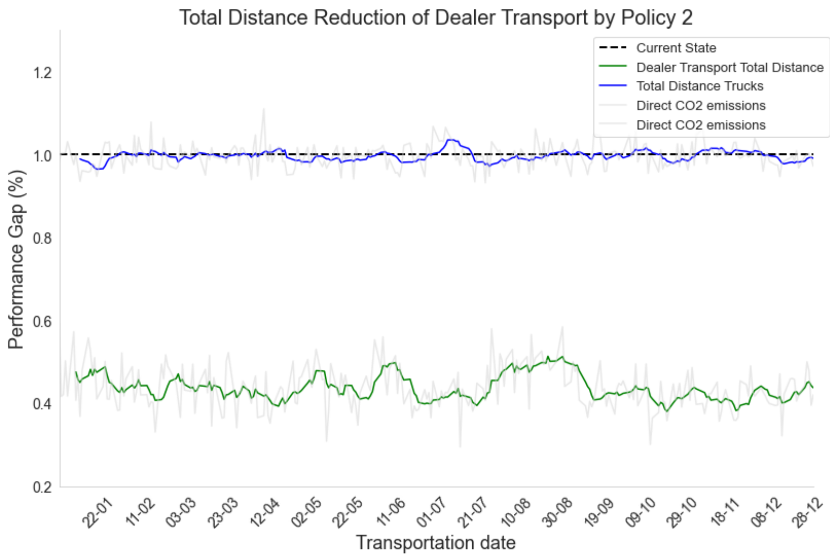

Figure 6.10: Total distance reduction by Policy 2, source (Author)

The total distance of dealer transport is decreased with 53,2%. This concludes that less vans are used per day by the implementation of Policy 2. Mainly, vans are used for transportation motions to an external parking to temporarily store cars. With the introduction of Policy 2, these trips are partly covered by Koopman, resulting in less transportation motions. The total distance of trucks by Koopman is decreased with of 0.05%, indicating no significant difference with the introduction of Policy 2. Similarly, there are no substantial changes in the number of trucks used, with an average increase of 0.8%. Consequently, it's clear that the average distance trucks travel per trip has not been significantly impacted by Policy 2. The average trip length for dealer transport remains unchanged as well. However, both the overall travel distance and the quantity of dealer transports have experienced notable changes, as explained above.

6.5.4. Average Transportation costs

After the implementation of Policy 2, the average transportation costs changes. The variable costs of trucks are remains the same, as minor changes in the total distance of Koopman are observed. In addition, the amount of trucks will not change. Focusing on dealer transport, the variable costs will change largely. The total distance of dealer transport is reduced by 56,7%, resulting in an average fuel reduction of 53,1% in the year 2022. Policy 2 results in a reduction of dealer transport. However, dealer transport remains necessary for special occasions and for retrieving trucks from external parking areas. Consequently, the requirement for vans with trailers persists, meaning that the fixed costs associated with these vans will not reduce.

6.6. Policy Interpretation

In this section, the policies implementations are interpreted. This is done by separating into interpretations of the performance between the benchmark and policies and the interpretation of the behavior of the model.

6.6.1. Model interpretation

In the verification, it is concluded that the model will find the optimal solution with using minimum number of trucks in 60% of the runs. On large scale, this percentage is decreased to 13% of the runs. The best solutions are found with 2 or 3 extra trucks than the minimum number of trucks. Focusing on the cases where more than the minimum number of trucks is used, multiple locations relatively close to the depot have high demands. Then, the best solution is made with more trucks then the minimum number. By doing this, the degrees of freedom becomes larger, which results in more efficient routes with more trucks, but a lower load density and lower average trip length. In runs where the minimum amount of trucks is used, locations relatively far away has a higher demand. Then, it is easier for the model, to send full trucks to a single location.
Another observations is the model behavior on large scale but with a low demand. This is seen in the months of may and June, where locations have relatively low demands. Here, larger fluctuations in the performance gap are obtained. This comes from the relatively high impact of adding a truck or not, when the total number of trucks is relatively low. This is seen in the performance gap of the direct CO_2 emissions is relatively large in June. When multiple locations spread over the graph have moderate demands, sometimes the model chooses to add a truck. This results in fluctuations in performance gaps, as the model can choose between more feasible options.

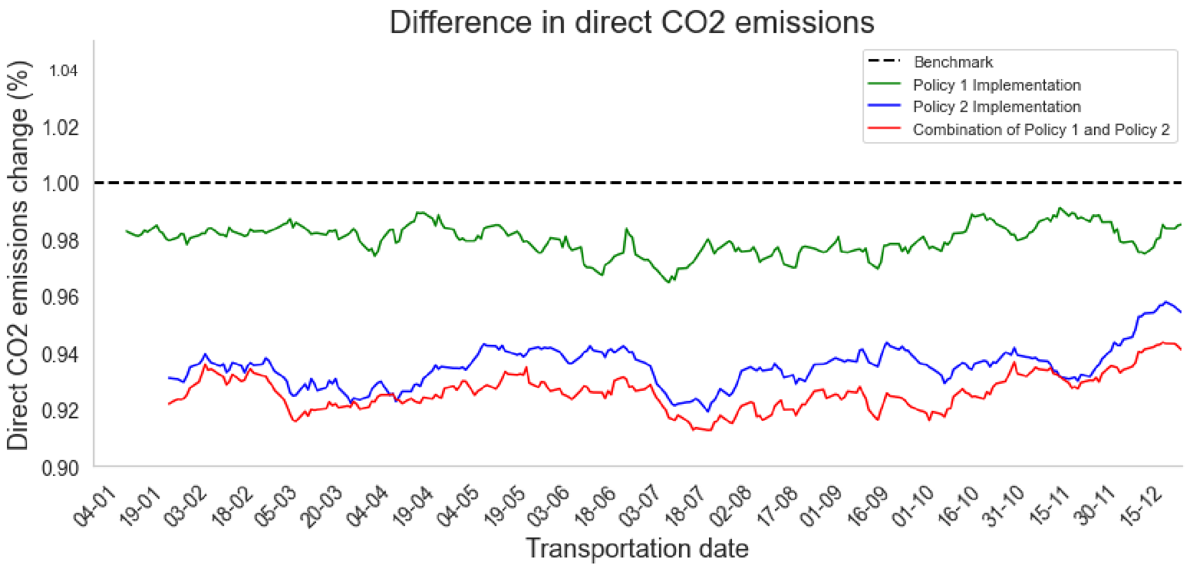

Figure 6.11: Direct CO_2 emissions, as a result of Policy 1 and Policy 2, source (Author)

6.6.2. Interpretation of Policy 1

For the estimation of CO_2 emissions, the load factor for each segment of the route is taken into account. Consequently, if the distance of the first destination is relatively long, the CO_2 emissions relative to this segment of the route are significantly higher in comparison to shorter first trips. Implementation of Policy 1 often results in a larger number of trucks, thereby increasing the system's flexibility to visit multiple destinations. As a result, the likelihood of undertaking longer trips decreases. This outcome is supported by the observation that the average distance traveled per truck is reduced by 8%. An explanation for this reduction might be that, in certain scenarios, it proves more efficient for the overall performance if a truck returns to the depot and another truck is dispatched to a different location. However, sometimes the performance of CO_2 emissions is relatively close to the benchmark, when the minimum number of trucks are used. Focusing on these situations, it is concluded that the demand of dealer locations far away is relatively high. As expected, the model chooses the same routes as the benchmark, full trucks to satisfy the demand. In addition, car dealerships are situated in clusters of a city. Hence, when there is a Policy limitation that restricts a truck to visiting no more than two dealerships, it forces the system to let another a second truck to service any additional dealership within the same cluster.

In the summer months, June and July, more variation in output is visible in the three graphs. The reason could be the decreases in activity during the summer period. On June 27, 26 cars were transported. After the implementation of Policy 1, two trucks are added, leading to relative large differences in performance compared to the benchmark. Thus, these fluctuations are not surprising. Also, due to the decrease in average distance per truck, it may be worth to consider using other trucks types, such as electric trucks.

Lastly, the financial impact per stakeholder is evaluated. As described in section **??**, the costs are simplified to look only to the direct distribution costs per day. These costs are dependent on operational costs and labor costs. Here, compared to the benchmark, the operational costs will be lower with an average of, as the total distance traveled is lower. However, because more stops can be made, and the average distances per trucks are lower than the benchmark, fuel costs may be higher. Also, 6,89% more trucks per day needs to be available, meaning more drivers and more costs of purchasing enough trucks. For Koopman, the costs will increase because more labor is needed, as relatively more trips need to be made. Lastly, with the adoption of Policy 1, there is an increase in the number of stops made at car dealerships. This leads to more frequent loading and unloading of trucks, which increases the risk of damages occurring during these processes.

6.6.3. Interpretation of Policy 2

The key conclusion is that the re-allocation of cars from dealers to external parking on average has no significant impact on the transport operations of Koopman transport operations. The total number of cars transported remains constant, and although there are slight variations in distances, these are not significant since external storage sites are, on average, only 10 kilometers away from the car dealers. The prioritization of cars based on NRB-period offers benefits to car dealers. Previously, dealers often received undesirable cars, meaning cars with a high NRB-period. However, undesired cars are directly transported to an external parking. This significantly reduces the need for dealers to make trips to these storage sites, as Koopman now handles these transports directly, representing a substantial saving. Trips are still required to eventually collect the cars, but this pick-up transport is unchanged. For this system to be implemented effectively, it is crucial that the capacity of the dealers is communicated in advance. Now, the capacity is based on the historical capacity per day in 2022, as mentioned in 6.2, but this can differ. Additionally, car dealers must be informed and provide their availability. Therefore, effective communication of preferences between stakeholder must be clear and transparent.

The implementation of Policy 2 is expected to impact variable costs significantly. A slight increase in total travel distance by 0.06% for Koopman-operated trucks, it becomes evident that changes in fuel costs are marginal. However, car dealers benefits from a substantial reduction in transportation costs, attributed to a 53.2% decrease in the total distance of dealer transport. This shift allows for the reallocation of personnel from transportation to other tasks. Fixed costs, however, will remain stable. The frequency of dealer transportation will reduce but not still occur. Given that dealers typically use on two to three vans for transportation, no significant adjustments in fixed costs are expected. This realignment under Policy 2 improves operational efficiency without substantially affecting basic financial requirements related to transport infrastructure.

6.7. Conclusion

This chapter aims for the the sub-question 6a: *What is the impact of redesigning car distribution procedures with new policies?* is answered.

Policy 1 demonstrates that allowing trucks to make more stops can lead to meaningful environmental benefits. By permitting trucks to conduct additional stops, there's an overall decrease in direct CO_2 emissions by 2.1%, despite an increase in the number of trucks by 6.9%. Policy 1 effectively lowers the average distance per truck by 8.0%, illustrating that more targeted and efficient routing reduces the direct CO_2 emissions but leads to increased costs due to extra trucks and extra personnel. The operational costs are lowered due to reduced total travel distance compared with the benchmark. These findings affirm that the implementation of Policy 1 can achieve a sustainable impact, but leads to higher costs. Policy 2, prioritizing car distribution based on the Not-Ride-Before (NRB) period, results in a 6.4% decrease in direct CO_2 emissions, mainly due to 53,2% less dealer transport. This highlights the effectiveness of aligning car dealer needs with distribution strategies. Here, 21,4% of the cars has switched to other locations, based on the NRB-period. Both policies offer potential for improvements of the distribution processes and positive environmental impacts. However, the increase in the number of trucks used in Policy 1 may lead to higher costs, whereas Policy 2's reallocation of transportation responsibilities could streamline dealer operations and reduce dealer transport. Transparency in capacity availability of car dealers is crucial to avoid accumulation, resulting in redundant dealer transport.

7 Future Designs

In this chapter, scenarios are constructed to test the model and to confirm its validity. As established in chapter 6, two policies have a positive impact on environmental performance. Nevertheless, the performance may be affected by external factors and potential developments. The purpose of this chapter is to examine the effects of external factors and the potential impacts on the distribution process. Understanding these effects and possible enhancements will provide deeper insights into future scenarios. To validate the model and assess its response, scenarios have been developed. These scenarios are supported by literature reviews, expert interviews, and the findings from 6. First, the scenario designs are presented in section 7.1. Second, the evaluation of each scenario is discussed in section 7.2.

Therefore, the sub-question 6b: *What is the impact of external factors on car distribution processes?* is answered.

7.1. Scenario Designs

Different scenarios are designed that include external factors and influences of stakeholders. This approach is designed to anticipate a system's response to unexpected events, allowing for an assessment of how the system's performance could vary in imagined best-case (optimistic) or worst-case (pessimistic) scenarios [20]. Furthermore, scenarios must be developed in a precise manner, taking into account various driving forces and uncertainties. Therefore, a commonly used rule can be used, where scenarios seems to be mutually exclusive and collectively exhaustive [81]. Each scenario should be distinct from the others, with no significant overlap. While it's not practical to account for every possible future, scenarios should collectively cover a wide range of plausible futures. This helps ensure that major potential changes in the environment are considered [81]. The primary goal is to examine the outcomes of the scenarios (those with higher probabilities and/or more significant impacts) to validate the solution approach. The scenario choice is based on the key variables of this research and related to the objective of the research. [20].The scenarios are presented in figure 7.1.

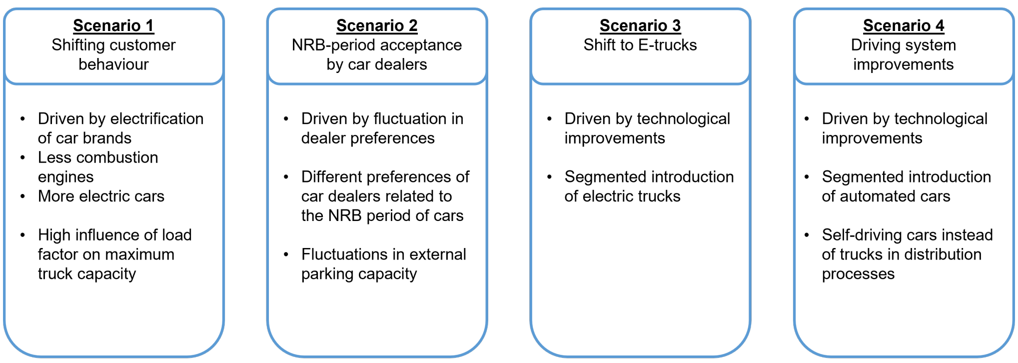

Figure 7.1: Overview of scenario designs, source (Author)

7.1.1. Scenario 1: Shifting Customer Behavior

Car electrification is a major market trend influenced by consumer awareness and companies' scope 3 responsibilities. Therefore, car companies are increasingly prioritizing the transition to electric cars. A clear shift towards electric cars has been observed over the past five years. This scenario predicts the impact of car electrification on distribution processes. The Netherlands, which can be seen as leader in car electrification, is likely to see a large increase in electric car purchases in the short term. In 2022, 23.8% of vehicles ordered from Pon Automotive were fully electric, increasing by 3.7% to 27.5% in 2023. This upward trend highlights a growing trend of electrification, supported by subsidies of governments. This suggests a robust increase in the number of electric cars.
Electric cars generally weigh more than 20% heavier than comparable cars with combustion engine, mainly due to the significant weight of battery packs. Moreover, there is a trend towards producing larger electric cars to accommodate larger battery packs, which has a significant impact on distribution processes. The solution approach includes adjustments for trailer capacity in car transport, using a load factor to account for the larger size and weight of electric cars. For example, trailers can carry four large electric cars instead of eight smaller combustion-engine cars. This scenario includes an increase in the use of electric cars compared to the amount of electric cars in 2022. Test scenarios over a 20 days period will evaluate the impact on distribution performance with 15% proportion increase of the electric cars in each scenario.

7.1.2. Scenario 2: NRB-period acceptance by car dealers

In this research, a Not-ride-Before (NRB) Period of 44 days for cars and 74 days for VW Bedrijfswagens consistently results in the relocation of cars to external storage facilities, as determined after detailed discussions with a variety of dealerships. This finding is based on agreements between Pon Automotive and auto dealerships, which holds that a customer-sold car must be assigned a license plate within 14 days and transferred to the buyer's name within 30 days. To add flexibility, this study sums these time frames to ensure, those cars are not desired at car dealers. However, when the NRB-period acceptance evolves, assessing the impact becomes essential. Consequently, this scenario assesses how differences in the acceptance of the NRB-period of a car affects direct CO_2 emissions from dealer transport and trucks. This evaluation involves modifying the NRB-period threshold by segments of 10%, 20%, and 50%, both upwards and downwards.

7.1.3. Scenario 3: Swift to E-Trucks

In the context of increasing corporate environmental responsibility, a shift is being observed towards improving Scope 1 emissions, as defined by the Corporate Sustainability Reporting Directive (CSRD) described in section 2. A crucial aspect is the reduction of direct emissions from transportation trucks, which serves as a key incentive for this scenario. This initiative is in line with the European Commission's objectives and underlines the urgency of meeting the targets set. This scenario examines the impact of truck routing on emissions and the sustainability of fleet operations. Although the transition to a sustainable fleet will involve significant costs, it is necessary for companies to comply with the Paris Agreement commitments [72]. Currently, companies starts with conducting pilots of electric trucks, with the latest electric trucks achieving a practical range of 200 to 400 kilometers [60]. Heavy trucks, especially those with full car trailers, are a challenging segment. Also, at Pon Automotive, a pilot has started with an electric truck of MAN. MAN has introduced a truck model equipped with six battery packs, offering a range of up to 400 kilometers for heavy duty transport [60]. Regulations require truck drivers to take 45-minute breaks after up to 4.5 hours of driving. By using this break to recharge the truck, up to 800 kilometers can be covered each day. The data in Chapter 6 shows that a truck travels an average of 192 kilometers, indicating that the range of a truck is not a limiting factor. However, the high purchase cost is a major barrier for companies to convert their fleets, especially those currently using efficient conventional trucks. This scenario assesses truck electrification, evaluating 20% segments. It is assumed that each truck, regardless of its range, can complete one route per day within its allocated working hours.

7.1.4. Scenario 4: Drive system improvement

This scenario contains the technological improvement of self driving cars, called the autonomous cars. These cars, which operate using advanced technologies without human intervention, could significantly reduce traffic accidents and congestion. In addition, their ability to communicate with each other and with traffic management infrastructures predicts a future with significantly less traffic congestion and delays. In the context of car distribution, autonomous cars could drive to pre-defined destinations, which implies that no transportation trucks is needed for these cars. In this scenario, a staged implementation is implemented in the model. This is done by separating the car dealers into two groups: car dealers close to the depot (1), and car dealers relatively far away (2). This adjustment will validate the performance of the HGS-CVRP model in different geographical designs. The demand will decrease by 30, 60 or 90 percent per location. this will be tested in both groups. In figure Group separation, the experiment setting is visualized.

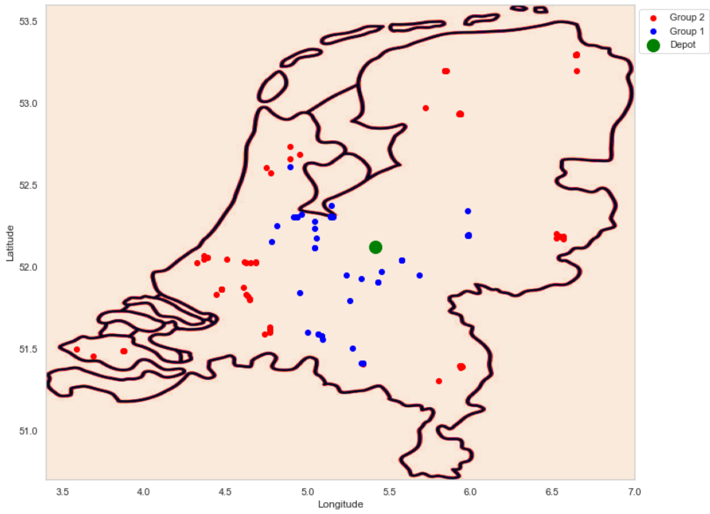

Figure 7.2: Group separation, source (Author)

7.2. Scenario Evaluations

In this section, the scenarios are evaluated. Each scenario evaluation starts with an outline what aspects of the system are affected by the design impacts. After that, the related key performance indicators, described in 5.1, are evaluated.

7.2.1. Evaluation Shifting Customer Behavior

The electrification of cars leads to an increase in the load factor of cars. Since the demand from dealers equals the sum of the load factors of individual cars, overall demand also rises and thus the direct CO_2 emissions. This scenario highlights how the growing number of electric cars affects the demand at locations, with the daily increase in electric cars being selected randomly. The impact on performance indicators is detailed in figure 7.3.

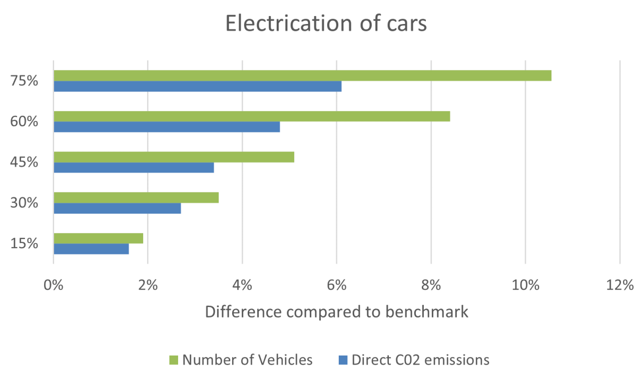

Figure 7.3: Scenario shifting customer behavior, source (Author)

In this context, the effect on trucks is large. The load factor significantly influences the number of trucks required. Additionally, total emissions are assessed. The key finding is that as the number of electric cars rises, so does the need for more trucks. In fact, there is an exponential increase in the required number of trucks. This is a logical outcome since the proportion of electric cars increases relative to the total number of cars, and electric cars take up twice the space of a standard car.

7.2.2. Evaluation NRB-period acceptance by dealers

It is concluded that the emissions of the truck is not influenced by the adjustment is the NRB strategy. This corresponds with the conclusions of the Policy 2 implementation. However, the dealer transport is influenced largely.

Table 7.1: Impact of Variable Adjustments on Emissions

Percentage difference	-50%	-20%	-10%	Benchmark	10%	20%	50%
Truck emissions	2.0%	−0.4%	−0.1%	0.0%	−1.1%	1.0%	4.0%
Dealer transport emissions	14.0%	6.1	5.8%	0.0%	−4.8%	−6.8	−5.2%
Total emissions	1.7%	1.3%	0.9%	0.0%	−0.7%	−1.0%	−0.9%

When the NRB-period acceptance is lowered, dealers receives more cars. As the capacity is limited at car dealers, car dealers must make more trips to the external parking locations. When the NRB-period acceptance is increased by car dealers, more cars will be transported to the car dealer locations. Then a new phenomenon occurs. Car dealers sometimes have free capacity, as most of the cars will be traveled to the external parking. This becomes particularly noticeable when the acceptance of cars during the NRB-period increases by 50%, which leads to car dealers making trips only for special needs as no further percentage decrease is obtained. The capacity of a dealership is determined by the difference between the number of cars arriving and those sent to external parking. If the acceptance during the NRB-period increases to a level where no cars are received by the dealership, it results in all cars being sent to an external parking, despite the possibility of having available space. This demonstrates that the HGS-CVRP model functions effectively, and it also suggests that allowing cars with shorter NRB-periods to be sent to dealerships could offer improvements. The information is based on data from 2022, a period when the ability of dealerships to accommodate cars was under significant pressure due to a ramp-up in production following the slowdown caused by COVID-19, leaving no room for gains at that time. Additionally, the analysis indicates that dealerships handling a large number of cars with lengthy NRB periods need to make more frequent trips. These dealerships are often larger and primarily serve the business-to-business (B2B) market, as detailed in the dealer segmentation (4.3.2). Hence, such dealerships are most influenced by changes in NRB-period acceptance.

7.2.3. Evaluation Swift to E-Trucks

In Design 3, the introduction of the E-truck is inserted within stages of 20%. It is assumed, that the E-trucks has the same load specifications as the current used trucks. The technical and price assumptions related to this scenario are presented in 6.2. The introduction of the E-truck has influence on the direct CO_2 emissions and the transportation costs. Transportation costs are based on the labor costs and the operational costs. It is assumed that the labor costs will not change, as E-trucks can be used on the same way as the conventional trucks. Therefore, the operational cost differences are analyzed in this design. Results are presented in figure 7.4.
Switching to E-trucks presents a promising opportunity for significant reductions in CO_2 emissions. The adoption of E-trucks has been shown to decrease direct CO_2 emissions by 42.6%. This analysis, detailed in Appendix **??**, highlights the E-trucks' role in promoting cleaner transportation options. From a financial perspective, the transition to E-trucks presents an decrease in operational costs. These costs, which are influenced by factors such as travel distance, fuel consumption, and load factor, are lower for E-trucks due to their technical efficiencies and the relatively lower cost of electricity compared to diesel and HVO (Hydrotreated Vegetable Oil) fuels. In the benchmark, conventional trucks using a mix of 70% diesel and 30% HVO, reveal that E-trucks can achieve a 37.6% reduction in operational costs. This decrease, documented in Appendix **??**, is primarily attributed to the higher energy efficiency and the economic benefits of using electricity as a fuel source. However, the shift towards E-trucks requires a large initial investment. In 2024, the average purchase cost of an E-truck is projected to be

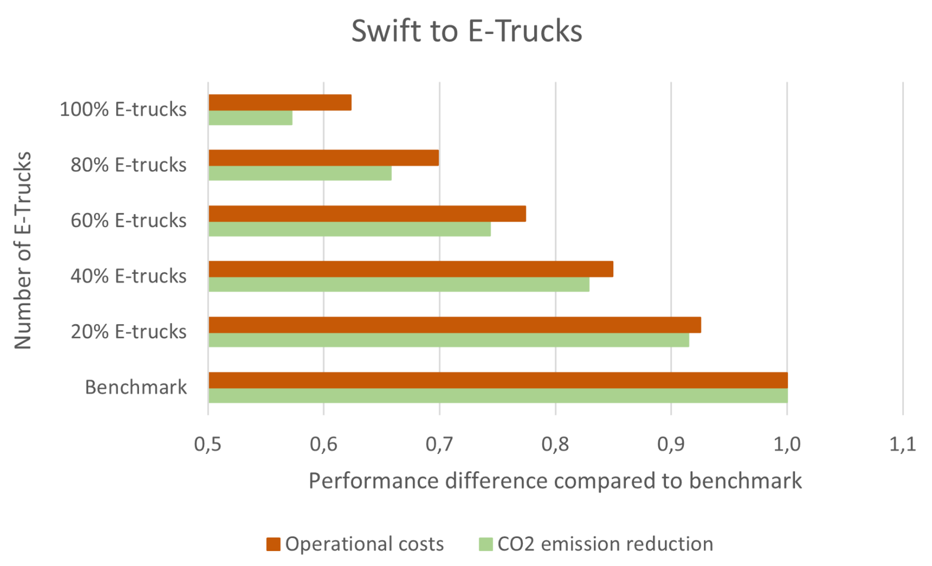

Figure 7.4: Scenario Swift to E-Trucks, source (Author)

around 280,000 euros [49]. This points the significant upfront investment companies must be prepared to make in order to gain the environmental and operational cost benefits of E-trucks. Despite these initial costs, the long-term savings in operational expenses, which are estimated to drop to 62.4% of those associated with conventional trucks, present a reduction of 42,6% in direct CO_2 emissions.

The operational statistics from 2022, noting an average usage of 49 trucks per day and a peak usage on December 22nd, underscore the scale of potential impact this transition could have. As organizations consider the switch to E-trucks, the initial investment emerges as a significant factor. Nevertheless, the prospect of substantially reduced CO_2 emissions and lower operational costs offers a strong incentive, suggesting that the investment in E-trucks could indeed be a worthwhile commitment to both financial savings and environmental responsibility.

7.2.4. Evaluation Drive System Improvement

In this section, the car dealers have will segmented be served with autonomous cars. To validate the model, based on geographical location of the customers, two groups are made. Each group will separately be served. Thus in total, six experiments are done.

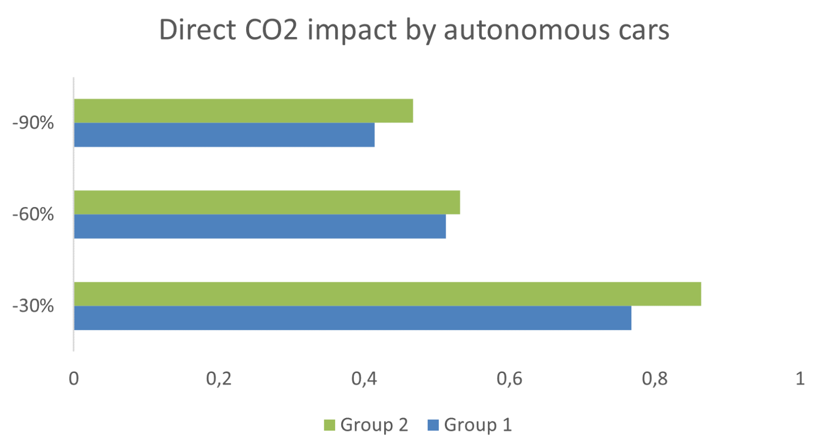

Figure 7.5: Scenario CO_2 impact caused by autonomous cars, source (Author)

In the benchmark, all cars are transported by truck. When comparing different groups, we can draw a logical conclusion: if Group 1 receives more self-driving cars, the direct impact on CO_2 emissions is smaller than if this occurs in Group 2. This is because self-driving cars save more distance on trips to far-away locations, resulting in fewer CO_2 emissions from trucks since they don't have to make those trips. But, when we look at a 60% savings, the CO_2 impact between the groups becomes more similar. Focusing on the a priori groups, we notice that Group 1 has many moderate groups of cars. This allows the HGS-CVRP model to generate more route solutions that with similar distances. Since diversity in distance is a factor in measuring how good a solution is, the HGS-CVRP model can reach the iteration limit faster if the distance per solution are similar. The number of runs terminated by the diversity criteria of the HGS-CVRP model is increased with 59% compared with the benchmark, when the largest proportion of the a priori groups is from moderate size. From this, we conclude that geographical location and the usage of dummy variables indeed impacts how well the HGS-CVRP heuristic works.

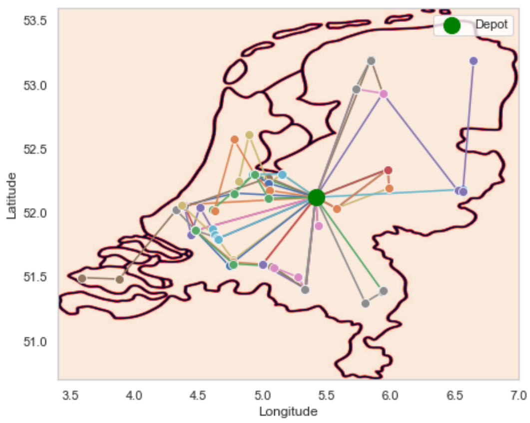

Figure 7.6: Routes of benchmark, source (Author)

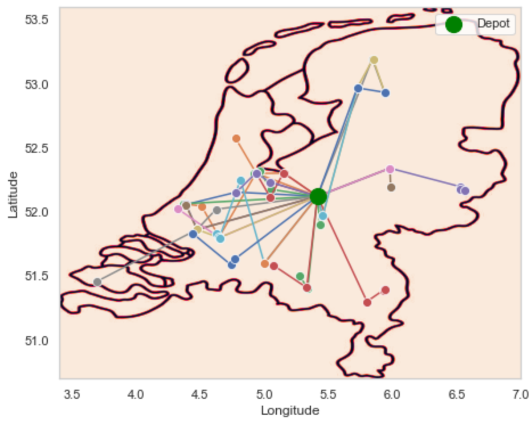

Figure 7.7: Routes of trucks, with 30% autonomous cars in Group 1, source (Author)

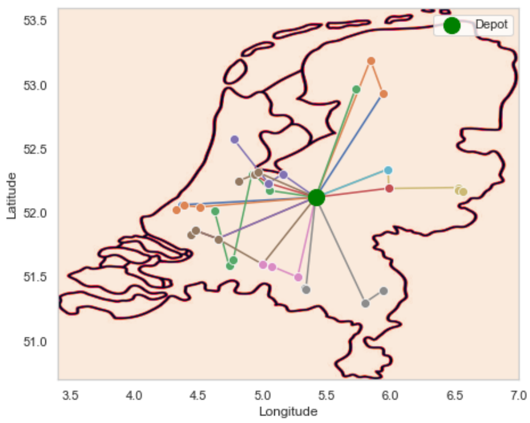

Figure 7.8: CO_2 impact with 60% autonomous cars in Group 1, source (Author)

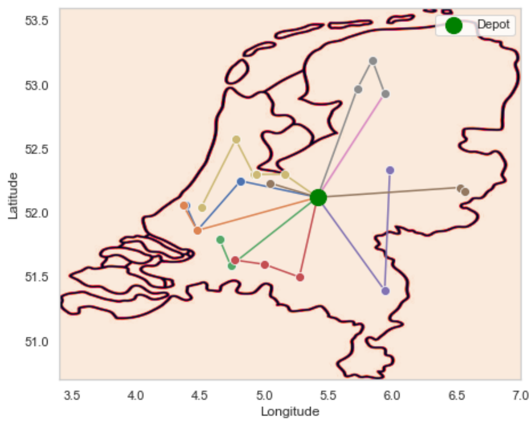

Figure 7.9: CO_2 impact with 90% autonomous cars in Group 1, source (Author)

7.3. Conclusion

In this chapter, the following sub research question is answered:

6b. *What is the impact of external factors on car distribution processes?*

The scenario analysis demonstrates the significant influence of the load factor on distribution logistics, particularly when integrating electric cars, which leads to an exponential increase in the number of trucks required for distribution. This is due to electric cars' larger size and weight, that highlights the logical and expected behavior of the HGS-CVRP algorithm when the load factor is influenced. Adjustments to the NRB-period acceptance also show logical outcomes. However, there's room for improvement, as the adjustments in NRB-period acceptance sometimes result in free capacity at car dealership locations. The swift to E-trucks presents a significant direct CO_2 emissions reduction. Despite these initial costs, the long-term savings in operational expenses, which are estimated to drop to 62.4% of those associated with conventional trucks, present a reduction of 42,6% in direct CO_2 emissions. The implementation of autonomous cars provides an opportunity to assess the adaptability of the HGS-CVRP model to geographical variations. It is observed that the model's efficiency decreases when nodes relatively close contains moderate a priori groups, due to diversity termination. With the introduction of dummy variables, the diversity of the solution decreases. The lack of diverse groups results in an earlier achievement of the HGS-CVRP ranking criterion for diversity, thus limiting the exploration of alternative solutions.

8 Conclusion and Discussion

In this chapter, the findings of this research are concluded. Each chapter concludes by answering a sub-question. Here, these insights are combined to answer the main research question. Next to that, the scientific relevance and the practical contribution is discussed. Also, the limitations of this research are described, followed by the recommendations for further research.

8.1. Main Findings

By setting strict and short term targets by the European Commission about reducing direct CO_2 emissions for heavy trucks, changes in the distribution process are needed, especially for companies using heavy trucks. In the automotive industry, a large proportion of cars in the automotive industry is transported via truck. Pon Automotive, the Netherlands' largest car import company, annually transports approximately 80,000 cars from a distribution hub to car dealer locations, all using diesel-powered trucks. Current sustainable techniques and alternatives, such as different transport modes, are limited and expensive due to standardized procedures and inflexibility of existing processes. However, companies have to provide short-term alternatives to reduce emissions by 2025 as set by the European Commission, to avoid fines. These short term alternatives to modify these processes are either unknown, gained from single perspectives or challenging to implement, creating a knowledge gap in how to reduce direct CO_2 emissions from truck-based transport on the short term.
Additionally, vehicle routing is been recognized as potential solution, but modeling distribution problems on large scale is been recognized as difficult, due to the complexity and size of these problems. State-of-the-art meta-heuristics are suitable for large Capacitated Vehicle Routing Problems (CVRP) , but not directly applicable for car distribution processes due to the lack of the split delivery ability. In car distribution processes, the truck capacity is limited compared to the high demand of car dealers [90]. Therefore, multiple trucks has to reach single nodes, requiring adjustments in the CVRP problem.
Therefore, this study first assessed the current state of the processes of truck-based car distribution to find bottlenecks and to generate proposed policies potential improvements of the distribution from holistic perspective. Second, a meta-heuristic is used to model car distribution processes on large scale, including a function to enable split delivery of cars, making a suitable solution approach in the car distribution processes.

"To what extent can redesigning car distribution processes reduce direct CO_2 emissions emitted by transportation vehicles?"

To address the main research question, an overarching methodology based on Dym, Brown, and Little [34] is employed. This three-stage method starts with the **Problem Identification** of the current state. For accurately defining the problem and discovering potential improvements, the car distribution process of the current state is mapped out by an an extensive field research including analyzing data from stakeholders, conducting expert interviews, reviewing literature, and utilizing process mapping frameworks. Second, the process outline is used to develop a **Solution Approach**. This approach functions as a representative model of the current state to enable an calculation and evaluation of potential improvements. Also, the aim of the solution approach is to implement a split delivery methodology on a large scale. The last stage is the **Future Designs**, where the solution approach is applied on a large scale problem to assess the performance of potential improvements, using a real-life case at Pon

Automotive. The robustness of the solution approach is evaluated through uncertainty and sensitivity analyses.

The detailed examination of the main question is achieved by answering sub-questions that encompass segments of the main question. The main findings are elaborated below:

1. What are key characteristics of the car distribution process of new cars? The system analysis highlights the complexities and challenges of reducing direct CO_2 emissions in the automotive distribution process. It emphasizes the importance of aligning individual objectives with system-wide goals to achieve environmental gains. With the direct CO_2 emission targets of the European Commission on the short term, distribution processes by trucks must become more environmental friendly. However, large adjustments in distribution processes of cars is not realistic on the short term, due to a lack of alternative transport modes, high costs and reduced operational performances. Alternatives such as improved route planning and the implementation of push-pull allocation strategies could help in avoiding redundant trips, which offer potential improvements in reducing direct CO_2 emissions.

2. Which methods can be used to analyze and evaluate the direct CO_2 emissions in the distribution process of new cars? An essential and important initial step in this approach is a detailed process mapping of distribution activities from stakeholders to identify the sources and contexts of direct CO_2 emissions. This includes direct CO_2 emissions, but also indicators in the operational and financial domains. The Swimlane analysis and IDEF-0 diagrams provides a complementary value in the process mapping of supply chain processes. By including a system requirement analysis, proposed improvements are obtained. By doing this, it becomes possible to analyze the emissions impact of these policies and adjust strategies systematically of the current state. The CVRP is recognized in literature as a suitable quantitative approach for modeling vehicle routing problems. By doing this, the current state can be modeled and proposed improvements can be analyzed. Among many methodological options, exact methods are known for their easy applicability, but often struggle with the computational challenges inherent in NP-hard problems. Therefore, most of the CVRP applications with exact methods are performed on small scale. On the other hand, state-of-the-art meta-heuristics are suitable for large CVRP problems, but often encountering obstacles in adapting to the unique requirements. In the car distribution process, split delivery requirements are needed to model the problem as the capacity of trucks is relatively small to the demand of dealer locations. Thus, requirement adjustments are needed to enable large scale CVRP calculations with split delivery.

3. How can the car distribution process for new cars be evaluated? In this research a System Engineering approach, based on Dym, Brown, and Little [34], is used as holistic framework. The problem is defined as a result of the current state analysis, consisting two process mapping frameworks: a Swimlane analysis and IDEF-O diagrams. These methods complement each other and provide the capability to map the process from holistic perspective. Also, through selected Key Performance Indicators, sub-processes can be measured to identify bottlenecks. Furthermore, there remains an opportunity to employ process-specific KPIs identified during the current state analysis, through reverse engineering. Next, the Solution Approach contains the Hybrid Genetic Search algorithm for Capacitated Vehicle Routing Problems (HGS-CVRP) meta-heuristic of Vidal [90] for route calculations as it represents as the state-of-the-art method for solving large scale CVRP problems. To integrate this into the car distribution processes, a priori split demand strategy of Chen et al. [27] is added, enabling the use of the split delivery function. Given that this combination has not previously been documented in the literature, its performance is verified on a small scale using an exact method. After this, the solution approach is applied on large scale instances of Pon Automotive, to evaluate the policy adjustments gained from the current state analysis. Furthermore, scenarios are set-up to examine the effects of external factors and the potential impacts on the distribution process.

4. What are bottlenecks in the current car distribution system? The current state analysis of Pon Automotive's distribution process revealed key inefficiencies, particularly in communication and operational constraints. These findings are validated by stakeholders and comparable automotive companies. The lack of transparency about 'Not-Ride-Before' (NRB) periods and the two-stop maximum for trucks limits distribution efficiency and are potential reasons for CO_2 emissions. In the process mapping analysis, it has become apparent that unnecessary dealer transport occurs as a result of cars not being desired by auto dealers. It is concluded that the Not-Ride-Before (NRB) period of cars is a cause for dealer transport, a car detail currently not accounted for in the process. By initially transporting cars to their desired location, dealer transport will be reduced. Furthermore, it has been revealed that a limit of a maximum of two stops per truck imposes significant restrictions on routing flexibility. Allowing more truck stops could reduce direct CO_2 emissions, as routes could be configured more efficiently. These issues highlight the need for a more integrated communication system and new vehicle routing strategies. Therefore, two policies are proposed, based on the actor and system requirements.

1. **Policy 1:** Unlimited location stops for trucks
2. **Policy 2:** Not-Ride-Before period prioritization

The aim of the policies is to create more operational flexibility and reduce direct CO_2 emissions by minimizing inefficient trips of car dealers.The implementation of these policies is expected to create a more adaptive and efficient distribution system, directly contributing to the reduction of unnecessary trips and the optimization of transport routes. These policies are validated by the second largest car import company of the Netherlands. This approach not only addresses the immediate operational inefficiencies but also aligns with broader environmental sustainability objectives, elaborated by the European Commission.

5. How is the car distribution system modeled? The methods used in the solution approach aim to redesign CO_2 emissions of truck-based distribution processes and to enable performance evaluations of large scale car distribution processes. This solution approach starts with a demand split strategy of Chen et al. [27] to divide initial demands of locations into moderate and small segments, allocated to dummy locations. This enables the application the HGS-CVRP heuristic including a Split Delivery function on large scale instances. By doing this, the routes of trucks to dealer locations are calculated based on minimum total travel distance. The performance of the model is evaluated by key performance indicators in three domains: Environmental Performance, Operational Performance and Financial Performance. Detailed methods for evaluating CO_2 emissions at sub-tour level is implemented, as the influence of the load can have sufficient influence. This solution approach is verified against an exact model on a small scale to ensure its functionality. After the verification with an exact method, is concluded that the behavior of the HGS-CVRP and performance is sufficient, by accepting all hypotheses. In the verification it is concluded that the *a priori* demand split strategy in combination with the HGS-CVRP reaches near-optimal solutions. However, special attention is needed for the input variable number of trucks, as the best solution is not always found with the minimum number of trucks.

6a. How do new policies affect the redesign of car distribution processes? Policy 1 demonstrates that allowing trucks to make more stops can lead to meaningful environmental benefits. By permitting trucks to conduct additional stops, there's an overall decrease in direct CO_2 emissions by 2.1%, despite an increase in the number of trucks by 6.9%. Policy 1 effectively lowers the average distance per truck by 8.0%, illustrating that more targeted and efficient routing reduces the direct CO_2 emissions but leads to increased costs due to extra trucks and extra personnel. The operational costs are lowered due to reduced total travel distance compared with the benchmark. These findings affirm that the implementation of Policy 1 can achieve a sustainable impact, but leads to higher costs. Policy 2, prioritizing car distribution based on the Not-Ride-Before (NRB) period, results in a 6.4% decrease in direct CO_2 emissions, mainly due to 53,2% less dealer transport. This highlights the effectiveness of aligning car dealer needs with distribution strategies. Here, 21,4% of the cars has switched to other locations, based on the NRB-period. Both policies offer potential for improvements of the distribution processes and positive environmental impacts. However, the increase in the number of trucks used in Policy 1 may lead to higher costs, whereas Policy 2's reallocation of transportation responsibilities could streamline dealer operations and reduce dealer transport. Transparency in capacity availability of car dealers is crucial to avoid accumulation, resulting in redundant dealer transport.

6b. What is the impact of external factors on car distribution processes? The scenario analysis demonstrates the significant influence of the load factor on distribution logistics, particularly when integrating electric cars, which leads to an exponential increase in the number of trucks required for distribution. This is due to electric cars' larger size and weight, that highlights the logical and expected behavior of the HGS-CVRP algorithm when the load factor is influenced. Adjustments to the NRB-period acceptance also show logical outcomes. However, there's room for improvement, as the adjustments in NRB-period acceptance sometimes result in free capacity at car dealership locations. The swift to E-trucks presents a significant direct CO_2 emissions reduction. Despite these initial costs, the long-term savings in operational expenses, which are estimated to drop to 62.4% of those associated with conventional trucks, present a reduction of 42,6% in direct CO_2 emissions. The implementation of autonomous cars provides an opportunity to assess the adaptability of the HGS-CVRP model to geographical variations. It is observed that the model's efficiency decreases when nodes relatively close contains moderate a priori groups, due to diversity termination. With the introduction of dummy variables, the diversity of the solution decreases. The lack of diverse groups results in an earlier achievement of the HGS-CVRP ranking criterion for diversity, thus limiting the exploration of alternative solutions.

8.2. Discussion

In this section, the practical and scientific contribution is discussed. Also, the limitations of this research are discussed, divided into methodological, results and data limitations.

8.2.1. Scientific contributions

Two main contributions are made in this research to the scientific field. First, this research provides a holistic approach where actor requirements of the main stakeholders in the distribution process are combined to propose short term improvements in the car distribution process with the aim to reduce direct CO_2 emissions. The need for these improvements is emphasized by the the short-term targets of the European Commission [72], but scarce emphasizes is provided on short-term alternatives in truck-based distribution processes of cars in literature. This study suggests an easy to implement and not earlier mentioned prioritization strategy, applicable on general car distribution systems. This prioritization strategy is verified by the two largest car import companies in the Netherlands, and based on extensive field research. Second, this study has designed a new solution approach, applicable on large scale CVRPs with split delivery function. The state-of-the-art HGS-CVRP meta-heuristic of Vidal [90] is combined with a novel *a priori* demand split approach [27], to enable split delivery functions on large scale instances. This method combination is verified on small scale by using an benchmark of an Exact Method and it concluded that this approach can reach near-optimal solutions. No other studies has applied the HGS-CVRP in a large neighborhood, including the split delivery function. Except one very recent study [24], no existing algorithms do scale. Therefore, this research contributes to solving a CVRP with larger instances than those in literature.

8.2.2. Practical contributions

The practical contribution made with this research can be separated in contribution from system perspective, and from stakeholder perspective.

System perspective

By adopting a holistic approach to vehicle routing and distribution, companies significantly improve the efficiency of their distribution networks. This lead to improved route configurations, reduced travel distances, and better collaboration with main stakeholders. In practice, this means more efficient trucks usage, precise delivery, and increased overall efficiency. Second, a more efficient routing system directly contributes to a decrease in CO_2 emissions. This is especially important in the context of distribution processes of the automotive industry, which is under large pressure to reduce its direct environmental impact on the short term. Improving process alignment by adding more route flexibility and the introduction of a new priority strategy, results in large reductions of the CO_2 emissions. Third, companies that successfully implement more efficient car distribution strategies gain a competitive advantage. By reducing emissions and improving efficiency, companies market themselves as both environmentally responsible and cost-effective, appealing to both environmentally conscious consumers and stakeholders looking for operational and environmental efficiencies. Further, addressing current process inefficiencies requires collaboration across the stakeholders. This collaborative approach not only improves the distribution process but also strengthens stakeholder relationships, leading to a more integrated process.

This research has identified critical practical gaps in the understanding and implementation of system-wide efficient car distribution processes from distribution hubs to car dealers. These gaps highlight the inefficiencies. Next, an extensive field research has introduced an easy to implement priority strategy, resulting in major environmental impact, without large differences in the current distribution processes. This research not only addresses this potential, but also proved large efficiency gains of the system. In a setting where stakeholders priorities their own goals and the maximization of profits, the focus on system efficiencies is often neglected. This research contributes to improved collaboration for both short-term and long-term objectives.

Stakeholder perspective

In this problem, three main stakeholders are identified: Car import company, Transportation company and Car dealers. Here the practical contributions per actor are discussed.

Car import company
Car import companies will gain significant value addition in their distribution processes. The performance of these companies heavily relies on the collaboration and performance of the stakeholders. Implementing the NRB-period prioritization at car import companies will lead to substantial differences and are applicable in current distribution processes. Specifically, 21.6% of the cars will be reassigned to different locations without an significant difference in the operations of the transportation company, implying that adaptions are not difficult. This strategy not only yields considerable profits for car dealers due to a reduction in the number of dealer transports but also enhances dealer satisfaction. Consequently, this increased satisfaction is likely to ensure car dealers remain a partner of the importing company. Currently, dealers express dissatisfaction and face challenges due to limited capacities. Given the high dependency on car dealers, improved communication with dealer companies is projected to secure significant gains in keeping a sustainable collaboration in the future.

Transportation company
By better aligning the distribution processes between import companies and car dealers, transportation companies will experience reduced inefficiencies. A key outcome is the minor changes in the current distribution process of transportation companies after the implementation of the NRB-period prioritization strategy, which results in a large reduction of CO_2 emissions within the system. In addition, adding more flexibility to routes of transportation companies enables better fitted route selections that lower CO_2 emissions. While this approach may increase the number of stops, it also reduces the average distance per trip. Given the strict requirements for transportation companies to present significant CO_2 reductions by 2025, route optimization by adding more flexibility in location stops represents a valuable initial step. This adjustment constitutes a realistic improvement with minimal negative operational impact on current processes. Additionally, beyond the initial step towards reduced consumption, this also serves as a starting point for considering alternative transportation methods for electric cars. Given the pressure to reduce direct emissions, as concluded in the sensitivity analysis, transitioning to electric trucks significantly impacts direct CO_2 emissions. Despite the more limited range of electric cars, the implementation of policies that result in even shorter trips makes the use of electric trucks increasingly viable.

Car dealers
Literature of car allocation strategies from system perspective indicates the necessity of a push allocation for car import companies, but highlights the need for pull allocation characteristics for car dealers. Aligning processes to incorporate the preferences of car dealers into the system allows for significant gains in operational and environmental performance. Specifically, in time and manpower at dealer locations through the reduction of dealer transport between external storage and dealer locations. Prioritizing cars based on NRB-periods enables car dealers to deploy their staff more effectively and improves daily plannings. Moreover, this research distinguishes between different types of car dealers. The benefits of the redesign will be significant for all dealers, but particularly for those with a large number of corporate clients, such as rental agencies and leasing companies. The car orders from these businesses often include a specific NRB-period due to fixed lease contracts and rental guidelines. Furthermore, this priority strategy proves to be robust, accommodating future changes in NRB-period preferences. For instance, if there's a shift towards preferring cars with lower NRB, more cars can be directed to external storage, allowing dealer performance to concentrate fully on the desired cars.

8.2.3. Limitations
This section discusses limitations of the research. First the limitations related to the scope and approach are provided. Subsequently, the limitations related to the methodology, results and data are provided.

Research scope, and Approach
According to the objectives outlined in the Paris Climate Agreement, the ambition for companies is to achieve net-zero emissions by 2050 [73]. This study specifically focuses on reducing the direct CO_2 emissions from truck-based car transportation on the short term. Despite its narrow scope, the transportation sector has a significant environmental footprint, and offers the potential for substantial reductions in emissions. Beyond direct CO_2 emissions, car distribution contributes to additional negative environmental impacts, including noise pollution, increased freight traffic, and heightened road

maintenance needs due to heavy transport. A more comprehensive analysis could extend to these areas for a better understanding of the sector's environmental impact. On the other hand, some companies, such as Pon Automotive, have already achieved net-zero status, which indicates that their net CO_2 emissions are zero. This is achieved through compensatory actions such as CO_2 compensation or investing in sustainable projects to offset emissions. This aspect, however, is not considered in this study.

Methods, results and data

The aim of this research is to identify issues within the current car distribution process and evaluate the impact of potential changes on performance. The development of the new solution approach involves a degree of subjectivity. To achieve as objective a representation of reality as possible, decisions are discussed with stakeholders and experts and made transparent. The impact of these decisions is verified against a benchmark using an exact model, and the HGS-CVRP model is extensively analyzed through scenario analysis. The results demonstrate a near-optimal solution on a small scale and a robust model on a larger scale, thereby this suggests an improvement of the reliability of the solution approach. Special attention is given to the selection of input variables for the HGS-CVRP heuristic during the large-scale verification of the solution approach. Although, the results provide a near-optimal solution, the used methods are proven in literature, interviews are conducted with both internal and external experts, and a second opinion from the second-largest auto import company is included, there is room for improvement in the solution approach. Nonetheless, the selection of scientific methods and data sources has been verified, reducing the risk of subjectivity.

The objectives of the solution approach is twofold. The first objective is whether designing a representative approach to model direct CO_2 emissions resulting from truck-based car distribution processes, focusing on taking into account system and actor requirements of the main actors and considering the chosen routes. Therefore, the current state is modeled by seeing the distribution process as a Capacitated Vehicle Routing Problem. This is a simplified, but novel approach of representing a distribution process. First a benchmark is considered, by using an exact method. Exact methods aim to find an optimal solution, but less practical for large scale problems due to the NP-hard nature of CVRP and the exponential growth of the solution space. However, several aspects are assumed and considered as logical. Examples are traffic conditions, varying delivery times, mandatory brakes for truck drivers and simplified routes. An exact method CVRP approach does offer numerous possibilities for model expansion. For instance, a split delivery function can be implemented by adding mathematical constraints, and it allows for the incorporation of verified assumptions into the model, thus enabling a more accurate representation of reality. In literature, heuristics are developed aiming to find near-optimal solutions. Through an iterative process, these heuristics attempt to quickly find a near-optimal solution, which is often used in large-scale instances. Thus, the HGS-CVRP is used, to model a CVRP, including split delivery to model an push-pull based distribution process, which is verified by an Exact model on small scale.

The second goal of this solution approach is to incorporate a split delivery methodology by integrating the state-of-the-art Hybrid Genetic Search algorithm for Capacitated Vehicle Routing Problems (HGS-CVRP), as outlined by Vidal [90], with the novel $a\ priori$ split strategy for demand proposed by Chen et al. [27]. In this study, the HGS-CVRP heuristic is applied and validated through comparison with an exact method, providing a highly accurate representation of the current situation. Nevertheless, specific assumptions are introduced to integrate a split delivery function into the HGS-CVRP heuristic, by Chen et al. [27]. This application has been verified, but as the verification of this research indicates, its effectiveness is heavily dependent on the problem. The HGS-CVRP algorithm employs a ranking system to evaluate solutions and decide which solution to eliminate, with diversity being one of the measurement criteria. This aims to maintain a varied group of solutions to test as many different solutions as possible. The algorithm stops when a maximum number of iterations have been reached (default nBiter = 20,000). The introduction of dummy variables means that solutions are more similar in distance when the maximum group size for split demand is moderate, thus reducing the number of solutions explored. Additionally, selecting large a priori group sizes reduces the solution space because fewer dummy variables are created, meaning not every solution is explored. For instance, with a maximum group size of four, a group of four will not be split into groups of 3 and 1. On a smaller scale, group sizes are tested and verified through 10 experiments, each with different instances. These tests showed that with a group size of four, in 8 experiments, an optimality gap of <5% is achieved. In each experiment, the demand of the instances is different. The sensitivity analysis revealed that experiments with nodes relatively close to the depot, and with many moderate-sized split demand groups, has a smaller difference in performance output compared with the benchmark. This concludes that the geographical positioning of instances could influence the model. A suggestion could be that a population with moderate sized split demands, close to the depot, has more routes tended to be similar. When many similar solutions are in the feasible solution space of the HGS-CVRP, the model stops improving as the maximum number of iterations is reached. A limitation is that the verification with the exact model did not vary the locations of instances to precisely determine the impact of geographical positioning on the model's effectiveness.

Further, according to literature and expert interviews the data is obtained. This is generalized data, suitable for other car distribution problems. However some assumptions are not taken into account, which may influence the results. First, the load factor is considered to determine the maximum load of trucks. This is a verified method, including the size and weight of trucks. However, this load factor is also used as demand for car dealers, to ensure that all demand is satisfied in the model. Next, the capacity of a dealer is determined based on the difference between the incoming and outgoing cars per day. This implies the same load factor determines the capacity of dealers. That is limitation, as the load factor of electric cars is 2 due to weight, but are not occupying 2 parking spots at dealer locations. In addition, the model's lack of flexibility in scheduling transportation is another drawback. Not being able to change transport dates means the model might miss out on the system efficiencies. In addition, the model calculates routes based on the Haversine distance between two points. This excludes the actual distance when using actual roads. An assumption is made for a high density road network in the Netherlands, by using the detour index of Boscoe, Henry, and Zdeb [23] based on an statistical research in the United States but adapted for dutch usage. A limitation is that this detour index is not accurate enough. Lastly, The implementation of policy 1 results in additional stops per truck. No assumptions are included for the potential increase in fuel consumption per truck. Increased stops can lead to higher fuel consumption due to more frequent travel on local roads, which involves numerous stop-and-go movements. Additionally, the engine of a truck will cool down between stops more often. Generally, a cold engine consumes more fuel because the combustion process is less efficient. When combined with carrying heavy loads, this additional strain on the engine can lead to increased maintenance costs on the long term.

8.3. Recommendations

This section proposes recommendations for future practice and research, derived from the findings, constraints, and new insights gained throughout this research. These recommendations aim to reduce environmental impact, enhance operational efficiency and improve stakeholder collaboration.

8.3.1. Operational Recommendations

For Distribution Companies (Pon Automotive):

- Increase data transparency regarding "Not Ride Before" (NRB) periods for individual cars at the Leusden distribution hub. This enables prioritization based on NRB-period, preferred by dealers and beneficial across environmental, operational, and financial aspects, with a reduction of CO_2 emissions by 6.4%.
- Communicate Not Ride Before (NRB) data to manufacturers to prioritize the production of cars with shorter NRB periods. This minimizes the risk of accumulation further down the supply chain.

For Transportation Companies (Koopman):

- Relax the constraint on the maximum number of stops of 2 per route, as more flexibility in the number of stops has the potential to decrease direct CO_2 emissions by 2.1%.
- Provide accurate information to car dealers about delivery schedules, to avoid surprise deliveries.
- Explore the impact on maintenance costs of trucks when more stops are made per truck. More stops means more short distance trips and more trips with a cold engine. This increases the fuel consumption and engine wear.

For Car dealers:

- Improve the frequency and accuracy of communication between car dealers and Pon. By updating capacity information regularly, redundant transport motions can be avoided, promoting a more responsive and lean supply chain.
- Develop workforce schedules aligned with Koopman's delivery timelines.
- Communicate car delivery preferences proactively, to reduce the number of unwanted cars at car dealers.

8.3.2. Model Recommendations

1. Implement time-related variables in route planning to account for drivers' working hours, mandatory breaks, and load/unload capacities, ensuring the viability of solutions especially when more trucks are required due to policy changes like increased stop allowances.
2. Expand the modeling time frame from a single day to multiple days. This allows for strategic holding of cars at the hub to create more efficient routing configurations for trucks.
3. Expand the Hybrid Genetic Search for the Capacitated Vehicle Routing Problem (HGS-CVRP) algorithm to include a built-in split delivery function. The sensitivity analysis indicates that the use of dummy variables leads to decreased performance as the termination criteria is reached earlier. By introducing new local search operators, adapting crossover techniques, and adjusting the delivery quantity information in the solution representation, split delivery can be implemented.
4. Utilize actual road distances rather than the Haversine formula, corrected with a validated detour index, to achieve more accurate routing. This results in more precise route calculations.
5. The model interpretation suggests that E-trucks are particularly effective for relatively long-distance trips, and self-driving cars are more suitable for shorter distances. It is recommended to explore the benefits of combining these two developments into the distribution system. This potentially decreases the direct CO_2 emissions more. Also, the likelihood of using 1 alternative is less realistic, so this could have a large practical contribution to reducing direct CO_2 emissions.
6. Test the feasibility of combining deliveries at external parking locations and deliver cars from external parkings to car dealers. This potentially results in extra reductions of dealer transport, as dealer pick-up cars every day.
7. Research the impact of geographical positioning on the performance of the HGS-CVRP, as the diversity constraint is reached earlier in moderate size groups of cars in combination with locations close to the depot.
8. Implement constraints that maximizes dealer capacity occupation at the dealer. Specifically, investigate how the capacity determined by the number of cars received in 2022, minus those transported to external parking facilities, could be optimized. During periods when dealers have excess capacity, there may be an opportunity to forward cars with higher NRB-periods to dealers. The sensitivity analysis suggests this practice is not currently being utilized.

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A
Scientific research paper

The scientific paper starts on the next page.

Redesign of the Car Distribution Process: a Dutch case study

A Holistic Approach in a Capacitated Vehicle Routing Problem to Reduce Direct CO_2 Emissions in a Truck-Based Car Distribution Process

W.S. Koopal

Dr. J.M. Vleugel, Dr. F. Schulte, Prof. Dr. R.R. Negenborn, J. van Assen, M. Schneider

Purpose - With the short term need to reduce direct CO_2 emissions of trucks in distribution processes, this paper aims to provide an easy to implement solution approach for distribution processes of new cars from holistic perspective. Scarce emphasizes is provided on short-term alternatives in truck-based distribution processes and approaches lacks applicable for large scale problems including split delivery function.

Design/methodology/approach - The distribution process and model methods are analyzed using a literature study and interviews with experts, resulting in the development of a solution approach. Combined with an extensive field research, a solution approach enables the performance evaluation of the current state, and the policy implications. Future designs are used to validate the solution approach by calculating performance differences in multiple relevant evaluation domains.

Findings - The analysis of the current state has identified critical bottlenecks, leading to the development of two promising policies. The application of a new and validated prioritization strategy and permitting more stops per truck has successfully yielded a significant reduction in CO_2 emissions. The performance of the solution approach demonstrates high precision on a small scale and yields results comparable to actual practices on a larger scale, suggesting the approach's effectiveness and potential for future application.

Research limitations/implications - This research provides a new solution approach for evaluating direct CO_2 emissions of model different designs of distribution processes. Despite its narrow scope, the transportation sector has a significant environmental footprint, and offers the potential for substantial reductions in emissions. From modeling perspective, further research is suggested in integrating split delivery function without using dummy variables.

Originality/value - This paper contributes by identifying critical gaps in the understanding and implementation of system-wide efficient car distribution processes from distribution hubs to car dealers. It not only addresses potential improvements, but also proved efficiency gains of the system with a new solution approach, using a new combination of a state-of-the-art meta-heuristic and a proven split delivery method applicable for large-scale problems.

Keywords: Direct CO_2 emissions, CVRP, Split-delivery, truck-based, car distribution

Acronyms

CSRD - Corporate Sustainability Reporting Directive
CVRP - Capacitated Vehicle Routing Problem
HGS-CVRP - Hybrid Genetic Search algorithm, specialized for CVRP
IDEF-0 - Integration DEFinition for Function - 0
KPI - Key Performance Indicator
NRB-period - Not-Ride-Before period
SDCVRP - Split Delivery Capacitated Vehicle Routing Problem
TOC - Theory of Constraints

I. Introduction

In the dynamic Dutch automotive sector, annual imports of 320,000 new cars from 350 global brands demand sustainable and efficient logistics [1–3]. The industry's resilience after COVID-19, marked by a increased number of car registrations, highlights the urgency for adaptive supply chains in response to environmental mandates, including the European Commission's CO_2 reduction targets for heavy trucks [4–7].

While long-term technological solutions are explored, the understanding of short term strategies for CO_2 emission reductions in car distribution lacks, especially from a system-wide perspective [8–10]. This study offers dual scientific contributions: a holistic analysis of new identified CO_2 emission bottlenecks in car distribution and a novel application of a meta-heuristic for a large-scale Capacitated Vehicle Routing Problem (CVRP) with split delivery capability [11–13].

The research question answered in this paper is: "To what extent can redesigning car distribution processes reduce direct CO_2 emissions emitted by transportation vehicles?"

Answering the research question of CO_2 emission reduction in car distribution on the short term, this paper outlines a newly devised process improvements and evaluates resultant policies through an advanced meta-heuristic solution approach, examining their impact across environmental, operational, and financial domains within a framework inspired by [14]. Subsequent sections detail the automotive distribution review, methodological approach, analysis of current Dutch processes, system design via CVRP modeling, policy impact assessment, and conclude with discussions and recommendations for future research.

II. Literature Review

Two research fields subjected to the automotive industry are discussed. First, the study examines the current automotive distribution process for new cars, detailed in the 'System Analysis'. Second, it evaluates modeling approaches and methods for identifying bottlenecks in truck-based car distribution in the 'Distribution Process Assessment Review'.

A. System Analysis

The automotive sector's global nature involves complex, unpredictable supply chains influenced by regional trends, government policies, and technological advancements [6, 15–17]. New cars' distribution from factories to consumers is a highly automated, mass production process tailored to meet each country's demands, despite challenges like material shortages and varying component availability [16, 18]. In the Netherlands, major car importers manage a significant portion of vehicle imports, using central hubs for temporary storage before distribution to dealers [1, 19]. Trucks are preferred for their flexibility, speed, and cost-effectiveness, allowing precise deliveries and quick market response [20]. The car distribution system involves three main actors: import companies, transport companies, and dealers, each with distinct objectives and collaborative arrangements [21], visualized in figure 1.

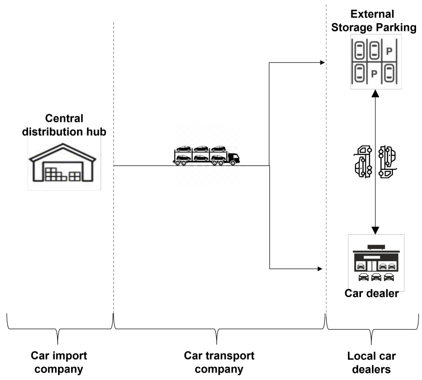

Figure 1. Dutch car distribution process, source (Author)

In Europe, heavy-duty vehicles like trucks and buses, though less than 2.5% of road users, contribute to 6% of the total CO2 emissions, underscoring the environmental impact of truck transport [3, 6]. To combat this, the European Council targets a 30% reduction in GHG emissions by 2030, with specific measures for heavy-duty vehicles to implement emission reduction from 2025 [22]. The Corporate Sustainability Reporting Directive (CSRD) further mandates companies to report on direct and indirect emissions, pushing for transparency and action in sustainability [6, 23, 24]. The Volkswagen Group, for example, is aiming to shift from road to rail transport and optimize current routes to reduce their carbon footprint, reflecting broader industry efforts towards sustainable distribution [10, 25, 26]. These initiatives are part of a larger push by the European Commission to decrease the environmental impact of transport by enhancing route efficiency and moving towards greener transport options [6].

In supply chain management, balancing the push and pull strategies is crucial for optimizing goods distribution. Push strategies, driven by forecasting demand, facilitate mass production and rapid distribution, yet often lead to excess inventory and increased environmental impact due to the lack of alignment with real-time consumer demand [27, 28]. Conversely, pull strategies, which are reactive to actual demand, support lean manufacturing and minimize waste by aligning production closely with consumption, but require robust communication systems to manage the just-in-time delivery challenges [29, 30]. The Corporate Sustainability Reporting Directive (CSRD) mandates comprehensive reporting on direct and indirect emissions, pushing companies towards more sustainable practices [6, 23]. Implementing a hybrid push-pull system offers flexibility, allowing for part of the production to be forecast-driven while another part responds directly to market demand, potentially reducing the environmental footprint of distribution [27, 31]. This approach necessitates clear communication and collaboration across the supply chain to mitigate the risk of inefficiencies and ensure the alignment of individual goals with system-wide sustainability objectives [32]. The evolution towards integrating push-pull strategies reflects an adaptation to the complexities of modern supply chains, where the aim is to balance efficiency, customer satisfaction, and environmental sustainability [33].

B. Distribution Process Assessment Review

Evaluating car distribution processes involves assessing environmental, operational, and financial performances. Environmental impact is often evaluated based on direct CO_2 emissions, operational efficiency considers resource utilization and customer satisfaction, and financial performance examines cost-effectiveness and economic impact [3, 6, 14, 34]. Process mapping tools such as IDEF-0, Swimlane diagrams, and the Theory of Constraints (TOC) play crucial roles in identifying inefficiencies and increasing collaboration within the supply chain proceses [35–38]. The Capacitated Vehicle Routing Problem (CVRP) and its variations, tackled through exact methods or meta-heuristics, address the logistical challenge of minimizing total traveled distance while adhering to capacity constraints [39–41]. Meta-heuristics, particularly the Hybrid Genetic Search (HGS-CVRP), show promise in approximating near-optimal solutions efficiently but is not able to use with split deliveries—an essential aspect for real-world applications of car distribution processes, where demands often exceed vehicle capacities [11, 42]. The Split Delivery Vehicle Routing Problem (SDCVRP) offers a potential solution by allowing multiple deliveries to a single customer, optimizing route efficiency and vehicle usage, yet presents computational challenges and necessitates innovative approaches for practical implementation [12, 43].

III. Current State Analysis

In this section, the current distribution process of new cars is analyzed. a case study at Pon Automotive is used, the largest Dutch car import company. A total of 70,560 vehicles were imported in the year 2022. Here, the cars are sorted and prepared for distribution to various local dealer holdings by truck. The objective is to understand the current distribution processes from different perspectives and to identify current bottlenecks in the distribution process. As it is unclear how the current car distribution can be improved, an extensive field research at the largest car import company of the Netherlands, Pon Automotive, is conducted. The usage of a case study in scientific research is a methodological approach that allows researchers deep-dive in a real-life context. The current car distribution process is mapped out and analyzed by using Swimlane Analysis, IDEF-0 diagrams and the Theory of Constraints to systematically detail and measure each step [14, 35]. Swimlane diagrams assign process steps to different actors, clarifying their roles and interactions, thereby identifying redundancies and bottlenecks [36, 44]. IDEF-0 diagrams complement this by providing a sequential overview of individual processes, offering a detailed view of each process stage.

For a deeper understanding, certain processes are quantitatively analyzed by using Key Performance

Indicators (KPIs). By doing this, influences of individual actors and process characteristics can be analyzed [17]. The related KPIs for this research are presented in table 1.

Table 1. Global Key Performance Indicators

Domain	**KPI**
Environmental	CO_2 Emissions (CO_2eq)
Operational	Number of Trucks (Units)
Operational	Load Density (load-cap ratio)
Operational	Average Distance (km)
Financial	Transportation Costs (Euro)

Besides the objectives set by each actor, and the system as a whole, various constraints arise from the process and the actors themselves. Analyzing constraints within car distribution processes, including contractual, practical, or external factors, allows for a systemic evaluation of their necessity and impact on the system [37]. By prioritizing constraints that significantly influence system functions, essential requirements for operational efficiency are identified, guiding the system's design and function. This analysis leads to identifying process bottlenecks, followed by proposed policies to improve the current distribution process. Therefore, two policies are proposed, based on the actor and system requirements.

1) **Unlimited location stops for trucks (Policy 1):** Revisiting the routing constraints to allow more route flexibility per truck.
2) **"Not Ride Before" period priority (Policy 2):** Implementing a strategic approach to prioritize the delivery of cars from distribution hub to car dealer and external parking.

IV. Solution Approach

Given the aim of this research, the car distribution processes can be regarded as a Capacitated Vehicle Routing Problem (CVRP) [39].In this research, the objective is to minimize the CO_2 emissions by optimizing the total distance traveled in the distribution process of new cars.

The objective of this model is twofold. First, this model aims to design a representative model that accurately quantifies the direct CO_2 emissions arising from truck-based car distribution processes, incorporating both the system and actor requirements of the main stakeholders and taking into account the routes selected for transportation. The second objective of this optimization model is to implement a split delivery methodology to combine the state-of-the-art Hybrid Genetic Search algorithm for Capacitated Vehicle Routing Problems (HGS-CVRP) and the novel approach of *a priori* split strategy of the demand [11, 12].

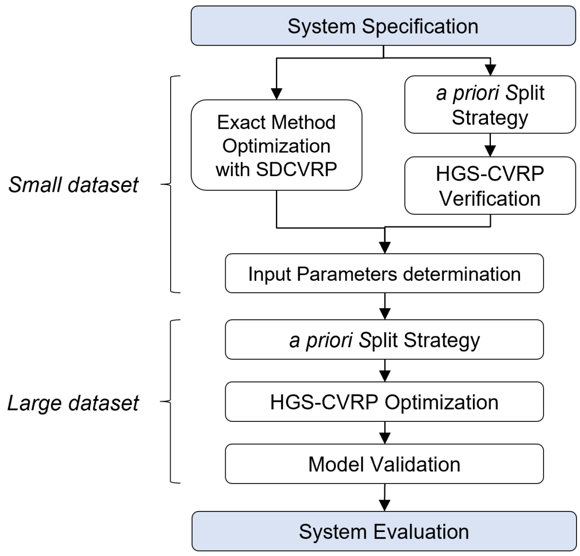

Figure 2. Outline Solution Approach

Exact methods and heuristics complement each other in this research. Exact methods offers a benchmark and insights into the problem structure on small scale, while heuristics offer practical, large scale solutions for real-world application. By doing this, the results of the HGS-CVRP in different experiments are compared with an optimal solution. This enables the determination of the input variables, maximum number of trucks and maximum group size of the demand set, of the HGS-CVRP for usage on large scales.

A. Mathematical modeling

The problem is on a complete graph $G = (N, A)$, where $N = \{0, 1, 2, ...n\}$ is the set of nodes [39]. Node 0 represents the distribution hub (DH), where a fleet of homogeneous trucks T is based. Nodes $1 \sim n$ represent the dealer locations (DL), which could be a car dealer, an external parking, or a dummy location.

Table 2. Mathematical model parameters and variables

Parameters	
D_i	Demand of dealer location i
N_t	Number of trucks
Q_t	Capacity of truck t
$TD_{i,j}$	Distance of the route between nodes i and j
L_t	Load of truck t at node i
FC_t	Fuel consumption of truck t
EF_t	Emission factor of truck t
FR_t	Average fuel reduction when truck t is unloaded
Variables	
$x_{i,j}^t$	1 if truck t drives from node i to j, 0 otherwise
$z_{i,t}$	1 if node i can be reached by truck t, 0 otherwise
u_i	Helper variable for node i
$f_{i,j,t}$	Fraction of the demand delivered from node i to j by truck t

$A = \{i, j | i, j \in N, i \neq j\}$ is the set of arcs, the routes from point i to point j [39].

The remainder of the notions used to formulate the Capacitated Vehicle Routing Problem (CVRP), including the adaptions to ensure split delivery possibilities, is formulated in thable 1.

Minimizing the Total Travel Distance (TTD) of trips:

$$\text{Minimize TTD} = \sum_{t \in T} \sum_{i \in N} \sum_{\substack{j \in N \\ i \neq j}} TD_{ij} \cdot x_{ij}^t \quad (1)$$

Subject to:

$$\sum_{t=1}^{T} z_{i,t} = 1 \qquad \forall i \in N \setminus \{1 \dots n\} \quad (2)$$

$$\sum_{t=1}^{T} z_{0,t} = N_t \quad (3)$$

$$\sum_{j=1}^{N} x_{j,i}^t = \sum_{j=1}^{N} x_{i,j}^t \qquad \forall i \in N, \forall t \in T \quad (4)$$

$$\sum_{j=1}^{N} x_{i,j}^t = z_{i,t} \qquad \forall i \in N, \forall t \in T \quad (5)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} TD_i \cdot z_{i,t} \leq Q_t \qquad \forall t \in T \quad (6)$$

$$u_j - u_i \geq f_{i,j,t} \cdot D_j - Q_t \cdot (1 - x_{i,j}^t) \qquad \forall i, j \in N \setminus \{1 \dots n\}, \forall t \in T \quad (7)$$

$$u_i \geq D_i \qquad \forall i \in N \setminus \{1 \dots n\} \quad (8)$$

$$u_i \leq Q_t \qquad \forall i \in N \setminus \{1 \dots n\} \quad (9)$$

$$x_{i,j}^t \in \{0, 1\} \qquad \forall i, j \in N, \forall t \in T \quad (10)$$

The objective function (1) minimizes the traveled distances of the trips. All cars are parked at the distribution hub, thus the starting point of each truck is the distribution hub(3). The trucks always leaves the depot and always leaves the dealer locations after satisfying the demand (4)(5). To ensure that a truck has a maximum capacity and this capacity cannot be exceeded, constraint 6 is implemented. However, when above constraints are taken into account, the solution can still be infeasible to the problem because of potential sub-tours. Therefore, constraint (7), constraint (8) and constraint 9 are added. Constraint (7) ensures that the next node of the trip can only be another dealer location when the fraction of the demand of node j is equal or larger then the load of location j at truck t. Here, a helper variable u_i is used to determine if visiting node j could be a dealer location, and must be equal or larger then the demand of node i to exclude the distribution hub (8). In addition, u_i must be equal or smaller than the capacity of truck t to ensure that the capacity is not exceeded (9). Lastly, the remaining constraint obligatory constraint 10 specify the domain of the variables. This CVRP model is known as a three-index truck flow formulation.

For the implementation of the split delivery possibility in exact methods, certain constraints of the CVRP model are adjusted and added to obtain a Split Delivery Capapcitated Vehicle Routing Problem (SDCVRP) model. This model is used for the exact method. The objective function of the SDCVRP model remains unchanged. First, a new continuous variable is introduced, called the fraction $f_{i,j,t}$. The constraints are adjusted as follows.

$$\sum_{v=1}^{T}\sum_{i=1}^{N} f_{i,j,t} = 1 \qquad \forall j \in N \quad (11)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} TD_j \cdot f_{i,j,t} \leq Q_t \qquad \forall t \in T \quad (12)$$

$$x_{i,j}^{t} = \begin{cases} 0 & \text{if } i = j \\ \geq f_{i,j,t} & \text{if } i \neq j \end{cases} \qquad \forall t \in T, \forall i \in N, \forall j \in N \quad (13)$$

Constraint 2 is adjusted, as the split delivery function enables locations to receive demand from multiple trucks. Instead, constraint 11 is added, and makes sure that all fractions have to be 1, per truck and per node, ensuring that all demand is fulfilled. With the introduction of the fraction variable, 6 is adjusted. Constraint (12) ensures that the demand of node j can be fulfilled, only when smaller than the Q_t. This results in no sub tours, and therefore constraint (7), constraint (8) and constraint 9 can be released. But, to combine the variable f_i, j, t with x_i, j, t, constraints 13 are used. In constraint 13 the demand fraction of each dealer location is coupled to the decision variable of using a route or not. These two constraints ensures that no truck will leave to another dealer until all fractions are equal to zero. Therefore, all demand is fulfilled.

B. *a priori* Split Strategy

The a priori Split Strategy has two functions. Enabling split demand by using the split strategy and eliminating the nodes without demand. A complete graph $G = (N, A)$ is used, and considers the total demand of each node. Each node without demand is eliminated, resulting in sub-graph $G' = (N', A')$, where $N' \subseteq N$ and $A' \subseteq A$. It has been discussed that there are many different ways to split the demand, but that a reasonable trade-off between running time and the quality of solutions have to be made [12]. Therefore, moderate sized groups and small demand groups are chosen. The maximum capacity (Q) of each truck is 8 cars. The model set the maximum group size to 4, which meant that demand for locations requiring more than four cars was split into groups of 4, 3, 2 or 1. This approach also introduces dummy locations with the corresponding demand. By using the 4/3/2/1 rule, the following procedure is used to make the groups:

- $m_4 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.5Qm \leq D_i\}$,
- $m_3 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.33Qm \leq D_i - 0.5Qm_4\}$,
- $m_2 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.25Qm \leq D_i - 0.5Qm_4 - 0.33Qm_3\}$,
- $m_1 = \max\{m \in \mathbb{Z}^+ \cup \{0\} | 0.125Qm \leq D_i - 0.5Qm_4 - 0.33Qm_3 - 0.25Qm_2\}$.

In the verification steps of the HGS-CVRP, with an Exact method as benchmark, these group sizes are determined.

C. Hybrid Genetic Search Algorithm

The HGS-CVRP is described by [11], and consists a meta-heuristic especially designed to solve large CVRP instances. The general structure of the search is based on the following process, visualized in figure 3.

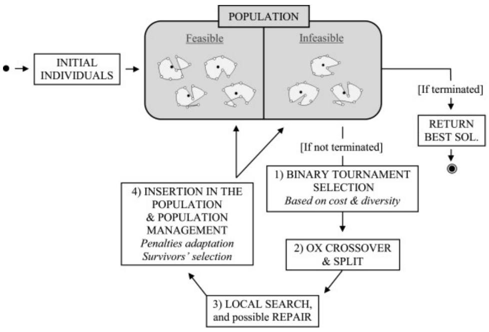

Figure 3. HGS-CVRP structure, retrieved from [11]

First, the algorithm starts with **Parent Selecting**, an approach known as random binary tournament selection. Here, two parents (routes) are randomly chosen with uniform probability, where the two parents are ranked based on the best fit. The fit ranking $f_{\mathcal{P}}(S)$ is based on two main factors: the objective value (the quality of the solution) $f_{\mathcal{P}}^{\phi}(S)$ and population diversity compared to other routes (contribution)$f_{\mathcal{P}}^{\text{div}}(S)$. Therefore, the following ranking formula is used [11].

$$f_{\mathcal{P}}(S) = f_{\mathcal{P}}^{\phi}(S) + \left(1 - \frac{n^{\text{Elite}}}{|\mathcal{P}|}\right) f_{\mathcal{P}}^{\text{div}}(S) \qquad (14)$$

Second, the **Recombination** makes an ordered crossover approach of two parents, by [45]. This enables HGS-CVRP to generate solutions by combining the optimal attributes of two parental solutions. Third, the **Swap* neighbourhood** offers an approach to exchanging customers between different routes. The Swap* neighbourhood allows for the exchange of two customers between different routes without requiring a direct positional swap. This method limits the potential new insertion positions for an exchanged customer to the most promising locations, based on a preliminary evaluation.

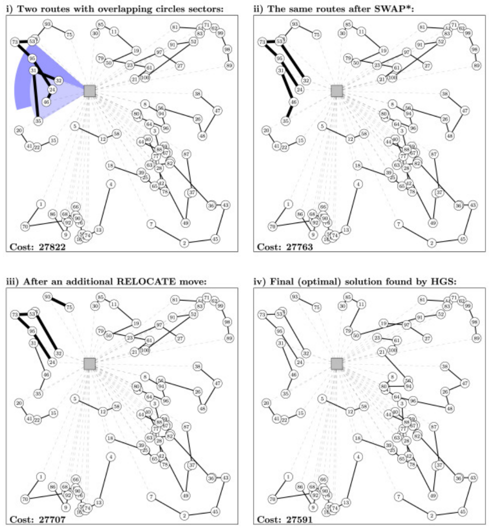

Figure 4. Swap* Neighbourhood illustration, retrieved from [11]

Last, once a solution is generated, it is **inserted** in one of the sub-populations of solutions: feasible and infeasible solutions. Each route produced during the preceding steps is immediately added into the appropriate sub-population. By defining parameters the total number of solutions is managed. The first parameter, μ, represents the minimum number of solutions in the sub-population. Also, λ is established as a predefined population size. The maximum population size is then determined as follows.

$$\text{Max sub-population size} = \mu + \lambda \qquad (15)$$

These parameters are predetermined. Initially, 4μ, random solutions are generated in the Parent Selection. The maximum sub-population size is reached, the sub-population will be reduced. During this process, identical solutions and the worst solutions are eliminated first. The algorithm operates under a termination condition, which can be set as either a specific number of consecutive iterations without any enhancement, defaulting to 20,000 (Nit), or a maximum CPU time limit (Tmax). In scenarios where the Tmax criterion is applied, the algorithm undergoes a restart after every $N_i t$ iterations.

D. Performance Evaluation

In three main domains, Environmental Performance, Operational Performance and Financial Performance, the model is evaluated. In this research, the focus lies on the direct CO_2 emissions. To achieve a detailed and valid calculation of the direct CO_2 emissions from a truck transporting cars, the Activity Based Approach has been used [46] [47]. This method is supplemented with detailed and validated additions, the load factor, the detour index and the Haversine distance, to calculate the CO_2 emissions as accurately as possible. Therefore, the following equation outlines the calculation method for the Direct CO_2 emissions produced in the distribution process:

$$\mathrm{CO_2 emissions} = \sum_{i\in N}\sum_{j\in N}\sum_{t\in T}\left(1 - FR_t + \frac{FR_t \cdot L_{i,j,t}}{Q_t}\right) \cdot \mathrm{FC}_t \cdot \mathrm{EF} \cdot \mathrm{TD}_{i,j} \cdot \mathrm{DI} \tag{16}$$

Where:

- FR_t = Fuel reduction (%) of unloaded truck t
- $L_{i,j,t}$ = Load of truck t on route i, j
- Q_t = Capacity of truck t
- FC_t = Average fuel consumption of truck t in liter per kilometer
- EF = Emission factor in kg CO_2eq per liter
- $TD_{i,j}$ = Total Distance of route i, j in kilometers
- DI = Detour index

Operational Performance is calculated as the ratio between the total capacity and the demand. Differences in the load density between runs suggests considerations are made between the number of trucks in the system related to the total travel distance. In addition, the average distance of a truck is the ratio between the total distance and the number of trucks in the system. The interpretation of the average distance per truck indicates effects in number of trucks or in the total distance traveled of the system. The Financial Performance is calculated by focusing on labor costs and operational costs.

V. Policy Implications

In this section, the Solution Approach is applied on a real life case, of Pon Automotive, to measure the impact of Policy 1 and Policy 2 on the distribution process of new cars.

A. Experimental plan

Here, the current state of the distribution processes function as the benchmark of this analysis. In 2022, 71,322 cars are imported by Pon Automotive, to the dealer locations. This could be an car dealer or external parking. In total 24 dealer holdings represents multiple car brands which Pon Automotive imports, 144 different delivery locations in total. The proposed policies, based on the the Current State Analysis, are defined as follows:

Policy 1 **Unlimited location stops:** Revisiting the routing constraints to allow more route flexibility per truck.
Policy 2 **Not-Ride-Before period prioritization:** Implementing a strategic approach to prioritize the delivery of cars from distribution hub to car dealer and external parking.

Literature and the transportation company, confirms a potential route efficiency increase due to relaxing constraint of maximum number of stops. In this research, the routes of the trucks by Koopman becomes more flexible, implying that the delivery can be executed by stopping at multiple locations, by implementing Policy 1. In addition, it is verified by 4 different dealer holding types that cars with a NRB-period of 44 days or higher always are transported to an external parking when they arrived at car dealers. Also, it became clear that 29% of the cars do have a NRB before period. Therefore, Policy 2 will align the preferences of the dealer with the priority system of Pon Automotive, to efficiently use the capacity of Koopman. the routes are calculated with the HGS-CVRP by minimizing the total traveled distance. The input-parameter settings are determined per policy. of the demand split is set to 4. The number of trucks is initially determined based on minimum amount of vehicles, as most of the cases this provides the best solution. However, as concluded in the model verification, to ensure the best solution is used, experiments with 1,2,4,8 extra trucks are executed.

B. Results Policy implementation

As a result, the direct CO_2 emissions from trucks are lower than the benchmark, resulting in reduced CO_2 emissions when Policy 1 is introduced, with an average CO_2 reduction of 2,1 %. In addition, Policy 2, on average, leads to a reduction in total direct CO_2 emissions by 6.4% compared to the benchmark.

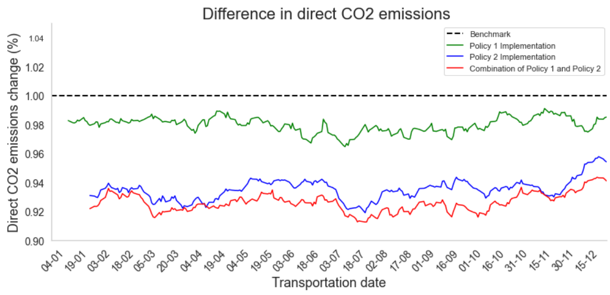

Figure 5. Direct CO_2 emissions, as a result of Policy 1 and Policy 2

Policy 1 demonstrates that allowing more trucks to make more stops can lead to meaningful environmental benefits. By permitting trucks to conduct additional stops, there's an overall decrease in direct CO_2 emissions by 2.1%, despite an increase in the number of trucks by 6.9%. Policy 1 effectively lowers the average distance per truck by 8.0%, illustrating that more targeted and efficient routing reduces the direct CO_2 emissions but leads to increased costs due to extra trucks and extra personnel. The operational costs are lowered due to reduced total travel distance compared with the benchmark. These findings affirm that the implementation of Policy 1 can achieve a sustainable impact, but leads to higher costs. Policy 2, prioritizing car distribution based on the Not-Ride-Before (NRB) period, results in a 6.4% decrease in direct CO_2 emissions, mainly due to 53,2% less dealer transport. This highlights the effectiveness of aligning car dealer needs with distribution strategies. Here, 21,4% of the cars has switched to other locations, based on the NRB-period. Both policies offer potential for improvements of the distribution processes and positive environmental impacts. However, the increase in the number of trucks used in Policy 1 may lead to higher costs, whereas Policy 2's reallocation of transportation responsibilities could streamline dealer operations and reduce dealer transport. Transparency in capacity availability of car dealers is crucial to avoid accumulation, resulting in redundant dealer transport.

VI. Future Designs

Scenario analysis in this section aims to validate the model and explore its applicability in future contexts by examining how external factors could influence the distribution process. This method assesses system resilience against hypothetical optimistic or pessimistic events, ensuring each scenario is unique and encompasses potential impacts and uncertainties [48].

- Scenario 1: Shifting Customer Behavior
  Car electrification is a major market trend influenced by consumer awareness and companies' scope 3 responsibilities. Therefore, car companies are increasingly prioritizing the transition to electric cars. This results in significant larger load factors of the cars.
- Scenario 2: NRB-period acceptance
  Differences in the acceptance of the NRB period of a car affects direct CO2 emissions from dealer transport and trucks.
- Scenario 3: Swift to E-Trucks
  As the direct CO_2 emissions has to be reduced on the short term, the transition to an electric fleet is analyzed.
- Scenario 4: Drive system improvement
  Driven by the technological improvement of self driving cars, they could drive to pre-defined destinations, which implies that no transportation vehicles is needed for these cars.

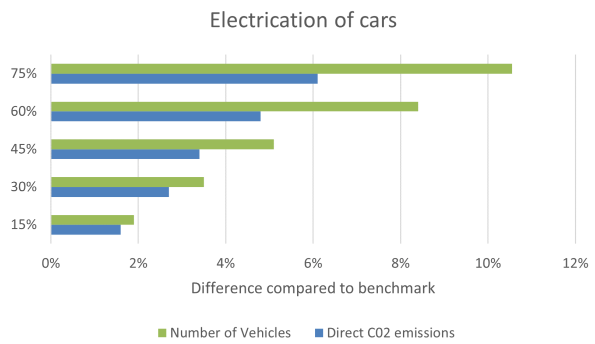

Figure 6. Scenario shifting customer behavior

The scenario analysis demonstrates the significant influence of the load factor on distribution logistics, particularly when integrating electric cars, which leads to an exponential increase in the number of trucks required for distribution. This is due to electric cars' larger size and weight, that highlights the logical and expected behavior of the HGS-CVRP algorithm when the load factor is influenced. Adjustments to the NRB-period acceptance also show logical outcomes. However, there's room for improvement, as the adjustments in NRB-period acceptance sometimes result in free capacity at car dealership locations. The swift to E-trucks presents a significant direct CO_2 emissions reduction.

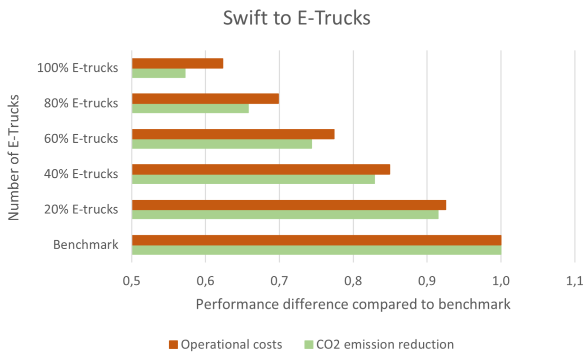

Figure 7. Design: Swift to E-Trucks

Despite these initial costs, the long-term savings in operational expenses, which are estimated to drop to 62.4% of those associated with conventional trucks, present a reduction of 42,6% in direct CO_2 emissions. The implementation of autonomous vehicles provides an opportunity to assess the adaptability of the HGS-CVRP model to geographical variations. It is observed that the model's efficiency decreases when nodes relatively close contains moderate a priori groups, due to diversity termination. The number of runs terminated by the diversity criteria of the HGS-CVRP model is increased with 59% compared with the benchmark, when the largest proportion of the a priori groups is from moderate size. With the introduction of dummy variables, the diversity of the solution decreases. The lack of diverse groups results in an earlier achievement of the HGS-CVRP ranking criterion for diversity, thus limiting the exploration of alternative solutions.

VII. Discussion

A. Solution Approach Verification

In this research, two verification steps are taken. First, the behavior of the models is verified by considering 4 aspects of the model. By doing this, the behavior of the model is analyzed systematically. By testing four hypothesis, it is concluded that the behavior of the two models is logical. Secondly, the performance of the HGS-CVRP model is verified with exact method solutions on small scale experiments. Here, the performance of an heuristic approach is compared with exact solution, with the aim to reach low performance gaps while differentiating the input parameters. These input parameters are the maximum a priori group size of split demand and the maximum number of trucks. By performing 10 experiments with 8 different with different group sizes per instance, the solutions with different number of trucks are evaluated.

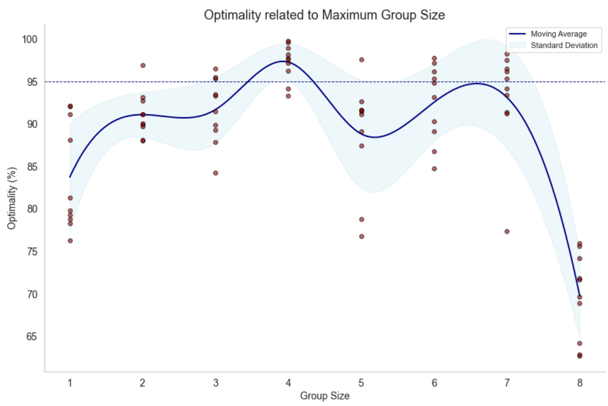

Figure 8. Optimality gap related to Maximum a priori group size

In 80% of tests involving groups of up to four cars, the difference between the expected and actual results is less than 5%. Moreover, the maximum number of trucks per run is tested by performing 10 experiments, varying the number of trucks used in 10 different instances. It is concluded that the minimum number of trucks often leads to the best outcomes, but solutions including extra trucks sometimes outperform the solutions with minimum truck requirement.

B. Validation

To assess the model on a grand scale, we engage in thorough testing and examination of its performance and accuracy via scenario analysis. This process utilizes four distinct scenarios, each designed to explore different facets of the model, employing a strategy where the scenarios are both mutually exclusive and collectively exhaustive. This approach significantly enhances the scenarios' reliability within the model. Also, output is compared with actual practices to validate performances of the model. Implementing the scenarios in the model shows that it can provide desired outputs, serve its purposes, and create valuable insights, validating the model and benchmark.

VIII. CONCLUSION AND FURTHER RESEARCH

A. Conclusion

This research has evaluated redesigns the distribution process of new cars, with the main focus on reducing the direct CO_2 emissions of transportation trucks. Also, a solution approach is developed, applicable for large scale distribution problems and including split delivery function. The implementation of new policies has resulted in new insights to help car distribution processes improve sustainability on the short term. The first scientific contribution is the introduction of an easy to implement prioritization strategy of cars, based on the "Not Ride Before" (NRB) period of cars, resulting in positive environmental impact, without large differences in the current distribution processes. Second, a new solution approach is developed, using a state-of-the-art HGS-CVRP algorithm in combination with the novel a priori split strategy of demand, applicable for large scale optimization problems requiring a split delivery function. Additionally, multiple practical contributions are made. First, by adopting a holistic approach to vehicle routing and distribution increases distribution efficiency for companies, leading to better route configurations, shorter travel distances, and improved collaboration with main stakeholders. Further, a more efficient routing system directly contributes to a decrease in CO_2 emissions. In addition, companies that successfully implement more efficient car distribution strategies gain a competitive advantage. Last, collaborative approach not only improves the distribution process but also strengthens stakeholder relationships, leading to a more integrated process. This research not only addresses this potential, but also proved large efficiency gains of the system. In a setting where stakeholders priorities their own goals and the maximization of profits, the focus on system efficiencies is often neglected. This research contributes to improved collaboration for both short-term and long-term objectives.

B. Furhter Research

This research offers several recommendations for improving environmental impact, operational efficiency, and stakeholder collaboration in car distribution. For distribution companies, it is recommended to increasing transparency on NRB-periods of cars at the prioritization department of the central distribution hub. By prioritizing cars, based on the NRB-period, a direct CO_2 emission reduction of 6.4% can be achieved. Also, the communication and integration of these car details to production processes of manufacturers is recommended to minimize the risk of accumulation further down the supply chain. Transportation companies are recommended to reconsider the maximum number of stops to a flexible number of stops per route to potentially lower emissions by 2.1%. Also, provide car dealers with accurate delivery schedules, to align work schedules. Furthermore, consider the impact of more frequent stops on more potential damages and maintenance costs. From a modeling perspective, incorporating time-related variables, extending the modeling time frame, and improving the Hybrid Genetic Search for the Capacitated Vehicle Routing Problem (HGS-CVRP) algorithm to include integrated split deliveries are recommended, instead of using dummy variables. Utilizing actual road distances, exploring the combination of E-trucks and self-driving vehicles, and researching the impact of geographical positioning on HGS-CVRP performance could further optimize distribution. Additionally, maximizing dealer capacity and exploring deliveries from external parking locations may offer further reductions in transport requirements. These recommendations aim to provide a comprehensive strategy for increasing the car distribution system while acknowledging the complexity and interdependence of the various stakeholders involved.

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B

Data Pon Automotive

For this research, data from various Excel documents was consolidated, focusing on the car distribution details for the year 2022. Due to a Non-Disclosure Agreement (NDA), only generalized data is shared. The dataset encompasses:

- A total of 71,322 cars,
- Distributed across 144 different delivery locations,
- All originating from a central hub in Leusden, with an average idle time at Leusden of 6.8 days.

The Excel files provided the following car details:

Dlr Brand-specific dealer location for purchase and delivery,
Komnr Car-specific unique identification number,
Regdat The date a car is registered to be built,
k-code The date a car has been sold,
Losdat The date a car arrives at the distribution hub in Leusden,
Financieel The date a car is financially settled by the end-consumer,
Kent aanvr The date a car is assigned a license plate,
Deel 2 The date a car officially has a personal ascription,
Verladen dlr The date a car is transported to a dealer location,
Alt best.1 Alternative destination, Dealer Holding specific External Parking number,
External Parking Location EP location, coupled with the car,
NRB number The Not-Ride-Before period at the date the car is transported from Leusden to a dealer,
Load Factor Load factor of each individual car.

Data pertaining to car dealer holdings in 2022 was gathered, encompassing:

- Car dealer holding de Waal data 2022,
- Car dealer holding Broekhuis data 2022,
- Car dealer holding Muntstad data 2022,
- Car dealer holding Ames data 2022.

Transport details obtained from these dealer locations include:

Afleverplaats Delivery location,
Ophaal plaats Pickup location,
Transporttijd Transport time,
Transport afstand Transport distance,
Transport date Date of transport,
Transportvoertuig Transport vehicle,

C
Research Gap Tables

Here, the research gap tables are presented.

Reference	Pull allocation	Push allocation	Perspective		Automotive industry	Key notes
			System approach	Individual		
[91],[64], [28], [31], [53], [88]	•		•			*Pull allocation is challenging for manufacturers with standardized procedures, especially when communication lacks. Not robust*
[47], [93, [56], [19], [67]		•		•	•	*The primary challenge of push allocation is the lack of collaborative planning, which can result in misaligned supply and demand, leading to inefficiencies and surplus inventory.*
[4], [47], [56], [32], [70], [45]	•	•		•	•	*The push-pull hybrid strategy offers the potential to stronger collaboration among stakeholders resulting in more efficient distribution processes. However, difficult to implement*
This paper	•	•	•		•	*This research provides a holistic approach where actor requirements of the main stakeholders in the distribution process are combined to propose short term improvements in the car distribution process with the aim to reduce direct CO2 emissions.*

Figure C.1: Research gap 1: Short term holistic approach, source (Author)

Reference	Exact Method	Meta-Heuristic	Split Delivery	Large scale	Automotive industry	Key notes
[42], [50], [77], [7], [51], [81], [51]	•		•		•	*Exact methods guarantee an optimal solution, their major drawback is computational intensity, especially for larger problem instances where the solution space grows exponentially, leading to increased computation time and resource usage.*
[1], [2], [11], [30], [80], [49], [3], [85], [87], [85]		•		•	•	*State-of-the-art meta-heuristics are suitable for large CVRP problems, but not directly applicable for car distribution processes due to the limited capacity of transportation vehicles compared to high demand of car dealers*
This paper		•	•	•	•	*New application of a state-of-the-art meta-heuristic including a priori split delivery function on large scale. This application is verified by an exact method on small scale.*

Figure C.2: Research gap 2: Large scale SD model, source (Author)

D
Dealer selection current state analysis

Dealer classification:

- Size (large or small)
- Market (lease or direct to consumer)

Dealernr (DAP)	Dealernaam	GSS (Direct-to-consumer)	Amount of cars	GSS (Direct-to-lease company)	Amount of cars	Total GSS	Totals in 2022
200079	Vallei Auto Groep B.V.	4,16%	1794	4,67%	1315	4,27%	3045
200082	A-Point B.V.	4,82%	2079	11,61%	3269	6,96%	4960
200091	Autobedrijf J. Maas B.V.	4,06%	1751	2,61%	735	3,36%	2395
200114	Huiskes-Kokkeler Automobielbedrijven B.V.	5,60%	2415	5,27%	1484	5,16%	3682
200143	Van den Brug B.V.	1,94%	837	0,42%	118	2,68%	1908
200164	Van Tilburg-Bastianen B.V.	4,77%	2057	2,73%	769	3,09%	2204
200173	Autobedrijf Van Mossel B.V.	4,82%	2079	12,61%	3551	9,46%	6743
200199	Automobielbedrijf M. de Koning B.V.	2,05%	884	1,20%	338	1,54%	1096
200204	Pouw Dealer B.V	7,21%	3110	5,67%	1597	6,53%	4652
200215	Auto Poppe Bevelanden B.V.	1,97%	850	0,36%	101	1,33%	948
200237	Wittebrug Autogroep B.V.	8,21%	3541	6,24%	1757	6,38%	4548
200241	**Auto Muntstad B.V.**	4,18%	1803	5,18%	1459	4,65%	**3312**
200317	Wealer B.V.	5,62%	2424	2,21%	622	4,50%	3211
200352	Autobedrijf Van den Udenhout B.V.	6,62%	2855	10,79%	3038	7,13%	5080
200355	Auto Hoogenboom B.V.	5,34%	2303	5,21%	1467	5,29%	3769
200404	**Ames Autobedrijf B.V.**	4,53%	1954	10,06%	2833	8,03%	**5728**
200454	Bourguignon Leeuwarden B.V.	1,87%	807	0,85%	239	1,02%	730
200461	Century Autogroep B.V.	4,47%	1928	2,06%	580	4,04%	2879
200481	**De Waal Autogroep B.V.**	3,84%	1656	2,61%	735	3,41%	**2432**
200493	**Broekhuis Alkmaar B.V.**	7,82%	3373	6,75%	1901	7,19%	**5128**
200900	Pon Dealer B.V.	4,79%	2066	3,00%	845	3,88%	2769
Totaal		100,00%	**43131**	100,00%	**28160**	1	**71291**

Figure D.1: Dealer selection for current state analysis, source (Author)