

Optimal Planning of Heavy Duty Electric Vehicles En-route Charging Network

Master Thesis

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TU Delft

Optimal Planning of Heavy Duty Electric Vehicles En-route Charging Network

by

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This paper is dedicated to Jianlong Zhao, my beloved grandfather.
May you rest in peace in heaven.

Preface

I still remember how excited I was when I received my offer from Delft University of Technology two years ago. At that time, I had no idea what awaited me in the future. Now, as I close this chapter of my life in the Netherlands, I am overwhelmed with emotions. Having lived in my hometown for the first 22 years of my life, moving to Delft was the first time I lived away from home independently. I struggled with the cultural differences, the language barrier, the unfamiliar environment, and the absence of my family and friends. However, these challenges made my journey memorable and helped me grow. This journey, while marked by my efforts, was illuminated by many who guided, assisted, and reshaped my path. I am eternally grateful.

First of all, I want to express my gratitude to my parents. Your unwavering support has been instrumental in shaping the person I am today. I consider myself lucky to have parents like you. Our trips to the Netherlands, Norway, and Denmark are some of my fondest memories, and I look forward to creating more unforgettable experiences with you in the future.

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Lastly, I'd like to thank my dear friends: Rui Su, Xinran Meng, Ximing Du and Chen Hu. The times spent chatting, traveling, eating and playing games with you all were truly joyful. Whenever I faced challenges in my studies or life, you supported me behind my back. I wish you all success and happiness in the future!

As I stand at this crossroads, I'm filled with anxiety and uncertainty about what the future holds. However, the past two years at TU Delft have equipped me with the skills and courage to seek and explore my own journey. I cherish the invaluable moments spent at TU Delft and hope to find my way back here someday.

Haoyu Rong
Delft, October 2023

Summary

Introduction

Since the Industrial Revolution, human activities have significantly increased the concentration of greenhouse gases in the atmosphere, leading to an enhanced greenhouse effect, commonly known as global warming. As road freight transport is a significant contributor to global warming due to the common use of Heavy Duty Vehicles (HDVs), it is essential to decrease the carbon emissions produced by HDVs to achieve the goal of EU's carbon neutrality by 2050.

In recent years, traditional fuel-driven HDVs are in the process of transitioning to electric power. As HDVs continue to shift towards electrification, it is crucial to prepare the necessary infrastructure to support these vehicles. Where to locate the charging station is one of the most crucial questions in this regard.

Knowledge Gaps and Research Question

Existing literature employs either Multiple Criteria Decision Analysis(MCDA) or optimisation models solely to solve the charging station location problem. The drawback of MCDA is its inability to account for the range constraints of electric vehicles, while the shortcomings of using optimization models include the high computational complexity and lack of consideration of multiple criteria. Besides, the majority of literature on charging station location problems concentrates on passenger vehicles, with only a few studies focusing on freight vehicles such as trucks or HDVs. Compared to passenger vehicles, freight vehicles have longer travel distances, higher driving ranges, and require a power supply system and charging station capacity with higher specifications. Lastly, existing literature lacks real-world verification of HDV charging station location methodologies that utilize national-scale transport network and traffic flow data.

To tackle the aforementioned knowledge gaps, the main research question is proposed as follows: **How to optimize the location of the En-route HDVs charging network?**

According to the main question, four sub-questions are proposed:

- What are the criteria for selecting a potential location for an HDV charging station based on multiple criteria decision analysis (MCDA)?
- What is the most proper MCDA method for selecting charging station locations?
- How to formulate the charging station location problem into an optimization problem?
- What are the key performance indicators for HDV charging station evaluation?

Methodology

The proposed methodology integrates MCDA with mathematical optimization. It consists of two steps. In the first step, initial candidate sites are found based on current infrastructure. Then, these initial candidate sites are ranked and filtered based on the MCDA principle. An

expert survey has been conducted to obtain the weight of these three criteria. In the second step, the optimal location for the HDV en-route charging network is selected using an FRLM-based optimization model. The generation of the en-route expanded network is the pre-processing step for the optimization model.

To test the feasibility of the proposed methodology, a case study has been conducted within the Netherlands and Germany using real-world transport network data and projected traffic flow data in 2030. The raw data was obtained from Synthetic European road freight transport flow data, as described in Speth et al. (2022). The three criteria for initial candidate site selection are the size of the service area(C_1), the Distance to the substation(C_2) and Traffic volume(C_3). Best-Worst-Method(BWM) is conducted as the MCDA method to calculate the weight of each criterion and it is calculated based on the results from an expert survey. Nine scenarios have been set based on different combinations of charging station penetration rates and the technology development of the HDV driving range. The key performance indicators for HDV charging station evaluation could be classified into global indicators and local indicators. The total number of traffic flows being covered and the flow coverage rate are two global indicators. The coordinates of the charging station, the annual load of the charging station and the load capacity ratio of charging stations belong to local indicators.

Main Findings

The results show that in scenarios where the driving range is 400km and 550km, the charging stations tend to be located at the center of the study area where its road section endures high traffic volume. The optimization model's inclination to position charging stations for optimal coverage of charging demand can be attributed to the central highway sections capturing the majority of the origin-destination (OD) flow between Germany and the Netherlands. This makes these sections a priority, especially when planning a limited number of stations. As the penetration rate of HDV charging station increase, new charging stations are built along the highway to which former stations belong and expand to the edge of the highway network. For scenarios where the driving range of HDV is 550km, the incorporation of more stations along these highways alleviates the congestion at the central stations. However, when the driving range of HDV is 400km, the expansion of surrounding charging stations cannot release the pressure of the current stations. This is because HDVs with limited driving range need more frequent charging, requiring an increase in charging stations to handle demand without overloading the stations. Different phenomena have been made in the scenarios where the range of HDV is 700km. Instead of starting with core locations at the center of the transport network and extending radically, the location of the charging stations tends to shift to different areas as the number of charging stations increases. Besides, the layout of the charging network is more scattered compared with scenarios where the driving range is 400km and 550km. These findings suggest that when drivers have a larger travel range, there's less immediate need for charging. Consequently, the demand for most charging stations isn't as intense as in scenarios with shorter HDV driving ranges.

Contributions

From a scientific perspective, before this study, existing literature predominantly employs either MCDA or optimisation models solely to solve the charging station location problem. The limitation of MCDA is its inability to account for the range constraints of electric vehicles, consequently failing to adequately meet the charging demands. On the other hand, the short-

comings of using optimization models include the high computational complexity and lack of consideration of multiple criteria. To address the challenges previously mentioned, this study introduces a novel approach by combining MCDA with mathematical optimization for the electric vehicle charging station location problem. The proposed methodology's performance was evaluated through the case study, and the results show that it can reduce computational time by up to 85% when compared to the optimization model without MCDA. Additionally, the flow coverage rate can increase up to 50% compared to using MCDA alone.

Furthermore, in the first step of the methodology, the BWM has been used as the MCDA method to calculate weight for the first time. It requires less comparative data and offers higher consistency in comparisons. In the second step, an innovation has been made during the pre-processing step: The construction of the en-route expanded network. It is built based on the original expanded network to tackle its drawback of the conflation of the road network with the charging network. Besides, a capacity constraint is added to the FRLM-based optimisation model for the first time. This helps to fill in the gap where HDVs have higher requirements in charging station capacity.

From a practical perspective, this research provides critical insights into HDV en-route charging station design, benefiting governments, infrastructure companies, and HDV drivers. For governments, the presented methodology equips governments with an actionable strategy for HDV electrification infrastructure planning. Infrastructure and logistics companies gain a robust framework for optimal charging station locations, supported by a comprehensive and cooperative approach, and insights from varying charging station scenarios. HDV drivers, particularly those in long-distance freight, benefit from improved flow coverage rates, mitigating charging anxieties and enhancing road freight efficiency.

Limitation and Future Research

The proposed methodology, particularly the en-route expanded network based FRLM optimisation model, is predicated on several assumptions that may not fully align with real-world complexities. For instance, the model assumes uniform HDV driving ranges and charging decisions based on common OD pairs, overlooks possible queuing during peak hours and potential route changes for HDVs. Additionally, while aiming to maximize flow coverage, it omits considerations for network coverage, potentially leading to equity issues. Real-world variables like varied charging station construction costs and constraints on electricity capacity remain unaccounted for.

Future research should focus on refining the optimization model to enhance its real-world applicability. Incorporating multi-objective optimization can balance efficiency and equity by considering both flow and network coverage rates. Infusing additional constraints, such as construction costs and electricity capacity, and allowing for more dynamic en-route network generation, can bring the model closer to real-world scenarios. Additionally, extending case studies to diverse settings and refining the MCDA with a broader stakeholder panel and wider evaluation criteria will offer a more comprehensive understanding of the model's versatility and efficacy.

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1

Introduction

Since the Industrial Revolution, human activities have significantly increased the concentration of greenhouse gases in the atmosphere, leading to an enhanced greenhouse effect, commonly known as global warming. According to the data from the International Energy Agency (IEA), road freight transport makes up 9% of global CO_2 emissions as shown in Figure 1.1, where heavy-duty vehicles (HDVs) take up about 41% of emissions from road freight transport. Hence, road freight transport is a significant contributor to global warming due to the common use of HDVs. To achieve the goal of EU's carbon neutrality by 2050, it is essential to decrease the carbon emissions produced by HDVs. As a part of this effort, transitioning towards alternative power sources for vehicles could prove to be an effective strategy to complement the modal shift in reducing emissions from HDVs. The electrification of HDVs could be a promising attempt.

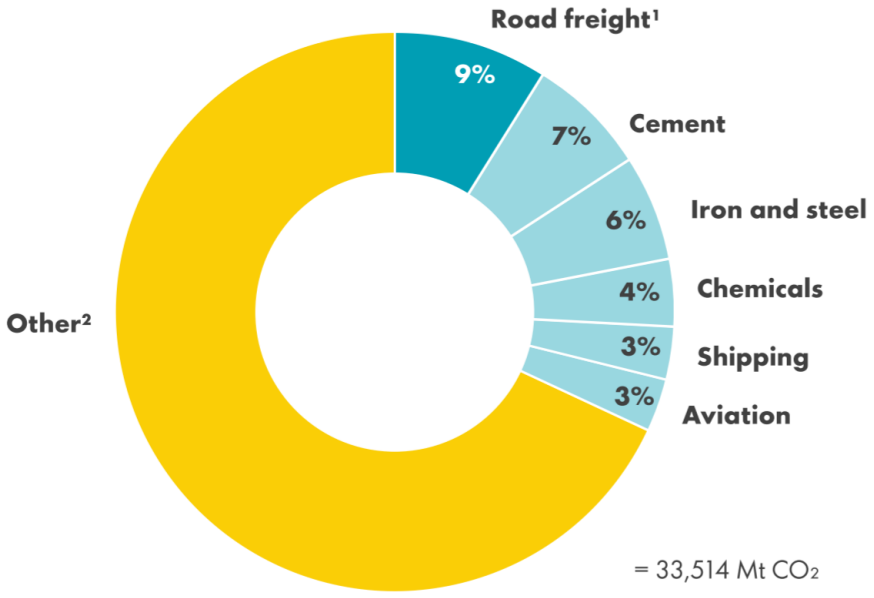


Figure 1.1: Global Freight Transport Emission, Source: Majoe (2017)

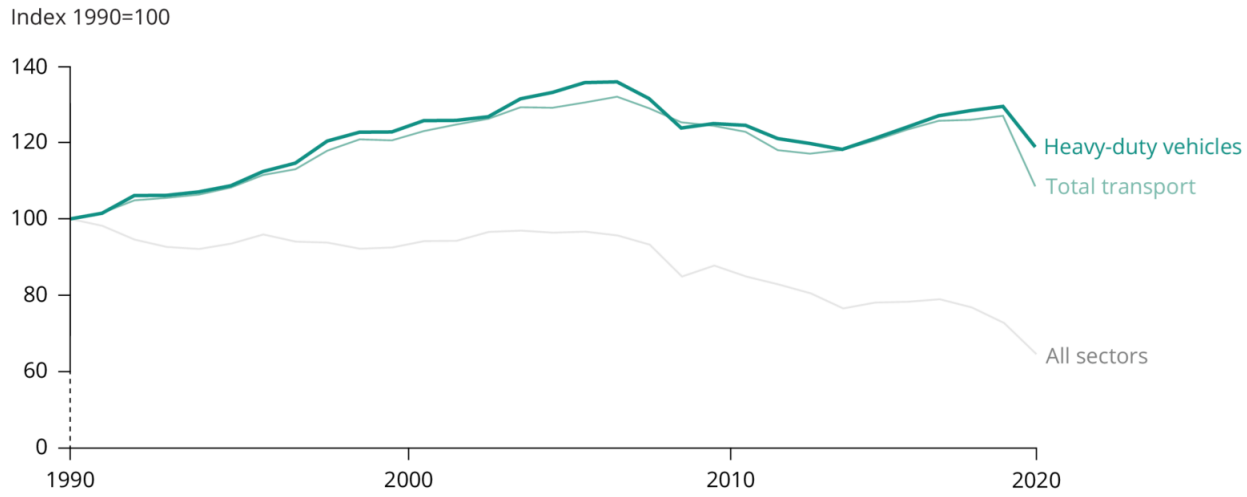


Figure 1.2: Trends in CO emissions from heavy-duty vehicles in the EU, 1990-2020, Source: European Environment Agency (2022)

1.1. Electrification of HDVs

A vehicle is considered to be in the heavy-duty category when its gross vehicle weight rating (GVWR) exceeds 26,000 lbs according to the definition from Federal Highway Administration (FHWA) (2019). GVWR refers to the maximum loaded weight of the vehicle, which is the weight of the vehicle in addition to its payload. HDVs could be further classified into Class 7 and Class 8 as shown in Figure 1.3 below.

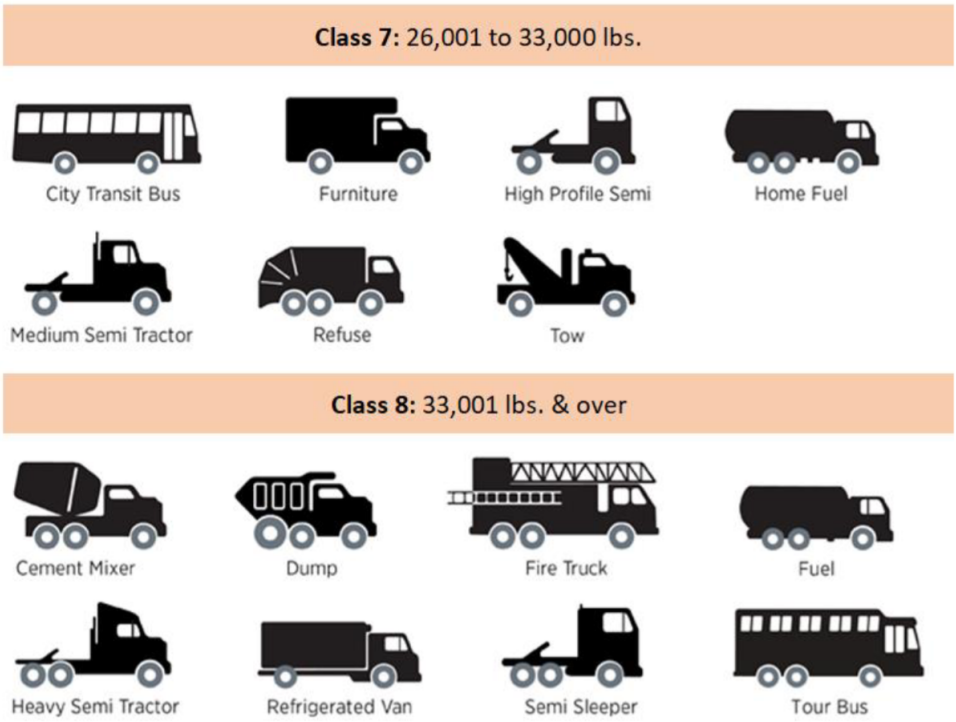


Figure 1.3: Classification of HDVs, Source: Cunanan et al. (2021)

Electric vehicles (EVs) have been gaining traction in recent years due to their potential to

reduce carbon emissions, and heavy-duty electric vehicles (HDEVs) are no exception. Policy guidance is the primary driving force behind the push for the electrification of HDVs. At the Glasgow Climate Summit in 2021, several transport sector companies and fifteen countries from four continents pledged to pursue clean heavy-duty transportation. The participants committed to a goal of making all new heavy goods vehicles and buses in their countries zero-emission by 2040, with an interim goal of 30% zero-emission new medium- and heavy-duty vehicle (ZE-MHDV) sales by 2030, through an agreement they signed. In order to accelerate this process, countries around the globe have made a series of policies and regulations as shown in Figure 1.4. For example, Dutch governments would provide subsidies for businesses wanting to purchase emission-free HDVs, allow a deduction for companies investing in charging points and implement zero-emission zones in the largest cities by 2025 according to Ministerie van Infrastructuur en Waterstaat (2021). Therefore, it is expected that the electrification of HDVs will become widespread in the next 10 to 20 years, thanks to the strong support from numerous national policies. It is becoming increasingly clear that the electrification of HDVs is not a matter of if, but when.

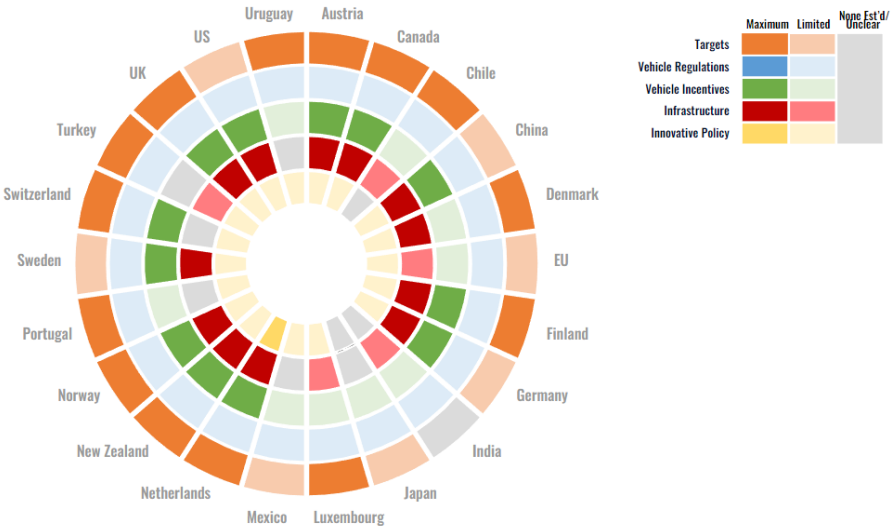


Figure 1.4: Global HDV Policy Tracker Dashboard, Source: Driver To Zero (2023)

1.2. Charging stations for HDEVs

As HDVs continue to shift towards electrification, it is crucial to prepare the necessary infrastructure to support these vehicles. According to the forecast from the Zero Emission Vehicles Transition Council (ZEVs), counties around the world have a huge demand for various HDEVs charging facilities in the near future as shown in Figure 1.5.

The charging stations could be classified into three types according to SAE J1772 standard as shown in Table 1.1. Note that levels 1 and 2 are commonly known as slow chargers whilst level 3 is known as fast chargers.

The charging stations can be also divided into two types based on their usage: depot charg-

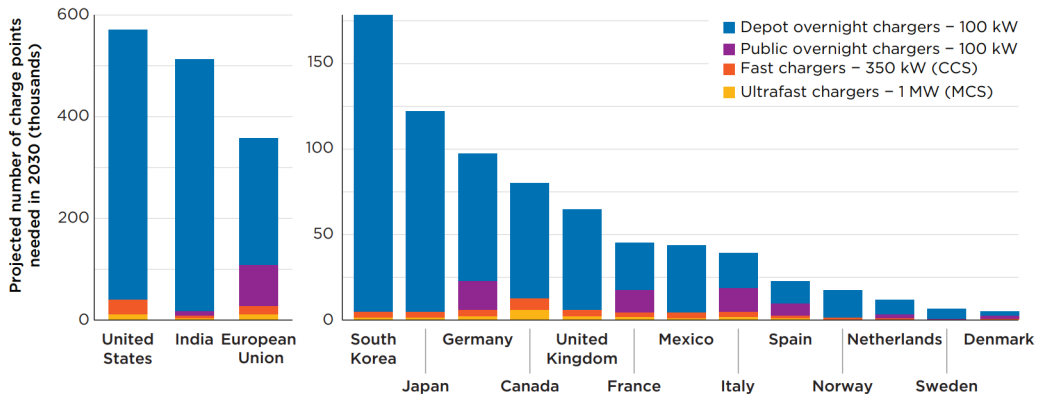


Figure 1.5: Number of charging points needed for HDEVs in 2030, Source: Rajon Bernard, Kok, et al. (2022)

Charging Levels	Level 1	Level 2	Level 3
Phase	AC (1 phase)	AC (1/3 Phase)	DC
Voltage (V)	120	230-400	400 - Higher
Current (A)	10-16	16,32 or 36	63-125, up to 400
Power(kW)	1.4-1.9	3.7-22	44 - Higher

Table 1.1: Charging levels of EV according to SAE J1772 standard, Source: Al-Hanahi et al. (2021)

ing stations, which are used for overnight charging of HDVs, and en-route charging stations, which are necessary for HDVs on long-haul trips. Compared with depot charging stations, on-the-go charging stations usually have higher power output (level 3) so that the charging time can be saved. Besides, on-the-go charging stations usually belongs to public charging infrastructure, in which commercial vehicles from different brand could be served at the same time, whereas depot charging stations are usually private infrastructure, which only serve certain type of HDVs. This research focuses on en-route charging stations for the reason that they are critical to the successful deployment of HDVs. A detailed comparison between different types of charging facilities for HDVs is shown in Figure 1.6.

Public or private	Location and type	Power output	Estimated upfront cost of charger in 2022	Use type
Private	Depot	50 kW DC	€44,700	Fleet returning to same location every night Small-medium size batteries
		100–150 kW DC	€91,700	Fleet returning to same location every night Small-medium size batteries
	Destination opportunity	350 kW DC	€231,700	Fleet idling for at least 45 min-1hr when loading and/or unloading goods
Public	Overnight	100–150 kW DC	€91,700	Fleet not returning to the same location every night
	En-route and destination fast	350 kW DC	€231,700	High mileage/heavily loaded fleets not returning to the same location every night 3-4 hours rest during the day.
	En-route and destination ultra-fast	1 MW DC	Unknown, as technology is not yet deployed. Estimates for 1 MW chargers are around € 615,000.	High mileage/heavily loaded fleets not returning to the same location every night Large batteries, needing a quick top-up during the day, 45 minutes rest.
		3 MW DC		

Figure 1.6: Summary of battery-electric HDVs wired stationary charging options, Source: Rajon Bernard, Tankou, et al. (2022)

HDV charging facilities are different from those designed for regular private vehicles, and they require careful planning and consideration. One of the most notable features of HDV charging facilities is its impact on the power grids. El Helou et al. (2022) simulates the impact of HDEVs on the electricity infrastructure by considering a synthetic Texas-based transmission and distribution grid. The analysis reveals that the presence of HDEVs, even at low levels, can cause voltage issues throughout the grid.

1.3. Planning of charging network and knowledge gaps

The availability of charging facilities is one of the most important factors for promoting the electrification of HDVs. To better serve the future charging demand of HDEVs, it is of utmost importance to plan the charging network in advance. The strategic planning of the charging network should at least include the following decisions: The location of charging stations, types of charging levels and the capacity of charging stations.

In scientific literature, strategical planning of charging networks and related topics has been a highly debated issue since 2010 and has gained increasing attention ever since. As shown in Figure 1.7, the number of documents which searched through Scopus using keywords 'Planning' AND 'Charging' AND 'Station' AND 'Vehicle' has grown rapidly over the past ten years.

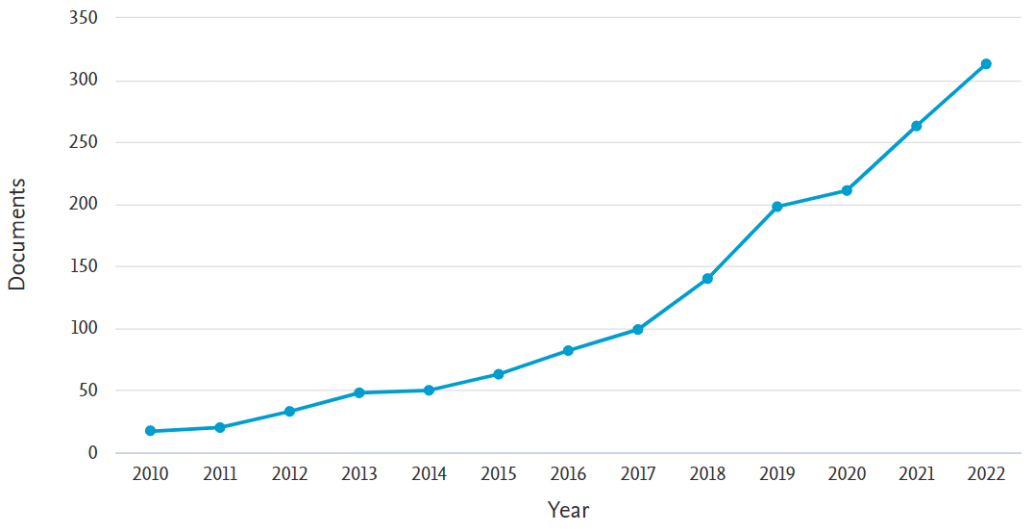


Figure 1.7: Search results related to strategical planning of charging network from 2010 to 2022 on Scopus

In order to find the knowledge gaps in the field of strategic planning of charging networks in an efficient way, eight state-of-the-art literature review articles that focus on different aspects have been reviewed. Table 1.2 represents an overview of these articles.

Al-Hanahi et al. (2021) observed that only a few studies have investigated the optimal location of charging stations for HDVs, whereas the majority of the research mainly focuses on charging station planning for passenger vehicles. Danese et al. (2022) concluded that there is a lack of studies that investigate how to plan electrification HDVs. Hence, it is meaningful to

Table 1.2: Overview of literature review

Author(Year)	Emphasis	Citation
Al-Hanahi et al. (2021)	Charging infrastructure planning for commercial electric vehicles	24
Ahmad et al. (2022)	Impact on distribution network	60
Danese et al. (2022)	Planning of high-power charging stations	4
Unterluggauer et al. (2022)	Integration of transportation and power distribution networks	11
Pagany et al. (2019)	Spatial localization methodologies	71
Metais et al. (2022)	Charging station planing modeling options	46
Deb et al. (2018)	Recent trends in charging infrastructure	83
Meyer & Wang (2018)	Planning on Ultra-fast charging stations	64

fill in the research gap in the strategic planning of HDVs' charging stations.

Unterluggauer et al. (2022) noted that the majority of the literature regarding charging facilities for HDV planning considers demand in very simplistic ways. Deb et al. (2018) mentioned that the uncertainty in road traffic is neglected in most of the literature. Pagany et al. (2019) stated that only a few studies have linked the demand for charging stations with the optimal locations for them. Hence, it is essential to propose a methodology that determines the position of charging stations that satisfies the HDVs' varying charging demand in space and time.

Pagany et al. (2019) found that a large number of studies are restricted in their methodology and lack practical justification due to insufficient data. Unterluggauer et al. (2022) also noticed that the majority of literature heavily focuses on planning approaches that are motivated by theoretical concerns rather than being relevant in practice due to a lack of real data. Hence, it is expected that future research should put more effort into a data-driven approach and apply it to realistic case studies.

1.4. Research objectives and questions

The motivation for this research stems from the critical need to transition towards sustainable forms of transport, especially in the HDV sector, to mitigate the adverse environmental impacts. Given that electrification is a promising solution, promoting HDV electrification by developing a charging infrastructure becomes an urgent and relevant problem to address. Therefore, this study is timely and vital for accelerating the shift towards electrified HDVs.

The research objective of this research is to find out the specific nodes and/or points of interest that can be considered as potential sites to provide charging services to HDV vehicles. This could help to enhance the promotion of HDV electrification.

Based on the gaps found in the literature and the research purpose, the main research question is proposed as follows: **How to optimize the location of the En-route HDVs charging network?**

According to the main question, four sub-questions are proposed:

- What are the criteria for selecting a potential location for an HDV charging station based on multiple criteria decision analysis (MCDA)?

- What is the most proper MCDA method for selecting charging station locations?
- How to formulate the charging station location problem into an optimization problem?
- What are the key performance indicators for HDV charging station evaluation?

The following is an outline of the thesis report. In Chapter 2, you will find the literature review on the use of MCDA and optimization methods in relative work. Chapter 3 describes the proposed methodology, which includes two stages: determination of en-route candidate sites and en-route expanded network based FRLM optimization. Chapter 4 provides an introduction to the basic settings of the case study, including the raw dataset, data processing techniques, and parameter settings. Chapter 5 presents the result analysis of the case study from five perspectives, namely MCDA results, the En-route expanded network results, the FRLM based optimization results, the proposed methodology's performance analysis, and the comparison with other benchmark methods. Finally, Chapter 6 summarizes the report by answering the research questions, highlighting the main findings, discussing the contributions to this research, pointing out the limitations, and suggesting future developments.

2

Literature Review

This chapter aims to provide a comprehensive overview and analysis of the related works in the field of HDV charging network planning through a literature review. The focus will be on two primary categories: Multiple Criteria Decision Analysis (MCDA) based research and Optimization based research. By examining the wealth of available literature, valuable insights into the diverse approaches, methodologies, and findings used to tackle the challenges associated with determining optimal charging station locations can be obtained.

2.1. MCDA

MCDA is a systematic and structured approach used to make decisions when multiple criteria or objectives need to be considered Hwang et al. (1981). In many real-world situations, decision-makers face complex problems where there are competing alternatives and various factors to take into account.

A problem is said to be an MCDA problem when a number of alternatives (options) need to be evaluated with respect to a number of criteria (attributes) in order to select the best alternatives, rank all the alternatives and sort the alternatives into a number of classes. MCDA method is a method to find a solution for (one or more parts of) an MCDA problem, where the main phases are:

1. Formulating the problem (identifying the goal(s); alternatives; and criteria)
2. Evaluating the alternatives with respect to the criteria
3. Finding the importance of the criteria
4. Synthesizing the data collected in the previous phases to find a solution
5. Checking the reliability and validity of the outcomes

MCDA methods could be classified into three categories: outranking methods, utility and value-based methods and multi-objective methods. The main differences among these three categories lie in the way alternatives are evaluated and compared. Outranking methods focus on establishing a preference order by comparing alternatives pairwise, utility and value-based methods assign weights or scores to criteria to calculate an overall utility or value, and multi-objective methods seek to find a trade-off between multiple conflicting objectives to identify

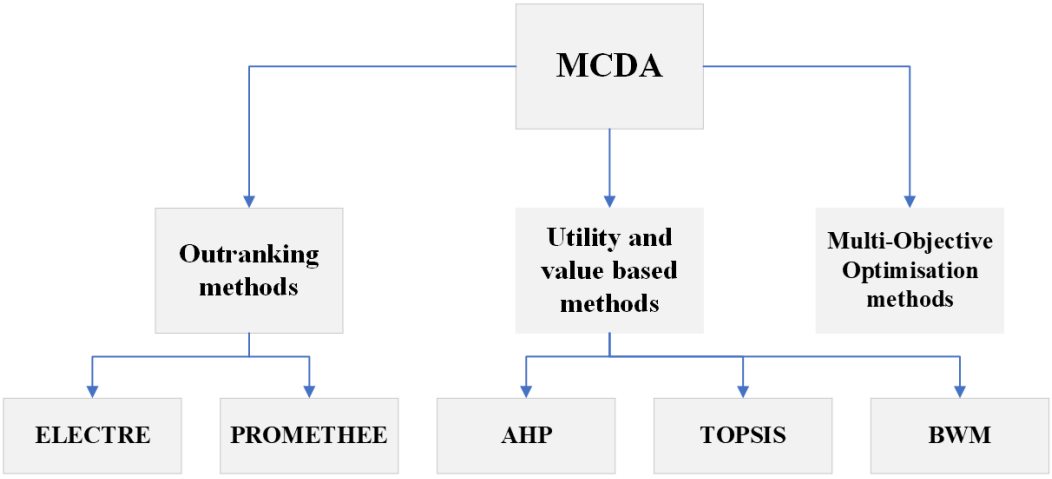


Figure 2.1: Classification of MCDA methods

a set of optimal solutions. The structure and common MCDA methods are shown in Figure 2.1.

The detailed introduction of each method in different categories is presented as follows:

ELECTRE (Elimination Et Choix Traduisant la Réalité)

ELECTRE, which translates as "Elimination and Choice Expressing Reality," is a family of methods that evaluate alternatives based on multiple criteria. The core principle of ELECTRE is to establish a dominance relation between alternatives according to Roy (1991). It involves building a matrix of evaluations, determining weights for criteria and establishing concordance and discordance indices for each pair of alternatives. Based on these indices, alternatives are ranked, and those that do not surpass specific thresholds are eliminated.

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations)

Developed in the 1980s, PROMETHEE provides a partial or complete ranking of alternatives. According to Behzadian et al. (2010), its primary steps include defining a pairwise comparison of alternatives for each criterion, assigning weights to each criterion, utilizing preference functions to calculate deviations for every pair of alternatives on each criterion and generating a flow (either positive, negative, or net) for each alternative. The alternatives are ranked based on these flows, providing a clear preference order.

AHP (Analytic Hierarchy Process)

Developed by Thomas L. Saaty in the 1970s, AHP breaks down a complex problem into a hierarchy of subproblems. According to de FSM Russo & Camanho (2015), the key features include decomposing the decision problem into a hierarchy of criteria, sub-criteria, and alternatives, conducting pairwise comparisons to generate a matrix, calculating eigenvectors and eigenvalues from this matrix to determine weights and aggregating the weights to generate a score for each alternative. AHP's unique feature is its ability to capture quantitative and qualitative aspects of a decision problem, but it demands consistent judgment in pairwise comparisons.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

Developed in the 1980s, TOPSIS ranks alternatives based on their distance from an ideal solution. According to Behzadian et al. (2012), the procedure of TOPSIS involves constructing a normalized decision matrix, identifying positive-ideal and negative-ideal solutions, calculating the distance of each alternative to these ideal solutions and calculating a relative closeness coefficient for each alternative. Alternatives are then ranked based on their relative closeness to the ideal solution.

BWM(Best-Worst Method)

Introduced in the 2010s, BWM simplifies the pairwise comparison process found in methods like AHP. Its main steps are introduced in Chapter 3.

In the past decade, numerous studies have employed various branches of MCDA theory to address the issue of charging station siting. Sisman et al. (2021), Erbaş et al. (2018) and Ju et al. (2019) utilize fuzzy AHP method to find the potential sites for electric vehicle charging stations(EVCS) in different contexts. Guo & Zhao (2015) and Erbaş et al. (2018) apply fuzzy TOPSIS method to select the optimal EVCS site. Zhao & Li (2016) used fuzzy Delphi method (FDM) to provide a comprehensive and effective method for optimal siting of EVCS considering subjective factors, while Liu et al. (2018) novel integrated MCDA approach DEMATEL for determining the most suitable EVCS site in terms of multiple interrelated criteria.

Although the MCDA methods employed in the aforementioned papers exhibit variations, there is a general similarity in the underlying research context and the resulting evaluation criteria. Specifically, most of the MCDA-related research on EVCS focuses on the urban environment. Consequently, environmental, economic, and social factors are commonly selected as the primary evaluation criteria. For environmental factors, commonly used sub-criteria include distance to water resources, distance to vegetation, and slope of land. In terms of economic factors, construction cost, land cost, and distance to power supply are frequently considered. Regarding social factors, distance to the main road, distance to junctions, and distance to other EVCSs are commonly used sub-criteria. However, it becomes evident that the current set of evaluation criteria is not suitable for selecting en-route charging stations along road networks.

To the best of my knowledge, in contrast to previous studies that have used MCDA methods to properly place EVCSs in urban areas and broader regions, only two researches focus specifically on the optimal placement of en-route EVCS. Skaloumpakas et al. (2022) propose an intuitive multi-criteria approach that optimally places EVSC on highways that (partially) lack such points. The evaluation criteria proposed in this research include average daily traffic, population-adjusted distance from major cities, number of EVCSs in close proximity, distance from the closest EVCS and distance from interchanges. Another study by Csiszár et al. (2020) developed a multi-criteria decision-making method that has been applied to evaluate the rest areas along motorways and main roads and to propose deployment locations for fast-charging stations. The evaluation criteria include traffic volume, settlements' population, service level and effect of the nearest fast-charging station. It is obvious to learn that these criteria are specifically tailored for en-route charging stations. It is worth noting that both of these studies primarily focus on en-route charging stations for private vehicles. However, there is currently a lack of research addressing the placement of charging stations for HDVs, which remains an unexplored area in academia.

2.2. Charging station location model

In scientific literature, in addition to utilizing MCDA methods to determine the optimal location for charging stations, another mainstream approach is to use mathematical models for optimization and solution-seeking. According to Kchaou-Boujelben (2021), different research approaches can be classified based on their representation of charging demand, namely the node-based model, flow-based model, and trajectory-based model.

In the node-based model, charging demand is assumed to concentrate on specific nodes within the network. According to Ko et al. (2017), node-based model could be classified into p-median model, p-center model, maximal covering model and set covering model. Among these four models, p-median model and its variants are the most widely used model in the field of optimal facility analysis according to Upchurch & Kuby (2010). In academia, node-based model is widely used in optimal location planning of EVCS due to its simplicity and directness. However, the main drawback of the node-based model is obvious, which is it assumes charging demand originates solely from specific nodes within the network. This assumption may oversimplify the reality of charging demand patterns, as it's not just parking areas that should have chargers, whereas chargers should also be built along the path. Consequently, the node-based model may not accurately capture the spatial distribution of charging demand and could potentially result in sub-optimal solutions for locating charging stations.

To address the limitations of the node-based model, the flow-based model has been proposed and widely applied in recent years. The flow-based model takes into account origin-destination (OD) trips and allows charging demand to be accommodated during journeys. For example, Hodgson (1990) modified the node-based maximal covering location model to create a flow-based flow capturing location model (FCLM). In the FCLM, a charging station is considered to capture the flow when it is located along the path of an OD trip, thereby satisfying the charging demand. However, the FCLM neglects the realistic constraint of the limited driving range of vehicles. To overcome this limitation, Kuby & Lim (2005) introduced the concept of combining charging stations and proposed the flow refueling location model (FRLM). By generating combinations of charging stations, the driving range constraint is considered. This means that the location of a charging station should be within the driving range of vehicles. Although the FRLM incorporates the driving range constraint into the model, the calculation of all possible combinations of stations becomes complex. In a network with n potential sites, the number of combinations is given by $2^n - 1$.

FRLM has become a classical model since its invention and lots of following models are developed based on FRLM. MirHassani & Ebrazi (2013) and Capar et al. (2013) developed expanded network based FRLM and arc covering based FRLM respectively in order to reduce the complexity of the combination of station generation. Besides, different more complex variants of FRLM came out in recent years to add more assumptions to the problem. For example, Hosseini et al. (2017) proposed a deviation-flow refueling model which considers the detour behaviour instead of only considering the shortest path. Upchurch et al. (2009) introduced a capacited station refueling model which not only optimizes the location of charging stations, but also the capacity of each station. The development of FRLM based model is depicted in Figure 2.2.

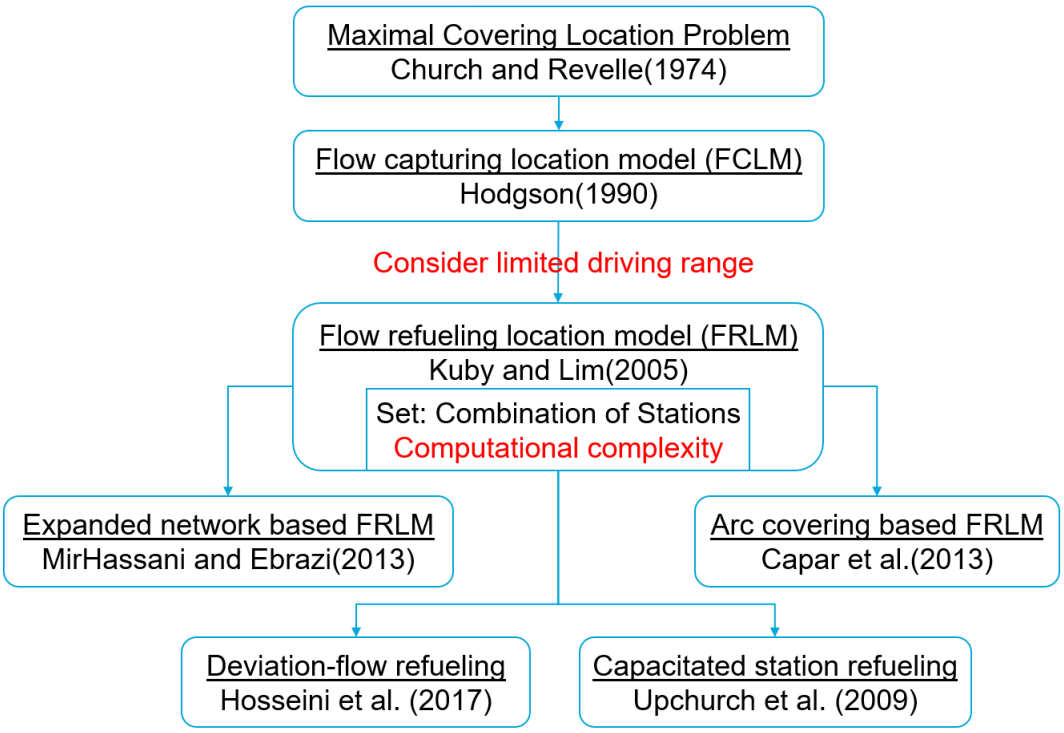


Figure 2.2: Development of FRLM based optimisation model

Although the FRLM based model has been mathematically proven to be valid, this series of models has several unrealistic aspects in the process of determining candidate sites. Firstly, some models blur the distinction between the transportation network and the charging station network. More specifically, these models assume that all nodes in the transportation network can serve as charging station locations, which hinders the effective optimization of en-route charging station locations. Secondly, models considering en-route charging stations, often use methods based on equidistant paths to determine the charging station locations, without considering whether the location is feasible or suitable for the construction or installation of charging stations in real-world scenarios. Lastly, the FRLM lacks the opportunity to validate its application in real road networks using actual traffic flow data.

2.3. Summary

In conclusion, MCDA based method and optimisation method are both effective and widely used methods in solving charging station location problems. However, the fundamental limitation of relying solely on MCDA is that it cannot consider the range constraints of electric vehicles, leading to inadequate fulfillment of charging demands. On the other hand, employing optimization models has a principal drawback where the emphasis is often placed excessively on generating candidate sites based on mathematical criteria to achieve an optimal solution, without sufficiently evaluating the practical feasibility of constructing charging stations at those locations.

Based on the current limitation of the literature, combining the advantages of MCDA and optimization methods can be a promising attempt. By integrating the strengths of both approaches, such a method has the potential to provide a comprehensive and effective solution

to the problem at hand. This hybrid approach can leverage the analytical decision-making capabilities of MCDA while incorporating optimization algorithms to optimize the selection of candidate sites. The integration of MCDA and optimization techniques can enhance the decision-making process by considering both practical feasibility and mathematical optimization, leading to more robust and realistic outcomes.

3
Methodology

In this chapter, a detailed description of the research methodology is presented. The structure of this chapter is as follows. Section 3.1 conceptually states the framework of the methodology. Then, the Best Worst Method (BWM) is introduced in Section 3.2, where the pros and cons analysis with other candidate Multiple Criteria Decision Analysis(MCDA) methods is presented as well. After that, the concept of the expanded network and the innovative en-route expanded network is explained in detail in Section 3.3 with basic assumptions and the generation algorithm. Finally, the mathematical optimisation model formulation and a toy network model test are discussed in Section 3.4.

3.1. Conceptual framework

As depicted in Figure 3.1, the proposed research framework comprises two interconnected stages: En-route candidate site determination and Expanded Network-Based Optimization. In stage one, Multiple Criteria Decision Analysis (MCDA) serves as the core method for evaluating and selecting candidate sites. In stage two, the Expanded Network-Based Flow Refueling Location Model (FRLM) takes center stage to optimize the network.

In the first stage, the search and selection of initial candidate sites for HDV charging networks are based on existing infrastructures. These target infrastructures are commonly found along the highway network, such as service areas (truck stops), parking lots, current gas or charging stations for private vehicles, and more. There are two primary reasons for choosing these infrastructures as potential locations for HDV charging stations. Firstly, these infrastructures typically offer ample space and necessary facilities, providing a practical foundation for either adding new charging stations or converting existing ones into HDV-compatible stations. For instance, truck parking lots have sufficient capacity to accommodate a considerable number of HDVs, service areas often feature shops, hotels, and restaurants for drivers to utilize during the charging process, and existing private vehicle charging stations have inherent advantages in terms of their grid layout. Consequently, selecting these infrastructures as potential addresses for HDV charging stations maximizes the utilization of existing facilities, minimizes construction costs, and facilitates the conversion of stations for HDVs. Secondly, these infrastructures are strategically built along the highway network, ensuring easy accessibility for HDVs. Furthermore, establishing charging stations at these sites can help prevent

HDVs from taking detours or entering lower-level road networks, thereby preventing potential violations of traffic regulations. By choosing these infrastructures as candidate sites for charging stations, we can align with HDV driving behavior, reduce transportation costs, and promote overall efficiency. Overall, the selection of these infrastructures as candidate sites for HDV charging stations takes into account various factors, including practicality, accessibility, compliance with regulations, and cost-effectiveness.

After the initial candidate sites are chosen, an MCDA method is used to further rank and filter the initial candidate sites based on their generalized score. The purpose of these steps is threefold. Firstly, by establishing diverse evaluation criteria, various stakeholders involved in the construction of charging stations can choose site locations that maximize their individual interests, thus enhancing the adaptability of this method. Secondly, the utilization of MCDA enables effective consideration of site factors that might have been overlooked during the optimization stage. This serves as a valuable complement to the demand-capturing-centric mathematical modeling approach. Lastly, the MCDA step plays a crucial role in data preprocessing during the optimization process in stage two. By setting an appropriate filtering threshold, it becomes possible to control the volume of data entering the mathematical model, thereby reducing computational complexity while maintaining accuracy. The steps of conducting MCDA include the determination of evaluation criteria, calculation of the weight of each criterion via expert survey, calculation of values of each criterion for each candidate site, and ranking and filtering based on generalized score. The detailed description of the steps is presented in Section 3.2.

The final candidate sites are generated in stage one and serve as inputs for stage two. By combining the shortest path for each OD trip and the driving range of HDVs, an en-route expanded network can be generated. This network consists of nodes and arcs. The node set includes origin and destination nodes, as well as intermediate candidate charging station nodes. While the set of arcs includes the possible charging decision of each OD trip. Note that trips with the same OD have the same charging decision. The purpose of the en-route expanded network is to simplify the computational complexity associated with possible charging network combinations, taking into account the range of HDVs. This network serves as the primary input for the Flow Refueling Location Model (FRLM). A detailed explanation of the en-route expanded network is provided in Section3.3.

The last step of the methodology is the mathematical optimisation based on FRLM. The inputs to the FRLM consist of the en-route expanded network for each OD pair, the demand for each OD trip, and the desired number of charging stations to be constructed. The objective of the optimization process is to maximize the coverage rate of charging demand while simultaneously adhering to the driving range restrictions of HDVs and the limitations of the maximum number of charging stations to be built. The optimization result yields the optimal locations for the en-route charging network specifically designed for HDVs. The detailed discussion of the model formulation is presented in Section 3.4.

To the best of my knowledge, this study marks the pioneering integration of MCDA with mathematical optimization to address the electric vehicle charging station location problem. As explained in Chapter 2, existing literature predominantly employs either MCDA or opti-

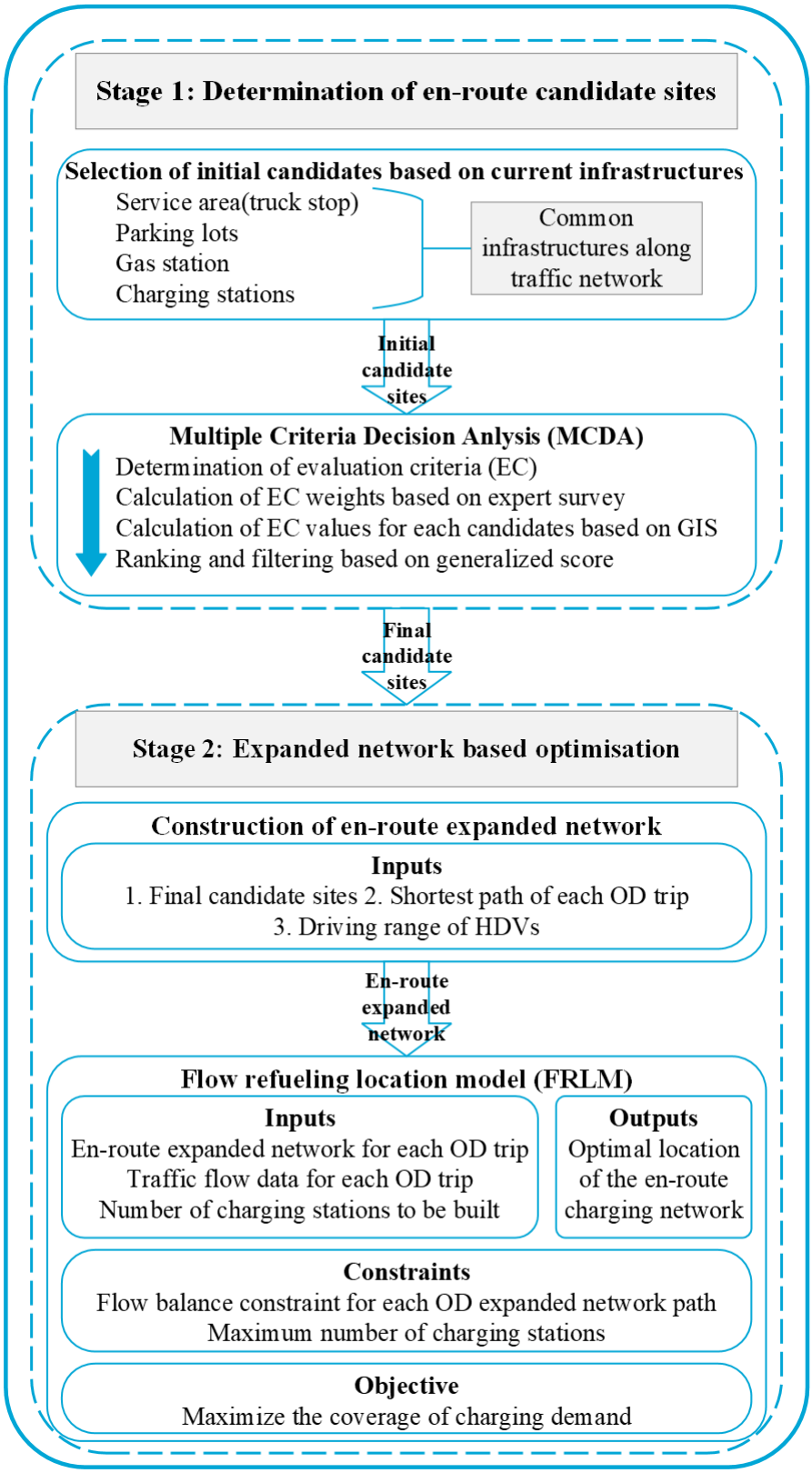


Figure 3.1: Conceptual framework of methodology

mization models in isolation to tackle this issue. One of the fundamental limitations of relying solely on MCDA is its inability to account for the range constraints of electric vehicles, consequently failing to adequately meet the charging demands. In contrast, the principal shortcoming of using optimization models is that the computational complexity increases dramatically as the size of the inputs increases to a city or even national level. Therefore, the integration of MCDA with mathematical optimization represents a robust approach that bridges this gap. This synergy ensures that the selection of charging station locations is not only underpinned by rigorous mathematical validation but is also pragmatically viable with an acceptable computational effort.

3.2. Best Worst Method

MCDA is a branch of methods that involves evaluating various alternatives based on multiple criteria to identify the most favorable option(s). Among the innovative methods in the field of MCDA, the Best Worst Method (BWM) was introduced by Rezaei (2015). In this chapter, a comparative analysis of the pros and cons of BWM with other MCDA methods is discussed. The procedure and mathematical foundation of BWM are then presented.

3.2.1. Pros and cons analysis

BWM is a vector-oriented approach that necessitates fewer comparisons than matrix-oriented MCDA techniques such as the Analytic Hierarchy Process (AHP). According to the literature review, commonly used MCDA methods in the field of charging station location determination include TOPSIS, AHP and BWM. A comprehensive comparison of these three methods is presented in Table 3.1 below.

In general, BWM stands out from other MCDA techniques due to two key characteristics. First, it requires less comparative data, making it a more streamlined method. Second, it results in more consistent comparisons, implying that it yields more trustworthy outcomes. However, it's not without its drawbacks. For instance, while BWM's reliance on integers simplifies its use, it may lack the flexibility of methods that permit fractional comparisons.

Table 3.1: Comparison of different MCDA methods

	Pros	**Cons**
TOPSIS	a. Simple and straightforward b. Provides a ranking of alternatives based on their similarity to the ideal solution. c. Allows for sensitivity analysis by altering the weightage of criteria.	a. Relies on subjective judgments to determine the criteria weights. b. Assumes that the criteria are independent and equally important. c. May not be suitable for complex decision problems with a large number of criteria and alternatives. d. Does not provide insights into the trade-offs between criteria.
BWM	a. Simple and straightforward b. Less comparative data needed c. Provides a comprehensive ranking of alternatives based on their performance. d. Provides consistency checks to ensure the reliability of decision-making.	a. Requires careful determination of the best and worst alternatives for each criterion, which may involve subjective judgments. b. Does not explicitly consider the trade-offs between criteria. c. May not be suitable for decision problems with a large number of criteria and alternatives.
AHP	a. Structured approach that breaks down complex decisions into a hierarchy of criteria and sub-criteria. b. Allows for the consideration of both qualitative and quantitative criteria. c. Provides a systematic method for determining the relative importance of criteria through pairwise comparisons.	a. Requires a considerable amount of time and effort to gather and analyze pairwise comparison data. b. Susceptible to biases and inconsistencies in expert judgments. c. Limited scalability for decision problems with a large number of criteria and alternatives. d. May not adequately capture the interactions and dependencies between criteria.

3.2.2. Algorithm

The mathematical basis of BWM lies in pairwise comparisons. The decision-maker initially identifies the best (most desirable or most important) and the worst (least desirable or least important) criteria. Subsequent pairwise comparisons are made between each of these two criteria (best and worst) and the remaining criteria. A maximin problem is then established and resolved to ascertain the weights of the different criteria. The same process is used to obtain the weights of the alternatives concerning the different criteria. The final scores of the alternatives are calculated by combining the weights from different sets of criteria and alternatives, which then helps in selecting the best alternative. The application of BWM involves five steps:

Step1: Establish a set of decision criteria C.

$$C = \{c_1, c_2, ..., c_n\} \tag{3.1}$$

Step2: Identify the best and the worst criteria. This step should include judgments by experts or decision-makers.

Step3: Ascertain the preference of the best criterion over all other criteria, assigning a number between 1 and 9. The resulting Best-to-Others vector is presented as follows. Note that B represents the best criteria selected in Step 2.

$$A_B = (a_{B1}, a_{B2}, ..., a_{Bn}) \tag{3.2}$$

Step4: Determine the preference of all the criteria over the worst criterion, assigning a number between 1 and 9. The resulting Others-to-Worst vector is presented as follows. Note that W represents the worst criteria selected in Step 2.

$$A_W = (a_{W1}, a_{W2}, ..., a_{Wn})^T \tag{3.3}$$

Step5: Calculate the optimal weights $(w_1^*, w_2^*, ..., w_n^*)$. The optimised problem is formulated as follows.

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \tag{3.4}$$

$$s.t. \sum_j w_j = 1 \tag{3.5}$$

$$w_j \geq 0, \forall j \tag{3.6}$$

Step6: The input-based consistency ratio is used to indicate the consistency level of a decision maker according to Liang et al. (2020).

$$CR = max_j CR_j \tag{3.7}$$

where

$$CR_i = \begin{cases} \frac{|a_{Bj} * a_{jW} - a_{BW}|}{a_{BW} * a_{BW} - a_{BW}}, a_{BW} > 1 \\ 0, a_{BW} = 1 \end{cases} \tag{3.8}$$

CR is the global input-based consistency ratio for all factors which can be compared with the threshold values in Table 3.2.

Table 3.2: Threshold for input-based consistency measurement

	Number of Factors						
Scales	3	4	5	6	7	8	9
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1898	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1330	0.1990	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

A BWM-solver in Excel has been generated which can directly calculate this model on the basis of the decision maker's preference. The consistency ratio in Table 3.2 is used to measure the reliability of the result. The result is acceptable if this ratio is lower or equal to the corresponding threshold. Otherwise, the decision-maker should repeat the pairwise comparison until an acceptable ratio is reached.

3.3. En-route expanded network

In this section, the concept of the en-route expanded network is introduced. To begin, the concept of the original expanded network is introduced, along with an analysis of the drawbacks of the original expanded network. The basic assumption of the innovative en-route expanded network is then presented. Based on these assumptions, a detailed discussion is provided on the algorithm used to generate the en-route expanded network. It should be noted that a fictitious network is presented within the introduction to help better understand the concept.

3.3.1. Basic assumption

The concept of the expanded network was initially introduced by MirHassani & Ebrazi (2013). In order to address the computational complexity associated with generating combinations of charging station locations in the FRLM model introduced by Kuby & Lim (2005), the expanded network serves as an alternative approach for generating charging station location combinations, resulting in a significant reduction in calculation complexity. However, there remains a notable drawback in the generation of the expanded network. In summary, the primary issue with the expanded network lies in its conflation of the road network with the charging network. Specifically, both the origin and destination nodes of each OD trip are indiscriminately treated as potential charging station locations, which does not reflect the actual situation. Stepping back, if the selection of trip generation nodes as charging stations holds significance, it gives rise to the issue of conflating depot charging stations with en-route charging stations. Depot stations are typically deployed at the trip's origin or destination, while en-route charging stations are positioned along the road network. This situation further impacts the model, as the constraint on the total number of charging stations cannot solely be restricted to the en-route charging network.

In order to solve the aforementioned problem, the innovative en-route expanded network is introduced based on the concept of the expanded network. The goal of generating the en-route

expanded network is stated as follows: **For each OD pair in the highway road network, the range-restricted HDVs are able to have a round trip without running out of battery**. The assumptions underlying the en-route expanded network are outlined as follows:

1. It is assumed that HDVs will return along the same route for their round trip and follow the shortest path.
2. The OD nodes of each trip are equipped with depot chargers, enabling HDVs to be fully charged at the start and end of the trip.
3. Only en-route candidate sites for charging stations are eligible for selection; nodes within the road network cannot be chosen, even if they are located along a path.
4. If an HDV can successfully travel from the origin node to the destination node without running out of battery, there is no need to generate the en-route expanded network for the return trip from the destination node to the origin node.
5. En-route charging stations have the capability to charge HDVs to full capacity within an acceptable charging time.

Note that all the assumptions are generated based on the problem formulation, characteristics of HDVs driving behaviour and the modification of the original expanded network.

3.3.2. Algorithm

Figure 3.2 illustrates a simple example path with four en-route candidate charging stations C1,C2,C3 and C4. It is assumed that an HDV with a driving range of R = 180km is going to have a round trip traveling from node O to node D and then back to O with the same route without running out of battery. Based on assumption 2, nodes O and D are equipped with depot chargers so that the HDV starts with a full battery at O and returns with a full battery at D as well. The purpose of generating an en-route expanded network is to find out all possible combinations of en-route stations on the path without running out of battery.

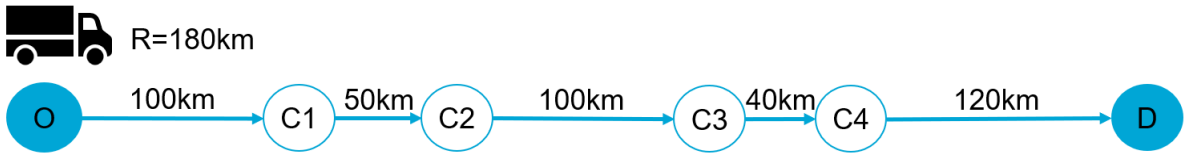


Figure 3.2: An example of a simple path of a trip from O to D

Before explaining the generation algorithm of the en-route expanded network, it is necessary to introduce some basic mathematical notations to better help the understanding of the algorithm as shown in Table 3.3.

Table 3.3: Notations for en-route expanded network

Symbol	Definition
q	the id of an OD pair
N^q	the set of nodes on path q expanded network
A^q	the set of arcs on path q expanded network

Table 3.3: Notations for en-route expanded network

Symbol	Definition
$d_q(i,j)$	the length of sub-path on path q expanded network between node i and j
$ord_q(i)$	the ordering index on path q expanded network of node i in the direction from origin node to destination D
R	the range of the HDVs

The four steps of en-route expanded network generation are as follows. Note that the detailed Python code for en-route expanded network generation is presented in Appendix A.

Step 1: Connect adjacent nodes in the network within the HDV range. As shown in Figure 3.3, the blue arcs represent the process of this step.

$$\forall i,j \in N^q, d_q(i,j) \leq R \cap ord_q(j) - ord_q(i) = 1 \tag{3.9}$$

Step 2: Connect the origin node to other nodes in the network that satisfy the following condition. Note that the red arc in Figure 3.3 is the illustration of this step.

$$\forall i \in N^q, \quad d_q(O_q,i) \leq R \tag{3.10}$$

Step 3: Connect any other node to the destination node in the network which satisfies the following condition. Note that the green arc in Figure 3.3 is the illustration of this step.

$$\forall i \in N^q, \quad d_q(i,D_q) \leq R \tag{3.11}$$

Step 4: Connect any two other nodes (except the origin node or destination node) in the network that satisfy the following condition. Note that the yellow arcs in Figure 3.3 are the illustration of this step.

$$\forall i,j \in N^q, ord_q(i) \leq ord_q(j) \cap \quad d_q(i,j) \leq R \tag{3.12}$$

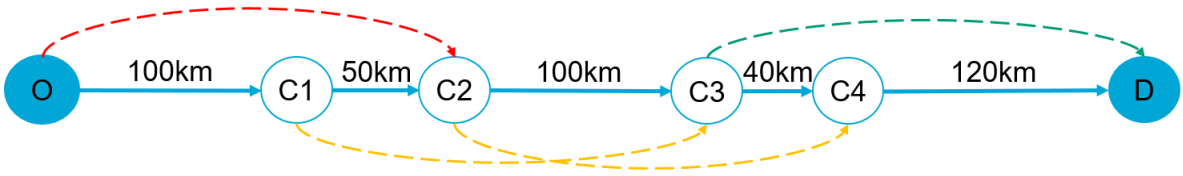


Figure 3.3: En-route expanded network of the example path

According to the aforementioned algorithm, the outcome of the en-route expanded network is shown in Figure 3.3, where the set of nodes includes $\{O, C1, C2, C3, C4, D\}$ and the set of arcs includes $\{(O,C1),(C1,C2),(C2,C3),(C3,C4),(C4,D),(O,C2),(C1,C3),(C2,c4),(C3,D)\}$. Different colors of arcs in the figure represent different steps of the en-route expanded network generation. Specifically, blue arcs represent step 1, red arc represents step 2, green arc represents step 3 and yellow arcs represent step 4. In order to find out all the possible combinations of charging stations, all the OD pairs along the arcs should be figured out. For instance, if

a HDV chooses the arcs $(O, C2)$, $(C2, C4)$ and $(C4, D)$ as the path $O - C2 - C4 - D$, then it represents a possible charging station combination: $\{C2, C4\}$. Therefore, the set of all possible combinations includes $\{C1, C2, C3, C4\}$, $\{C1, C2, C3\}$, $\{C1, C2, C4\}$, $\{C1, C3\}$, $\{C2, C3, C4\}$, $\{C1, C3, C4\}$, $\{C2, C4\}$ and $\{C2, C3\}$. Each of the combinations could support a HDV with a range of 180km, to travel from node O to node D and then return without running out of battery.

3.4. Expanded network based FRLM

First of all, the notation of the sets, parameters, and decision variables in the model is explained as follows.

Sets:

- Q: Set of all the OD trips in the transport network.
- N: Set of all nodes in the transport network, which includes the trip origin and destination nodes and candidate nodes for charging stations.
- $G(Q, N)$: Set of all expanded networks which exists in N and Q.
- Q_i: Set of all trips that passing through node i in the network
- N^q: Set of nodes in the en-route expanded network of trip q.
- A^q: Set of all arcs in the en-route expanded network of trip q.

Parameters:

- $g(N^q, A^q)$: En-route expanded network of trip q, $g \in G$
- i: One of the nodes in the transport network and charging station network, $i \in N$
- q: One of the trips in the OD pair set Q, $q \in Q$
- f_q: Traffic demand of OD pair q, usually in the unit of traffic flow of HDVs.
- p: Number of charging stations to be built.
- Cap_i The capacity of En-route charging station i. Capacity is defined as the maximum volume of HDVs that can be charged in a unit of time.

Decision variables:

- x_{od}^q: A binary variable, $= 1$ if no station is needed along trip q; $= 0$ otherwise.
- x_{ij}^q: A binary variable, indicating the charging choice of HDV in trip q. $= 1$ if the arcs (i, j) in the en-route expanded network is selected; $= 0$ otherwise.
- y_i: A binary variable, $= 1$ if a charging station is built in node i in the network; $= 0$ otherwise.

The objective function and constraints of the model are presented as follows.

Objective function:

$$\max Z = \sum_{q \in Q} f_q (1 - x_{od}^q) \tag{3.13}$$

Constraints:

$$\sum_{j|(i,j)\in A^q} x_{ij}^q - \sum_{j|(j,i)\in A^q} x_{ji}^q = \begin{cases} 1 & \text{if } i = o \\ -1 & \text{if } i = d \\ 0 & \text{otherwise} \end{cases} \quad \forall q \in Q, \forall i \in N^q \tag{3.14}$$

$$\sum_{j|(j,i)\in A^q} x_{ji}^q \leq y_i \quad \forall i \in N, \forall q \in Q_i \tag{3.15}$$

$$\sum_{i\in N} y_i = p \tag{3.16}$$

$$\sum_{q\in Q_i} (f_q * \sum_{j|(j,i)\in A^q} x_{ji}^q) \leq Cap_i \quad \forall i \in N \tag{3.17}$$

$$x_{ij}^q \geq 0 \quad \forall q \in Q, \forall (i,j) \in A^q \tag{3.18}$$

$$y_i \in \{0,1\} \quad \forall i \in N \tag{3.19}$$

Maximizing the flow coverage is the objective of the model, as shown in Equation 3.13. In this context, flow coverage refers to the charging demand of the transport network. It is worth noting that the decision variable x_{od}^q is introduced for the first time in the FRLM-based model. This variable can be seen as an additional arc that connects the origin and destination nodes of trips that have OD pair q in the en-route expanded network. If $x_{od}^q = 1$, indicating that the OD arc is selected by the HDV driver, there is no need to charge along the path of trip q since the distance between the origin and destination is too small to require charging in between.

The explanations of constraints are introduced as follows. Constraint 3.14 represents that flow in the en-route expanded network is balanced, including all the paths from O to D in each OD pair q. Note that the flow in this context represents the arcs in the en-route expanded network, instead of the traffic flow f_q. Constraint 3.15 makes sure that all the paths with common nodes can make a site active. Constraint 3.16 guarantees that the total number of charging stations being built should equal the number being planned p. Constraint 3.17 prevents the charging load of each charging station in the network from exceeding its capacity. Constraints 3.18 and 3.19 are the properties of decision variables x_{ij}^q and y_i.

3.5. Sensitivity analysis

As mentioned in Chapter 3.1, MCDA is the first stage of the proposed methodology. During the process, the weights of each evaluation criterion are determined based on an expert survey, which is a subjective procedure. Hence, it is crucial to consider the impact of different weight combinations on outcomes.

To observe the degrees of impact of different weight combinations on the final candidate sites, a brute force principle is conducted to test all the possible combinations of weight based on the results from the expert survey. Assuming that the weights for three selected evaluation criteria C_1, C_2,C_3, based on results from an expert survey, are W_1, W_2, and W_3 respectively. Since the weights are calculated using the BWM algorithm, they should have a magnitude

relationship. Assuming that $W_1 > W_2 > W_3$, then the scenarios for sensitivity analysis based on a brute force principle are presented in Table 3.4. Note that the first six scenarios are generated by finding all the combinations of weights through permutation. The seventh scenario is generated based on an equally weighted principle.

Table 3.4: Sensitivity analysis scenario settings

Scenario/weight	C1	C2	C3
1(Expert Survey)	W_1	W_2	W_3
2	W_1	W_3	W_2
3	W_2	W_1	W_3
4	W_2	W_3	W_1
5	W_3	W_1	W_2
6	W_3	W_2	W_1
7	$(W_1 + W_2 + W_3)/3$	$(W_1 + W_2 + W_3)/3$	$(W_1 + W_2 + W_3)/3$

4

Case Study

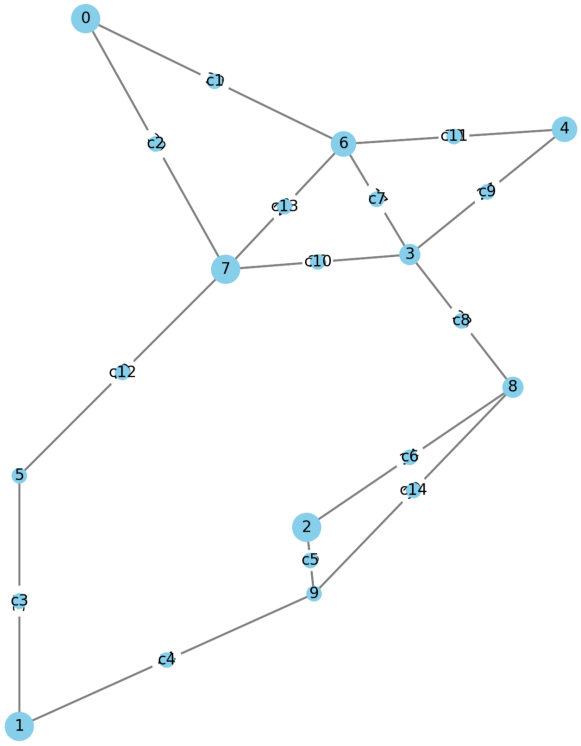
This chapter delves into a comprehensive case study that illuminates the application and analysis of the theoretical concepts introduced in the previous chapters. The basic setting of two case studies will be introduced.

Chapter 4.1 introduces Case Study 1. The first case study is conducted in a 25-node fictitious toy network, where the initial candidate sites are predefined as the mid-point of each edge in the network. Each node in the toy network is assigned a random weight and the OD generation data is obtained using the gravity model. It is assumed that the trajectory of each OD pair follows the shortest path in the network. Note that the purpose of conducting this case study is to assess the feasibility of the FRLM-based optimisation model (second stage of the proposed methodology).

Chapter 4.2 introduces Case Study 2. For the second case study, real highway network data and HDVs flow data from the Netherlands and Germany were used. The raw data was obtained from Synthetic European road freight transport flow data, as described in Speth et al. (2022). Unlike the first case study, this one followed the complete process of the proposed methodology. The structures of this section include the introduction of the raw dataset, the data processing techniques and the parameter settings.

4.1. Case study 1: A 25-node fictitious toy network

To assess the feasibility of the FRLM-based optimisation model, a simplified network with 10 nodes (labeled from 0 to 9) where each node is randomly connected to its two nearest neighbors is generated, as depicted in Figure 4.1a. The x-axis and y-axis coordinates range from 0 to 100. The numbers displayed on the links represent the lengths of those links. Then, 14 candidate nodes (labeled from c1 to c14) are added to the network at the midpoint of each link. This is a simplification of adding final candidate sites into the network after MCDA. The coordinates of candidate nodes are presented in Figure 4.1b. Each node in the network is assigned a weight randomly ranging from 0 to 100, indicating its size or importance. Larger nodes have higher weights. These weights are used as inputs to generate OD trip demand using a gravity model. 45 fictitious OD pairs are generated including the origin and destination nodes, the path of each OD pair, the shortest distance and the trip generation. Part of the data is presented in Figure 4.2.



(a) A 10 nodes toy network with different radii representing its weight

	Node Name	Link ID	Coordinates
0	c1	0	(42.5, 90.5)
1	c2	1	(34.5, 82.0)
2	c3	2	(16.0, 20.0)
3	c4	3	(36.0, 12.0)
4	c5	4	(55.5, 25.5)
5	c6	5	(69.0, 39.5)
6	c7	6	(64.5, 74.5)
7	c8	7	(76.0, 58.0)
8	c9	8	(79.5, 75.5)
9	c10	9	(56.5, 66.0)
10	c11	10	(75.0, 83.0)
11	c12	11	(30.0, 51.0)
12	c13	12	(52.0, 73.5)
13	c14	13	(69.5, 35.0)

(b) Coordinates of 14 fictitious candidate sites which are located at the mid-point of each network edge

Figure 4.1: A toy network used to test the feasibility of the optimisation

	origin	destination	path	shortest_distance	od_trip_generation
0	0	6	[0]	39	265
1	0	7	[1]	39	483
2	0	3	[0, 6]	56	111
3	0	4	[0, 10]	69	118
4	0	5	[1, 11]	79	8
5	0	8	[0, 6, 7]	79	59
6	0	1	[1, 11, 2]	113	54
7	0	2	[0, 6, 7, 5]	113	54

Figure 4.2: Part of the fictitious OD trip data

4.2. Case study 2: Real traffic network within NL and DE

The second case study is conducted within two distinct yet interconnected geographical contexts: the Netherlands (NL) and Germany (DE). In this case, rather than only implementing the second stage of the proposed methodology, the entire process will be conducted, starting from the generation of initial candidate sites, to the final candidate sites generation via MCDA, followed by the formulation of the En-route expanded network and finally, optimization based on FRLM. The raw data being used originated from Synthetic European road freight transport flow data by Speth et al. (2022). The structure of this chapter is organized as follows. In section 4.2.1, the introduction of the raw dataset is presented. In section 4.2.2, the detailed process of data preparation, as well as data cleaning and filtering is explained. Finally, in section 4.2.3, the settings of different scenarios are discussed.

4.2.1. Introduction of the raw dataset

The raw dataset originated from a data article published by Speth et al. (2022). This article delves into the intricacies of European road freight traffic. It meticulously details truck traffic flows spanning 1,675 regions across Europe. The dataset not only captures road freight flows in terms of tons and the number of vehicles, but also provides insights into the shortest path between these regions on the European highway network, commonly referred to as E-roads.

The foundational data for this research is rooted in the results from the European Transport Policy Information System, abbreviated as ETIS. The origin-destination Road Freight Matrix from the ETISplus project was instrumental in modeling the transport flows presented in this research. The ETIS project, which initially provided data for the year 2010, was pivotal in shaping the dataset's structure and content. The dataset described by this article was updated using Eurostat data to reflect the road freight volume for subsequent years and a forecast extending up to 2030 was incorporated. This freight volume was then converted into the number of vehicles traveling. The highway network pertinent to trucks was extracted from the ETISplus project and was manually updated to align with the current E-road network. Each origin-destination freight volume was then allocated to this network using Dijkstra's algorithm, resulting in a

synthetically generated road freight traffic volume for each road section.

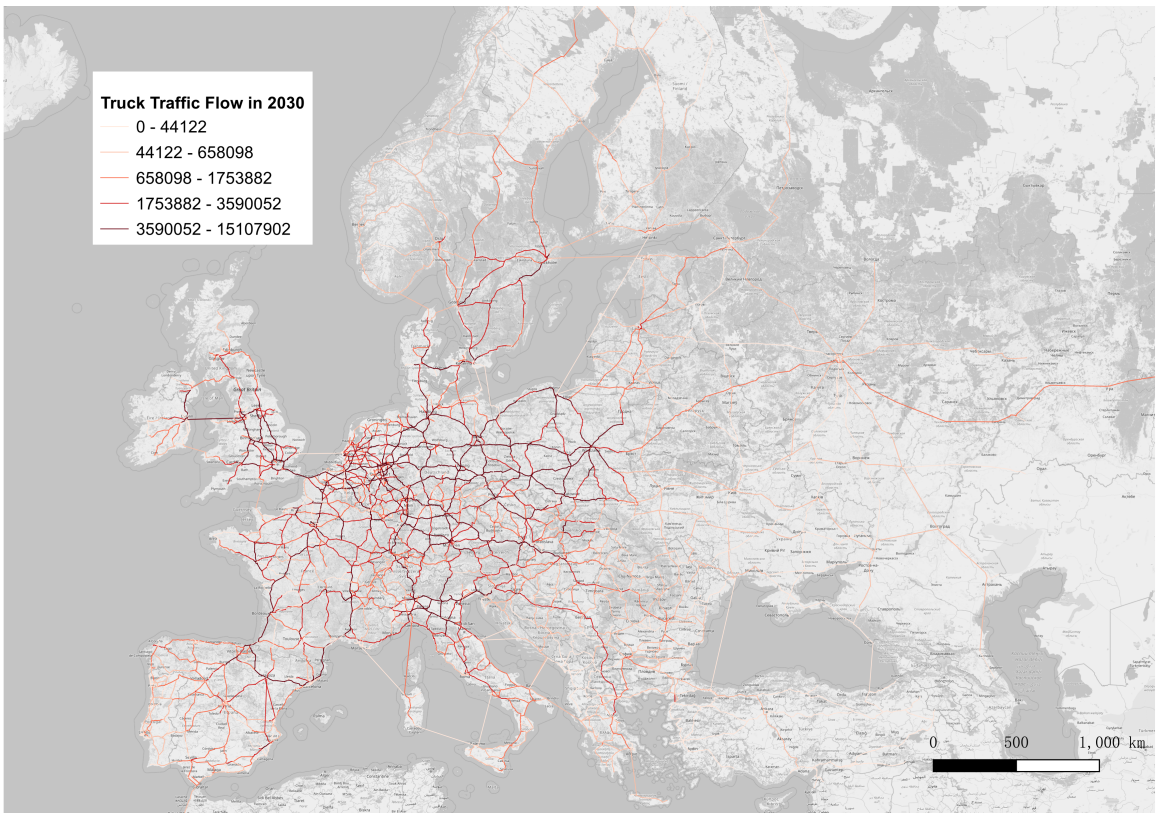


Figure 4.3: The visualization of the forecasted truck traffic flow data in 2030

To project the traffic flows to the year 2030, the authors faced a challenge as there wasn't a single growth value consistently found in the literature. The European Commission, for instance, cited growth values ranging between 26% and 40% across different publications. Given this variability, the authors made an assumption for their forecast: they posited that countries would continue to grow between 2019 and 2030 at the same growth rates observed between 2010 and 2019. In order to evaluate the quality of the data, the author conducts a comparison between the projected data with the real data from the automatic traffic census in Germany (BASt). The results show that the dataset reaches a high degree of consistency on long-haul routes and between cities as shown in Figure 4.4.

Diving deeper into the dataset's composition, it comprises four distinct datasets. These are the truck traffic flow data, an overview of the NUTS-3 regions, a list of the network nodes, and a list of network edges in the road network. These four datasets are available in the .csv format and can be retrieved from *Mendeley*. The detailed descriptions of each dataset are presented as follows:

1. **Truck Traffic Flow Data**: Named '01_Trucktrafficflow', this dataset provides information about the updated traffic flows between each NUTS-3 region, considering 1,514,573 directed transport flows between 1630 different origins and 1667 destinations. It captures freight flows for the years 2010, 2019, and 2030 in tons and the calculated annual

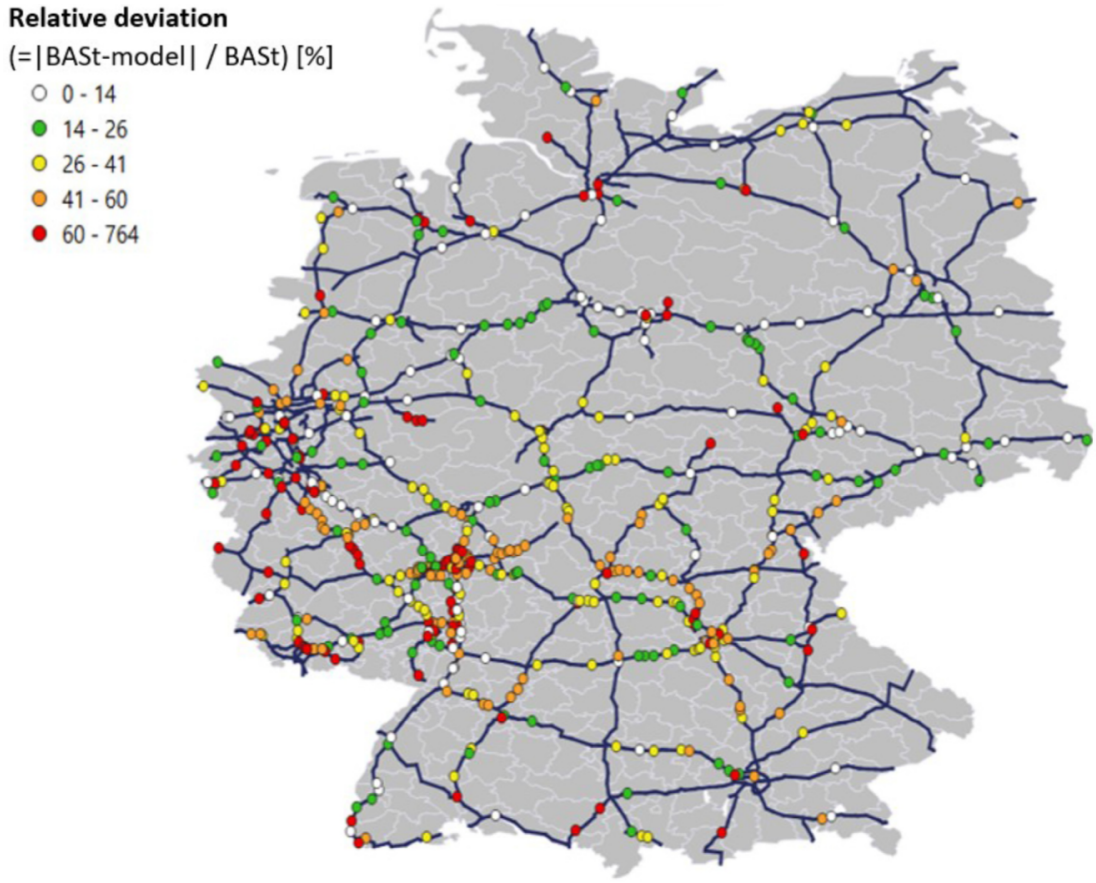


Figure 4.4: Relative deviation between traffic flows in model and BASt counting data, Source: Speth et al. (2022)

number of trucks traveling the relevant route for these years. It's worth noting that the modeling of traffic paths and the projected traffic flows have been subjected to certain simplifications. Furthermore, it is also essential to notice that the name of this dataset 'truck traffic flow' refers to OD trip, where the origin and destination, the sequence of passing edges on the network, the shortest distance and the trip annual generation of each trip are recorded.

2. **Overview of the NUTS-3 Regions**: The '02_NUTS-3-Regions' dataset contains information on the considered 1,675 NUTS-3 regions. The content was sourced from the original ETISplus project file '_EZ_2006_3.csv'. Data on the regions themselves, such as ID, name, country, and the location of their centers, are included. Additionally, the nearest point in the E-road network to each region is also identified.
3. **List of the Network Nodes**: The '03_network-nodes' dataset describes the nodes in the underlying E-road network. The network comprises 17,435 nodes. Each node has a unique ID and unique coordinates. Additionally, both the NUTS-3 region and the country in which the node is located are identified.
4. **List of Network Edges in the Road Network**: The '04_network-edges' dataset describes the edges in the underlying E-road network. The network consists of 18,447 edges, each represented as individual lines in the dataset. Each edge has a unique ID and always connects exactly two nodes. For each edge, it's indicated whether it origi-

nates from the ETISplus dataset or was added manually. Truck traffic volumes for both 2019 and 2030 are provided for each edge. The visualization of the forecasted truck traffic flow data on highway networks covered in pan-Europe regions is presented in figure 4.3.

4.2.2. Data processing

In order to obtain clean and compatible data inputs for the case study, raw datasets have to be processed. As mentioned in Chapter 3, there are mainly three sources of data inputs: highway network data, truck OD trip data and initial candidate sites data. The former two data inputs are extracted and filtered from Synthetic European road freight transport flow data, while the last data input is extracted and processed from OpenStreetMap.

Modeled highway network formulation

The case study focuses on the Netherlands (NL) and Germany (DE) for two reasons. Experimentally, NL and DE own the densest highway network across the EU. Moreover, the volume of truck traffic in these regions surpasses that of others, as illustrated in Figure 4.3. This selection, therefore, ensures a comprehensive evaluation of the proposed methodology and provides rich insights. Practically speaking, NL and DE's strategic positioning anchor them at the heart of the pan-European road network, making them pivotal in EU trade dynamics. Furthermore, both countries are pioneers in HDV electrification. Consequently, researching the placement of on-the-go charging stations for HDVs in NL and DE not only holds high relevance but also promotes the broader electrification of HDVs in Europe.

To procure highway network data for NL and DE, a filtering procedure is applied to the '04_network-edges' dataset. Network edges tagged with 'NL' and 'DE' are extracted from the CSV file and subsequently converted to a GeoJSON format. This GeoJSON file is then imported into QGIS, where the coordinate system is transitioned from 'CRS:4326' to 'CRS:3857'. This conversion is essential as it changes the distance measurement unit from degrees to meters, aiding subsequent computations. The finalized highway network data for NL and DE is depicted in Figure 4.5.

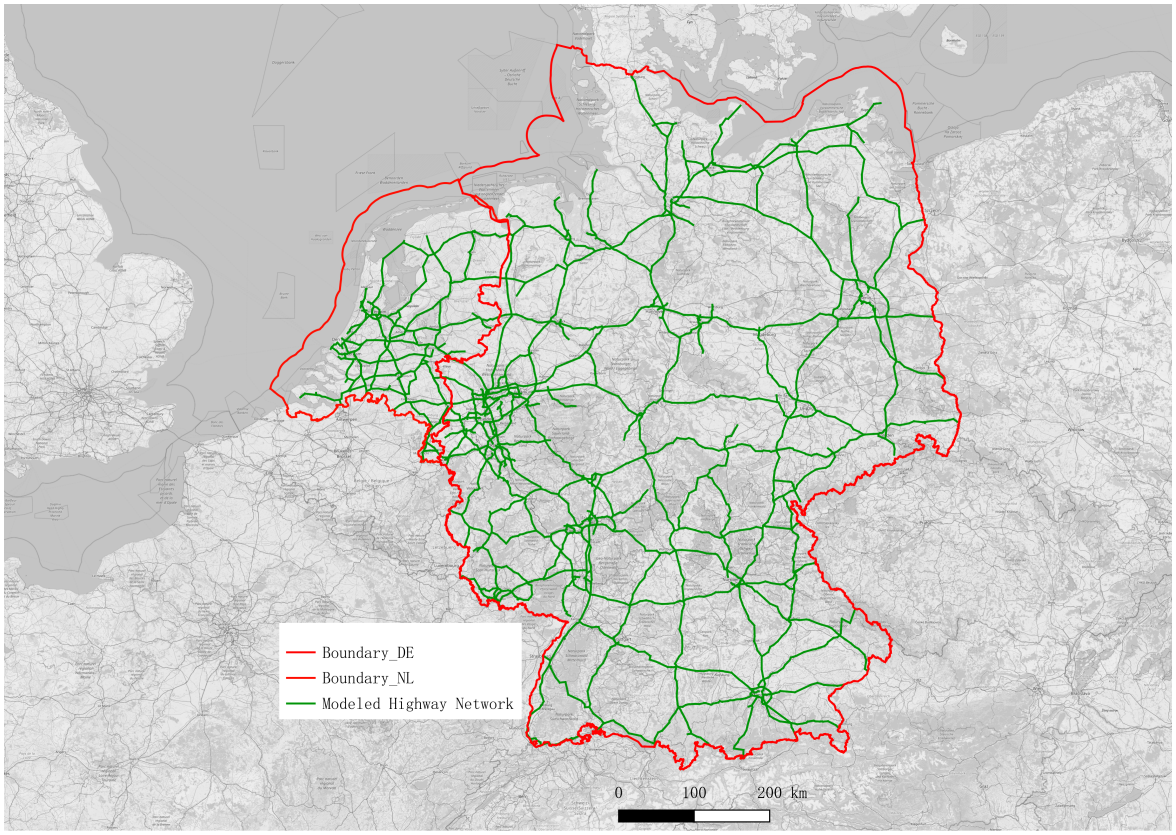


Figure 4.5: Highway network within the region of NL and DE

Truck OD trip data filtering

The case study concentrates on the regions within NL and DE; hence, truck trips outside this specified terrain are not taken into account. In the raw dataset '01_Trucktrafficflow', each row contains columns 'ID_origin_region' and 'ID_destination_region' that denote the ID of the origin and destination locations, respectively. Information about which country these location IDs pertain to can be found in the '02_NUTS-3-Regions' dataset. By integrating data from these two datasets, the origin and destination countries could be determined. To identify trips within the NL and DE regions, trips where both the origin ID and destination ID belong to either 'NL' or 'DE' are searched for. This method helps in filtering out truck trips that operate outside NL and DE.

The OD pair flow and cumulative traffic flow on each edge of the highway network flow within NL and DE are presented in Figure 4.6. The traffic flow has been categorized into five classes using different colors, while the OD pair flow has been classified into five classes with different line widths based on OD trip generation. It's important to note that the origin nodes and destination nodes of OD flow are not generated from nodes on the highway, but from urban areas which are classified into different regions. This information can be found in the raw datasets '01_Trucktrafficflow' and '02_NUTS-3-Regions'. As depicted in the figure, the majority of OD flows are between mega city areas, such as Hamburg, Berlin, and Munich in Germany, and Amsterdam and Rotterdam in the Netherlands. These flows travel through highways A1, A2, A5, and A8, which experience heavy traffic.

After excluding truck trips outside NL and DE, OD trips with a travel distance shorter than the HDV's range were filtered out. Such OD trips would also be excluded during the en-route expanded network generation. Hence, removing them upfront conserves computational time in subsequent phases. For instance, in a scenario where the HDV's range is 550km, the travel distance distribution of all truck trips from the raw dataset is depicted in Figure 4.7a. The justification of the value will be presented in Chapter 4.3. Meanwhile, the distribution after filtering out trips under 550km is illustrated in Figure 4.7b. Note that the time period for these data is one year.

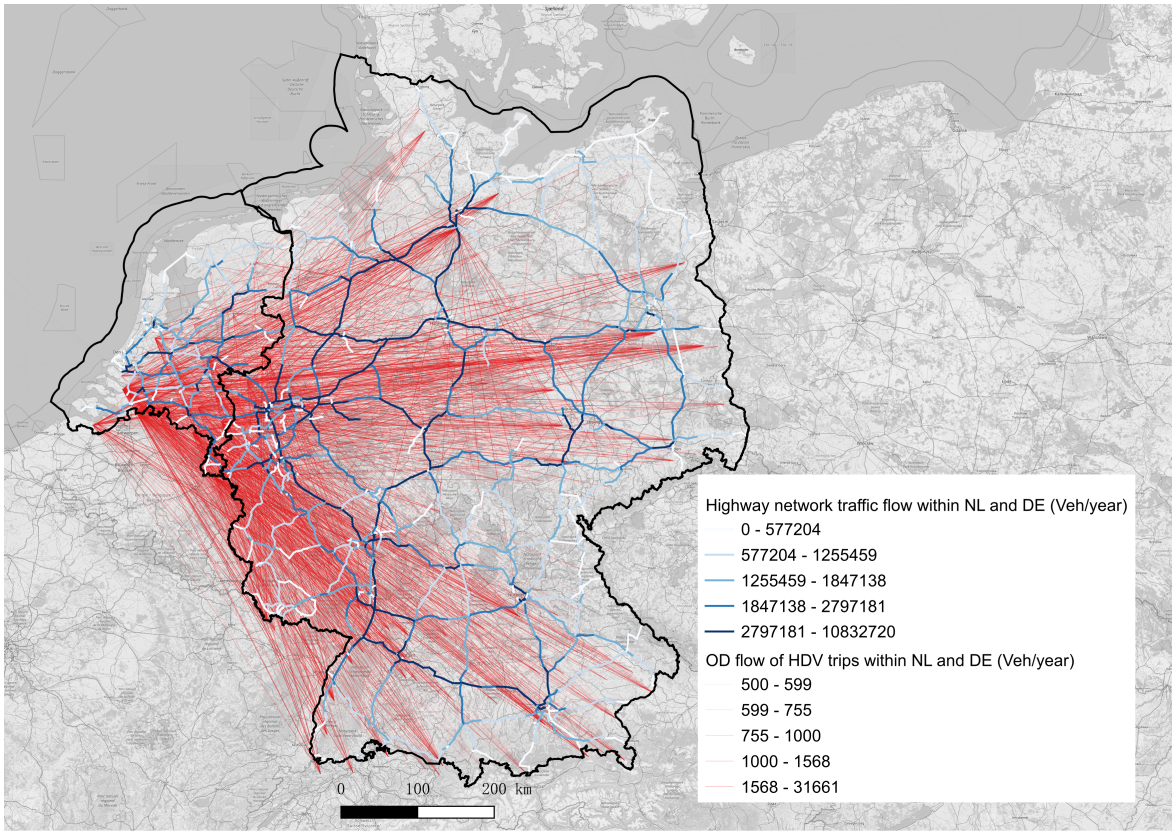
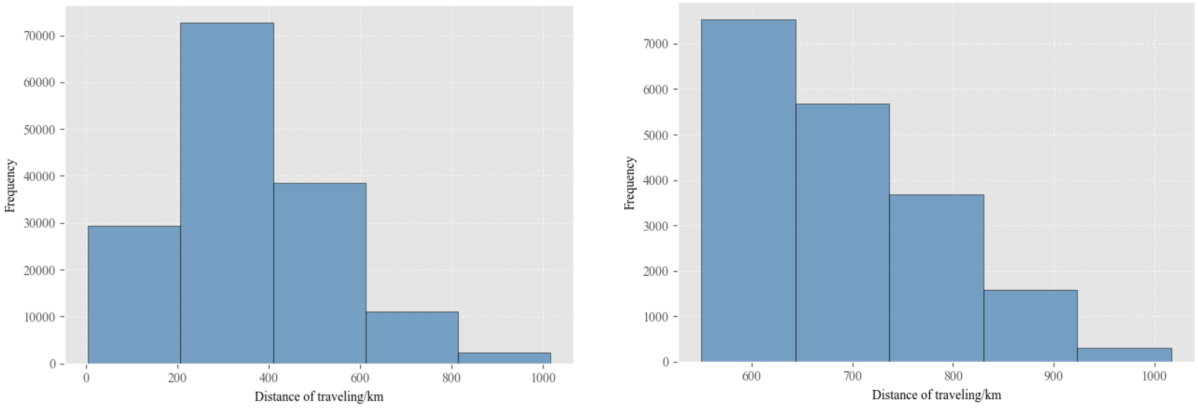


Figure 4.6: The OD pairs flow within NL and DE, the width of the red line represents the trip generation



(a) Raw dataset

(b) Filtered dataset

Figure 4.7: Travel distance frequency distribution

Generation of initial candidate sites

The initial candidate sites are extracted from OpenStreetMap(OSM) with the help of quickOSM plugin in QGIS. OpenStreetMap is a collaborative geospatial platform initiated in 2004, which seeks to provide a comprehensive, editable map of the world. The data is contributed and edited by a vast, globally distributed community, much like the way Wikipedia operates for encyclopedic information. In the context of utilizing OSM data within geographical information systems (GIS), the quickOSM plugin for QGIS—a prominent open-source GIS software—merits attention. This tool streamlines the process of querying specific subsets of data from OSM, enabling direct integration into GIS projects. The specific querying for elements is operated by a tagging system, each tag comprises a key and value. This information could be easily found on the website: *OpenStreetMap wiki-Map feature*.

To begin the generation of initial candidate sites, extract all service areas along the highway network using the quickOSM plugin. The query is defined as 'Highway=service', and the search area is confined to the highway network domain. The specific highway network in the case study is derived from '04_network-edges', as detailed in Chapter 4.2.1. Following this, all elements associated with the service area on the highway are imported into three distinct layers: a node layer, a line layer, and a polygon layer. This step is essential because the geospatial data for service areas on OSM is not consistently organized. Consequently, different layers with varied data structures may not align with one another.

To address the mentioned concern, begin by converting the line layer to a polygon layer using the 'Polygonize' tool in QGIS. Next, merge the original polygon layer with this newly converted layer using the 'Merge Vector Layer' tool. This action produces a unified polygon layer. As a final step, employ the 'Centroids' tool to generate a new node layer, where each node represents the centroid of its corresponding polygon. The original node layer can be discarded because its data is not as reliable as that of the polygon layer.

After producing a consolidated service area node layer and polygon layer, data cleansing remains crucial. This cleaning process comprises two primary steps. The first step involves removing nodes that aren't aligned with the model's highway network. Many of these nodes are situated on alternative road networks (e.g., lower-level roads), which are not part of the des-

ignated highway network in the model. Figure 4.10a provides an illustration of this situation. The second step focuses on filtering out redundant nodes that are in the opposite direction of the highway network. This step is critical because service areas typically run parallel or with minimal gaps on both sides of the highway. Given the case study's OD trip data is directional — meaning an HDV can only charge at a station on its side of the road — retaining service areas from the opposite direction would result in an overestimation of flow coverage rates in subsequent optimization processes. Based on the premise that the distance between opposing service areas is trivial and their sizes are comparable (resulting in similar attributes), it's imperative to retain service areas from only one direction. This situation is depicted in Figure 4.10b.



(a) A service area that is not accessible

(b) Two service areas are built on both sides of the highway

Figure 4.8: Two examples of the service area that need to be filtered

The last step is to project the filtered service area node onto its nearest modeled highway network. Given that the model simplifies the highway network, the raw data doesn't always align perfectly with real-world highway layouts. Additionally, the foundational assumption in the FRLM-based model is that each candidate site must be located on the network. Therefore, to proceed with subsequent steps, it's imperative to project the service area node from its original position to the modeled highway network. The projection process involves several steps:

1. Create a vertical line to the nearest highway network using the 'align points to features' tool.
2. Extract the two vertices of the vertical line with the 'Extract vertices' tool.
3. Add a one-meter buffer to the highway network using the 'buffer' tool.
4. Retain the overlapping vertices in the buffer zone with the 'clip' tool.

The outcome of this projection is depicted in Figure 4.9, where 553 nodes in total are generated as the initial candidate sites. The ID for each site is given from $c1$ to $c553$, where 'c' refers to the charging station.

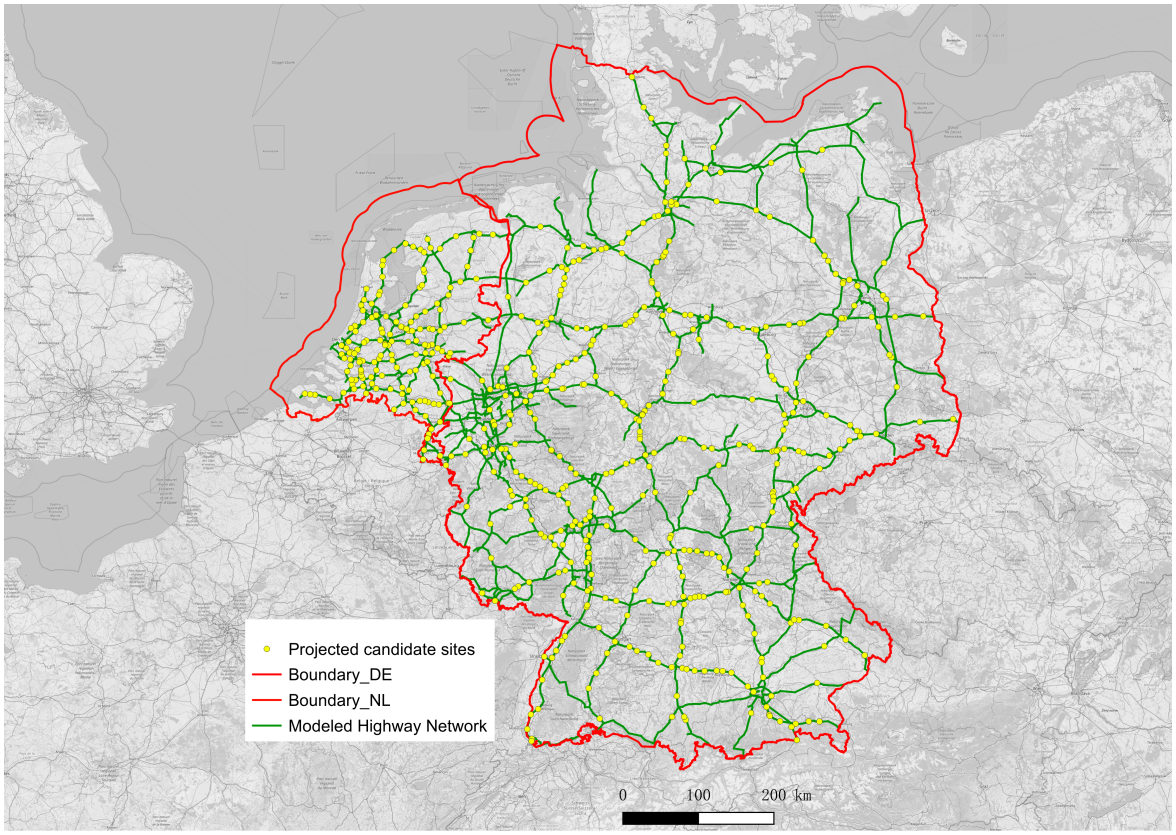


Figure 4.9: The location of initial candidate sites

4.2.3. Parameter settings

In this section, the basic parameter settings and their way of obtaining parameters are discussed. First of all, all the parameters used in this case study are listed in Table 4.1.

Table 4.1: The overview of parameter setting in case study

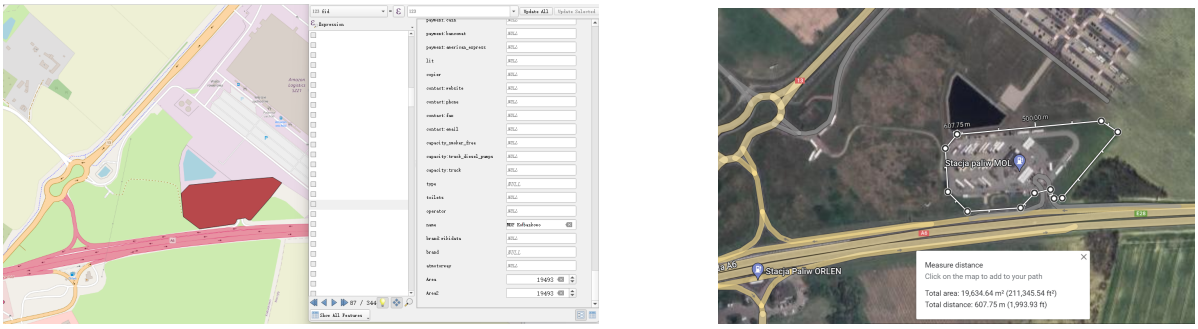
Stage	Notation	Meaning	Generation method
MCDA	C_1	Criteria 1: Size of service area(m^2)	QGIS
	C_2	Criteria 2: Distance to substation(km)	QGIS
	C_3	Criteria 3: Traffic volume	Given in raw dataset
	W_1	The weight of criteria 1	Expert survey
	W_2	The weight of criteria 2	
	W_3	The weight of criteria 3	
FRLM	P	No. Charging station to be built	Penetration rate
	R	Range of HDVs(km)	Technology development
	Cap_i	Capacity of candidate site i	$chargers_i$ * 365
	$chargers_i$	No. HDV parking lots in candidate site i	C_1^i * α / θ
	θ	Unit size of HDV parking area	Design standard
	α	Parking area ratio	

Parameters in stage 1

In the first stage of the methodology, BWM is the key method be be applied. During this process, the type of criteria for each alternative, the value of each attribute for each alternative and the weight of each criterion have to be decided and calculated. In this case study, three criteria are selected to determine the standard of the first filtering of the candidate sites: Size of the service area(C_1), Distance to substation(C_2) and Traffic volume(C_3).

C_1 refers to the topological size of each candidate size, it is the total extent of land or space enclosed within its boundaries, usually measured in square meters. It could determine the capacity of an on-the-go charging station, where capacity refers to the maximum number of HDVs that could be charged in a unit of time. Hence, the area of the site could be regarded as the key indicator to describe the capacity of an on-the-go charging station. The larger the area of the site, the higher the capacity to contain more HDVs and charging facilities in each charging station.

The value of C_1 is calculated by QGIS using 'Open field calculator' tool with the formula '$Area' on each element in the service area polygon layer. Note that before calculating the area of each alternative, the coordinate system has to be reprojected from 'CRS:4326' to 'CRS:3857' in order to transform the unit of measurement from degree to meter. The outcomes are compared with the results using a measurement tool on Google Map to guarantee the accuracy of the results as shown in an example in Figure 4.10. The final C_1 value distribution of the 553 candidate sites is presented in Figure 4.11. It could be seen from the figure that the majority of the candidate sites own a size of area lower than $60000m^2$.



(a) Area calculation in QGIS

(b) Double check the outcome via Google Map

Figure 4.10: An example of service area size calculation

C_2 refers to the nearest distance to the nearest substation of each candidate site. In a power supply system, a power substation, or in short, substation, is a vital infrastructure component of an electrical grid that facilitates the transmission and distribution of electricity by transforming voltage levels, ensuring efficient energy transfer, and controlling the flow of electricity to maintain a stable and reliable supply. The distance to the substation influences the investment cost of the charging station due to the fact that long transmission lines require more materials (copper, aluminum, steel, etc.), labor, and maintenance. Hence, it is crucial to determine the distance to the substation in the field of charging station design and it is beneficial to choose the location where substations are close to the charging station.

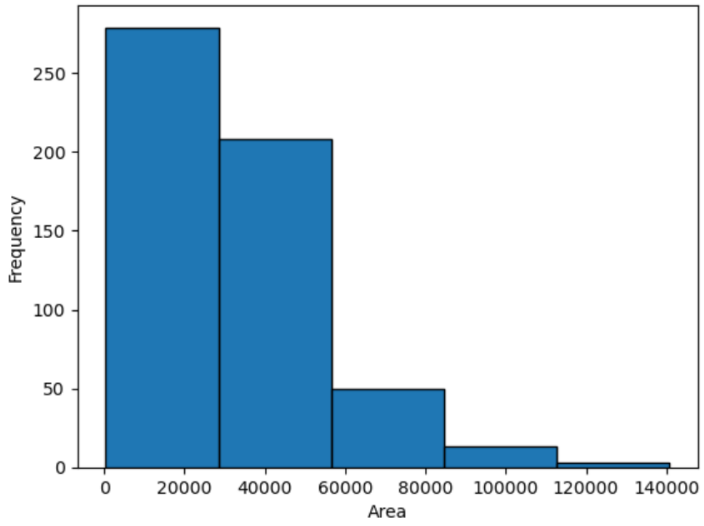


Figure 4.11: Histogram of C1 value distribution with frequency

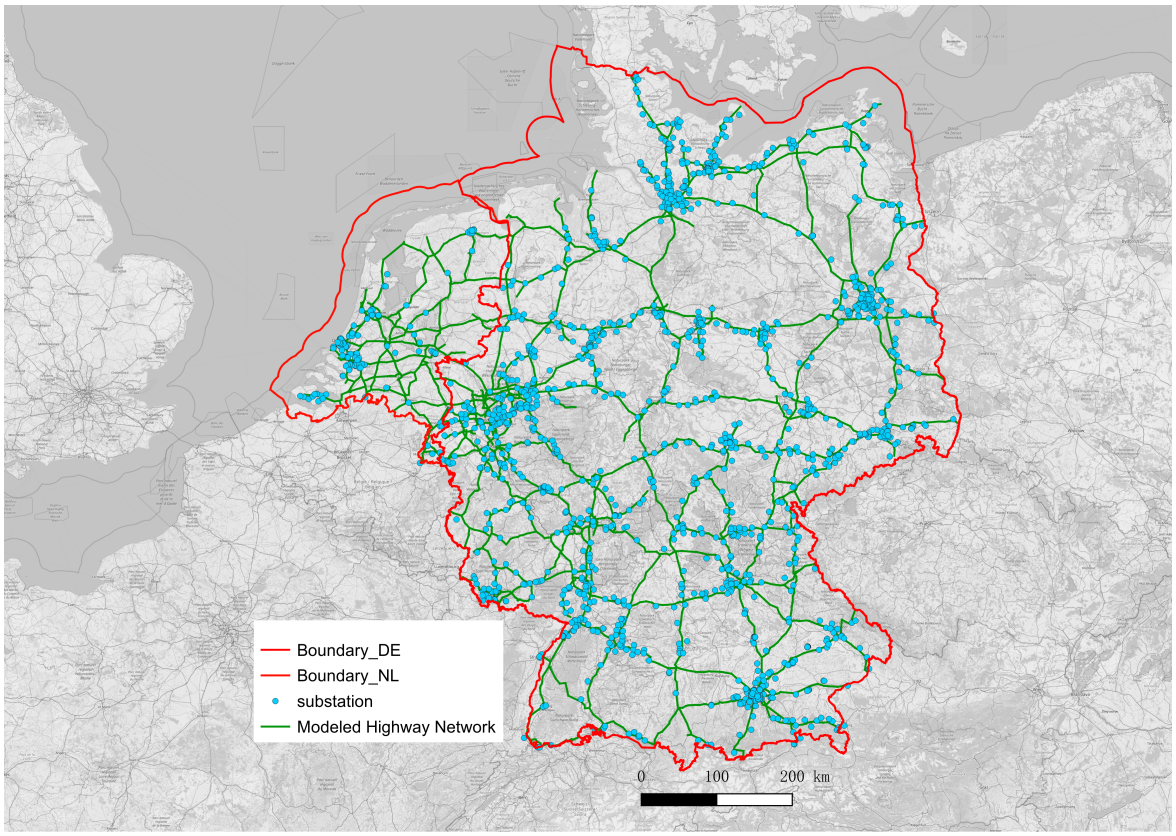


Figure 4.12: The location distribution substations near the modeled highway network

The value of C_2 is calculated in QGIS. First of all, substations surrounding the modeled highway network are extracted using quickOSM with the formula 'power=substation'. Then, the data is cleaned to the node, line and polygon layers of substations. This process is similar to the data cleaning process when generating service area, hence omit this process. After that, use 'buffer' and 'clip' tools to eliminate substation nodes that are far away from the highway (10km away). The final distribution of substations within 10km of the highway network is pre-

sented in Figure 4.13. Finally, use the 'Distance to nearest hub' tool to calculate the shortest distance between the service area and the substation. The final C_2 value distribution of the 553 candidate sites is presented in Figure 4.13. It could be seen from the figure that the majority of the candidate sites are located close to a substation within 10km.

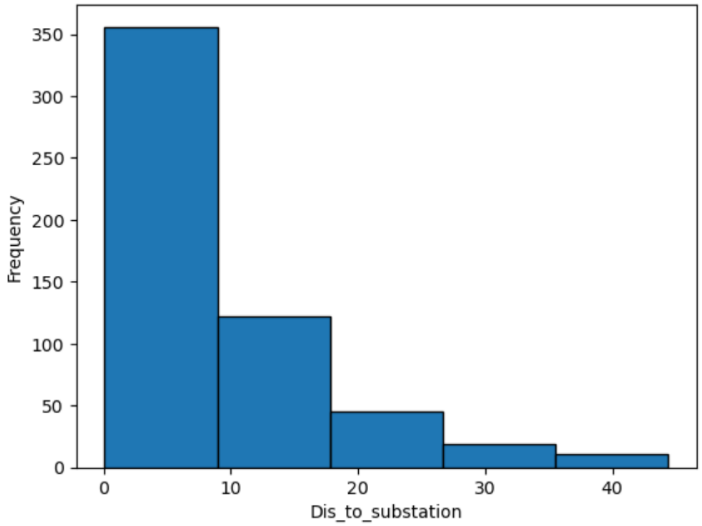


Figure 4.13: Histogram of C2 value distribution with frequency

C_3 represents the projected traffic volume for a specific road link within the highway network for the year 2030. Traffic volume on a road link refers to the total number of vehicles that pass through a specific section of the road during a given time period, measured in vehicles per year (VPY) in this case study. Considering that on-the-go charging stations are strategically situated along certain links in the traffic network, a significant portion of their charging demand originates from HDVs navigating these routes. Hence, the factor traffic volume could be used to evaluate the potential charging demand of an on-the-go charging station. The higher the traffic volume of HDVs passing through, the more charging demand being covered by an on-the-go charging station.

The raw dataset provides values for C_3, which includes columns for 'traffic volume in 2019' and 'traffic volume in 2030' within '4_network-edges'. Given that the 553 preliminary candidate sites have been mapped onto their closest highway network, as detailed in Chapter 4.2.2, each site is allocated traffic volume data corresponding to its respective link. For this study, the forecasted traffic volume for 2030 is utilized. The distribution of C_3 values across the 553 candidate sites is depicted in Figure 4.14. As observed from the figure, the majority of these sites experience an annual truck traffic of less than 8,000,000 vehicles.

Based on the distribution of the values C_1, C_2 and C_3, five ranges have been determined, with distinct scores assigned to each range. Each numerical interval is based on a quintile value between the minimum and maximum values of each scenario. The result is presented in Table 4.2. It should be noted that the score of $C2$ decreases inversely with its value, reflecting the preference against a candidate site as its distance to the substation increases.

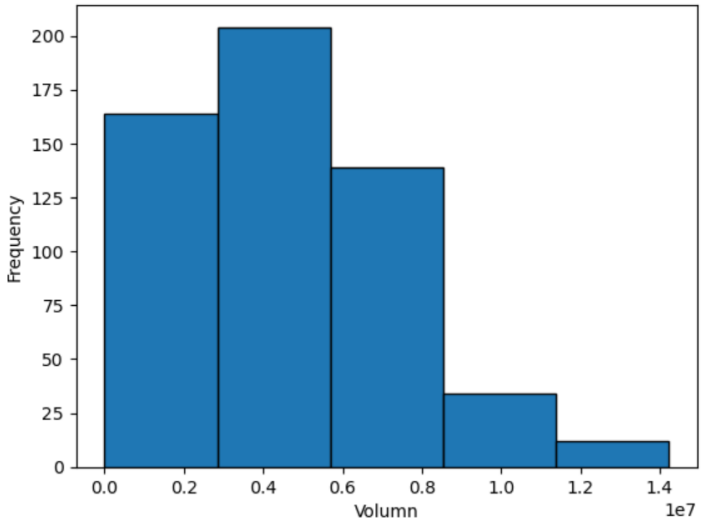


Figure 4.14: Histogram of C3 value distribution with frequency

Table 4.2: Scores for each range of criteria

Criteria/Range	C_1 (m^2)	C_2 (km)	C_3 $(VPY * 10^6)$
Score = 10	[420, 28497]	[35.543, 44,411]	[0.0, 2.85]
Score = 20	[28497, 56574]	[26.675, 35.543]	[2.85, 5.69]
Score = 30	[56574, 84651]	[17.808, 26.675]	[5.69, 8.54]
Score = 40	[84651, 112728]	[8.940, 17.808]	[8.54, 11.39]
Score = 50	[112728, 140805]	[0.073, 8.940]	[11.39, 14.23]

W_1, W_2 and W_3 refers to the weight of C_1, C_2 and C_3 respectively. Multiplying the weight with the score of the corresponding criteria to get the sub-score and then summing up all the sub-score to generate the final score for each candidate site. The weights are generated based on the results of the expert survey. The further results of MCDA are present in Chapter 5

A three-page survey was developed using Google Forms. The initial page introduces the study and collects data on the participants' professions. The second page provides detailed explanations of each criterion. Participants then select the most crucial criteria for determining on-the-go HDV charging station locations. They are subsequently asked to rate the importance of their chosen criterion relative to others, using a scale from 1 (equally important) to 9 (absolutely more important). In a similar fashion, participants identify the least significant criteria and rank other criteria's importance in comparison, using the same 1-9 scale. The concluding page extends gratitude to the respondents and invites comments and suggestions about the survey. The link to this survey is presented as follows: *Where to locate? Exploring the key factors that affect the location of on-the-go HDV charging stations*.

An expert in the field of charging station design industries took the survey. The inputs of the survey and corresponding weight values are presented in Figure 4.15 as shown below, the most important criteria that the participant chooses is C_1, while the least important criteria being chosen is C_3. The resulting outcome of W_1, W_2 and W_3 are 0.6, 0.25 and 0.15 respectively. Since the value of input-based CR is lower than the associated threshold, the pairwise comparison consistency level is acceptable. Note that one expert is chosen to be the input of

Criteria Number = 3	Criterion 1	Criterion 2	Criterion 3
Names of Criteria	Size	Dis_substation	Traffic volume

Select the Best	Size

Select the Worst	Traffic volume

Best to Others	Size	Dis_substation	Traffic volume
Size	1	3	5

Others to the Worst	Traffic volume
Size	3
Dis_substation	2
Traffic volume	1

Weights	Size	Dis_substation	Traffic volume
	0.6	0.25	0.15

Input-Based CR	0.1
Associated Threshold	0.1354

The pairwise comparison consistency level is acceptable

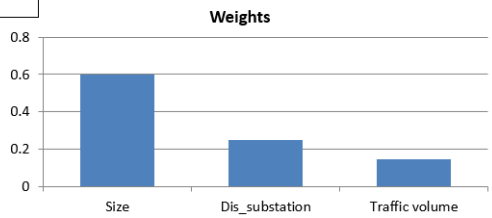


Figure 4.15: Results of BWM method

survey data in this study. The number of experts or different opinions will significantly impact the results. However, these results are supposed to be dynamic and should be varied according to the preferences of different stakeholders.

Parameters in stage 2

In the methodology's second stage, the Expanded network-based FRLM optimization is pivotal. As elaborated in Chapters 3.3 and 3.4, various parameters, including P, R, and Cap_i, must be delineated. This section will delve into the detailed configuration of each parameter. Distinct combinations of these parameters will form various scenarios for observation.

P represents the total number of on-the-go charging stations planned for construction. It influences the decision variable $y = 1$ in the optimisation model. For this study, the value of P is determined based on the anticipated penetration rate of HDV on-the-go charging stations by 2030. This penetration rate is categorized into low, medium and high levels. The corresponding values for each level are presented in Table 4.3. The total number of charging stations slated for construction is derived by multiplying the total number of candidate sites by the penetration rate. Given that there are 553 initial candidate sites in this study, this implies that 10, 30, and 50 charging stations are earmarked for 2030 under the assumptions of low, medium, and high penetration rates, respectively.

Table 4.3: Assumption of the penetration rate of en-route HDVs charging station in 2030

Penetration rate	Low	Medium	High
Value	2%	5%	10%

R denotes the projected range of HDVs by 2030. It's assumed that all HDVs within the charging network will share a common range. R plays a pivotal role in the creation of the En-route expanded network. The determination of R hinges on the current HDV range combined

with anticipated future technological advancements. Table 4.4 showcases five of the latest HDV brands currently available, reflecting the present state of bulk energy storage technology. Extrapolating from these current ranges, we project HDV ranges of 400km, 550km, and 700km by 2030, under low, medium, and high technology development scenarios, respectively.

Table 4.4: Ranges of current mainstream electric HDVs on sales, Source: Fischer (2022)

Brand	Model	Range
Chevrolet	Silverado EV	up to 550 km
Ford	F-150 Lightning	300-500 km
GMC	Sierra EV	up to 400 km
Rivian	R1T	300-400 km

Based on the combination of different P and R, 9 scenarios are created. The formulation is presented in Table 4.5.

Table 4.5: Scenario setting

Scenario	P	R(km)
1	10	400
2	30	400
3	50	400
4	10	550
5	30	550
6	50	550
7	10	700
8	30	700
9	50	700

The last parameter to be introduced is Cap_i, which refers to the capacity of candidate site i. Capacity is the maximum number of HDVs that can be charged in the unit of time. It is calculated based on the Formula 4.1 shown as follows:

$$\text{Cap}_i = C_1^i \times \frac{\alpha}{\theta} \tag{4.1}$$

where α is the parking area ratio and θ is the unit size of a HDV parking lot.

No established design guidelines for service areas on highways in the EU were found. Factors such as the layout of the service area and the arrangement of parking lots play a role in determining parameters α and θ. Based on empirical observations, α is set at a value of $1/3$ and θ is derived from the design layout of a truck parking lot construction company, which is $19 * (3.3 + 4.5)m^2$, as depicted in Figure 4.16. It's assumed that parking areas for HDVs adopt a parallel design.

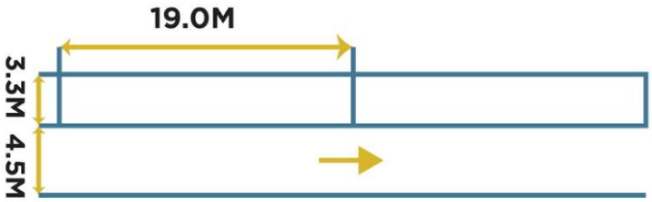


Figure 4.16: Unit size of a parking area, Source: *Truck Parking Layout & Dimension* (2022)

5

Result Analysis

In this chapter, the results analysis of case study 1 and case study 2 are presented. For case study 1, the result analysis includes general objective values and flow coverage rate, an example of en-route expanded network formulation and the location of charging stations when the range of HDVs is 100km and 10 charging stations are planned to be built. The contribution of case study 1 is not only to prepare for case study 2 but also to prove the value of the framework for further tasks. For case study 2, the results include the analysis of MCDA results, the en-route expanded network results, the optimisation results of nine scenarios, the computational performance of the proposed methodology and the comparison of the proposed methodology with other benchmark methodologies.

5.1. Results of case study 1

The optimization model is programmed using Python and solved by Gurobi Optimizer Version 10.0.0. The solving time of the En-route expanded network based FRLM model ranges from 1s to 5s. Three different optimization scenarios were tested, with the range of HDVs set at 25km, 50km, and 75km, respectively. Note that these values are not realistic ranges. They are just being set for testing purposes and proportional to the network size. The number of charging stations to be built (p) was varied from 1 to 14. The flow covering rate was calculated for each scenario, and the results are shown in Figure 5.1. The results demonstrate that the flow covering rate increases as the number of charging stations increases. Additionally, for the same number of charging stations, a higher driving range for HDVs leads to a higher flow covering rate. These findings align with our initial expectations.

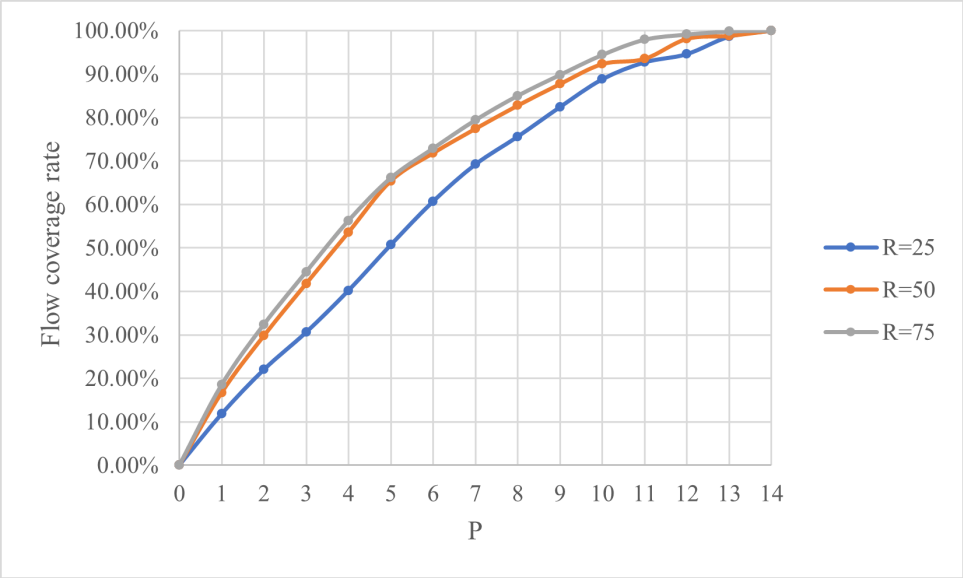


Figure 5.1: The trade-off between the number of charging stations and flow covering rate

To provide a better understanding of where charging stations should be located, Figure 5.4 displays the outcome for a scenario in which the range of HDVs is 100km and 10 charging stations are to be constructed. It is worth noting that the green circles in the figure depict the optimal charging station locations. In order to better explain the mechanism of the En-route expanded network based FRLM model, the result of OD pair 7 is proposed and its trajectory is represented by purple dashed lines. As shown in Figure 4.2 and Figure 5.4, OD pair 7 starts at node 0 and ends at node 6. During the journey, it passes through 4 links including link 0 (node 0 to node 6), link 6 (node 6 to node 3), link 7 (node 3 to node 8) and link 5 (node 8 to node 2). The candidate sites on each of the links are $c1$, $c7$, $c8$ and $c6$ respectively. Based on the coordinates in Figure 4.1b and the generation algorithm, the En-route expanded network of trip 7 is presented in Figure 5.3. Similar to the example in Figure 3.3, different colors of arcs represent different steps. After the optimisation, the results of the selected arcs for OD pair 7 are presented in Figure 5.3. Note that only two arcs are selected. This result illustrates that all the vehicles following the path of OD pair 7 will charge at the charging station at node $c8$ and continue their journey to the destination without running out of battery.

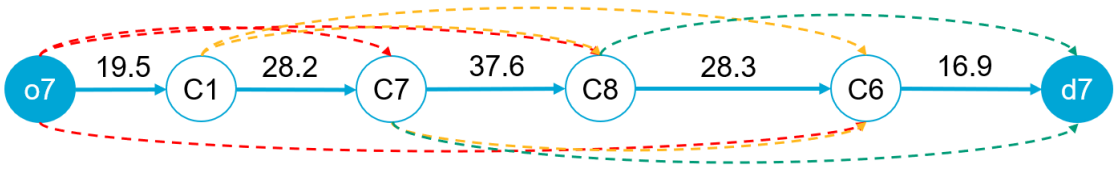


Figure 5.2: The En-route expanded network of OD pair 7

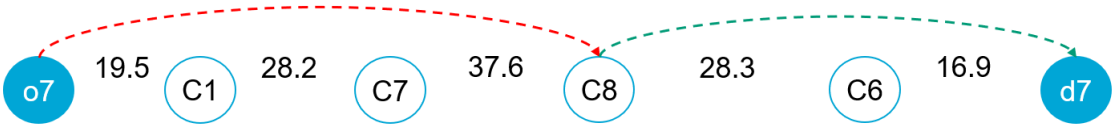


Figure 5.3: Optimised results of charging behaviour of OD pair 7

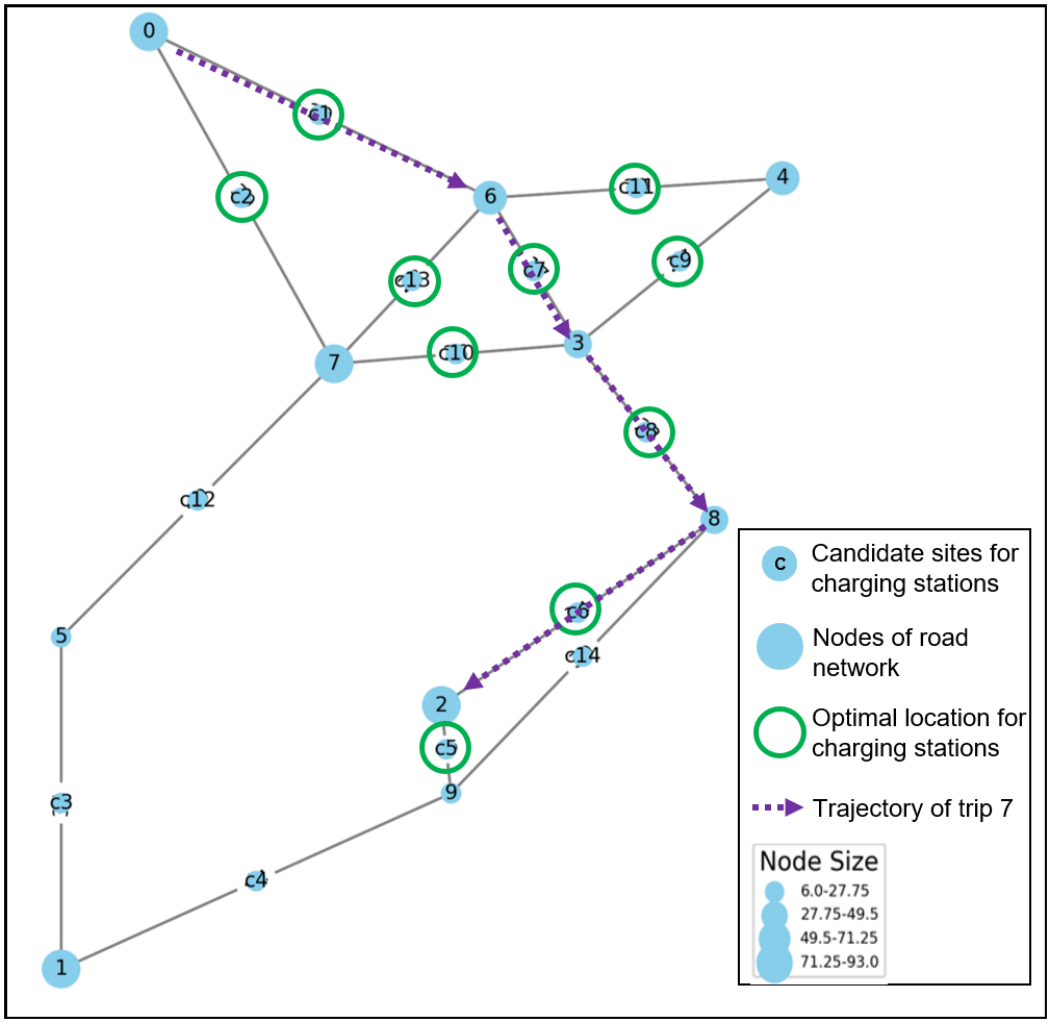


Figure 5.4: Optimal solution for charging stations location when R=100km and p=10

5.2. Results of case study 2

In this chapter, the results of the case study 2 across nine scenarios are presented and analysed. Additionally, the sensitivity analysis of the MCDA in the methodology's initial stage is conducted. The performance of the En-route expanded network-based FRLM optimization, both with and without MCDA as a preliminary step, is also assessed. The structure of the following sections is outlined as follows:

- **Chapter 5.2.1**: The analysis of MCDA results, which includes the analysis of the results from expert survey scenario and the sensitivity analysis of MCDA which is undertaken across seven scenarios.
- **Chapter 5.2.2**: The analysis of the en-route expanded network results, which includes

the comparison between several indicators across three scenarios with different ranges.

- **Chapter 5.2.3**: The detailed analysis of the optimisation results of nine scenarios which include the location of the charging network, the load of each charging station and the load capacity rate of each charging station.
- **Chapter 5.2.4**: The performance of the proposed methodology is evaluated. The computational times are recorded and compared based on different volumes of inputs from the MCDA step.
- **Chapter 5.2.5**: The performance of the proposed methodology is compared with other benchmark methods which include randomly chosen methods, Top criterion methods and the solely MCDA methods.

Each scenario is run on an AMD Ryzen 7 5800H with Radeon Graphics (instruction set [SSE2|AVX|AVX2] Thread count: 8 physical cores, 16 logical processors, using up to 16 threads). The optimization model is programmed using Python and solved by Gurobi Optimizer Version 10.0.0. The solving time of the En-route expanded network based FRLM model ranges from 50s to 2000s according to the amount of data inputs.

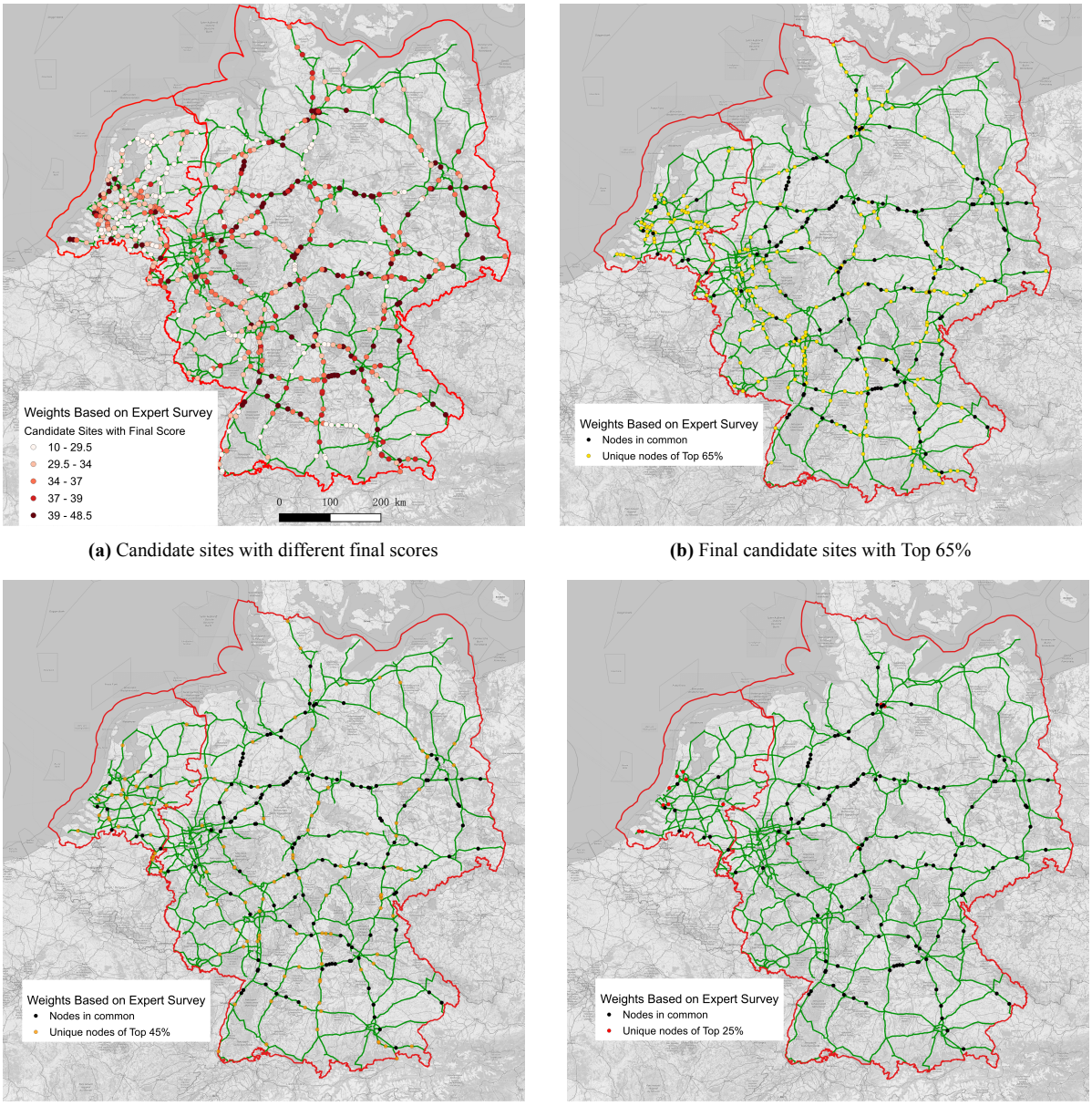
5.2.1. MCDA Results

In this section, the results from the expert survey scenario are first presented, where the weight of each criterion is determined by the BWM. The results include the final score distribution of each candidate site and the location of final candidate sites based on different filtering rates. Then, the results from the sensitivity analysis of MCDA are illustrated, where the weight of each criterion is classified into seven scenarios (expert survey scenario included). The final score distributions and the location of the final candidate sites will be compared among different scenarios in order to find out the effect of different weights.

Results from expert survey scenario

As explained in Chapter 4.2.3, the final outcome of weights for the Size of the service area(C_1), Distance to substation(C_2) and Traffic volume(C_3) are 0.6, 0.25 and 0.15 respectively. Multiplying the weight with the score of the corresponding criteria to get the sub-score and then summing up all the sub-score to generate the final score for each candidate site. The final score distribution of each candidate site is presented in Figure 5.6a. The majority of the candidate sites have a final score that ranges from 17 to 30.

To further analyse the results of the expert survey based on BWM, the location of initial candidate sites is displayed with different colors representing a different range of final scores as shown in Figure 5.5a. Then, a ranking and filtering process is conducted, where the final candidate sites are reserved from the top 65% (360 nodes), 45% (250 nodes) and 25% (140 nodes) of the final score ranking as shown in Figure 5.5b, Figure 5.5c and Figure 5.5d respectively. Note that the black nodes in the figures represent the common nodes of the final candidate sites under the different filtering rates. These figures illustrate that as the filtering rate increases, the density of the candidate sites decreases and the location of the candidate sites is distributed evenly across the whole highway network.



(a) Candidate sites with different final scores

(b) Final candidate sites with Top 65%

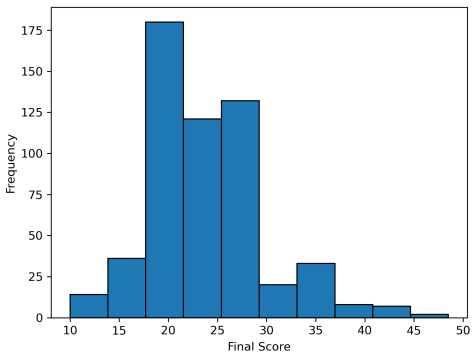
(c) Final candidate sites with Top 45%

(d) Final candidate sites with Top 25%

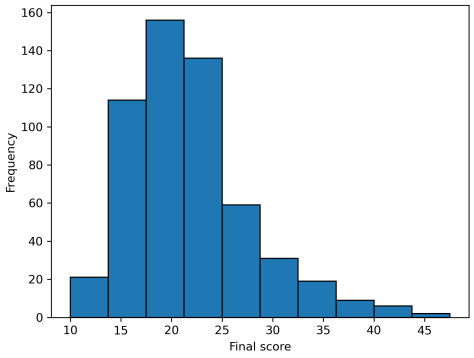
Figure 5.5: Location of final candidate sites based on expert survey

Results from sensitivity analysis of MCDA

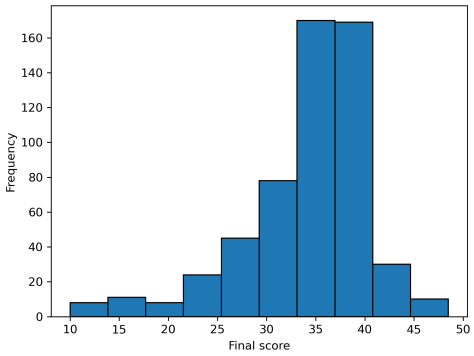
As highlighted in Chapter 4, an expert survey was conducted to determine the weight of each criterion using the BWM principle. However, the certainty of the MCDA producing distinct candidate sites based on varied weight combinations remains unclear. Consequently, to assess the efficacy of MCDA as the preliminary stage in the methodology, a sensitivity analysis was carried out across seven scenarios. The weight ratios for these scenarios are detailed in Table 5.1. The first six scenarios were arranged according to the relative magnitudes of the three criteria, while the seventh scenario was designed under the assumption of equal weighting. The outcome of the final score distribution for these seven scenarios is displayed in Figure 5.6.



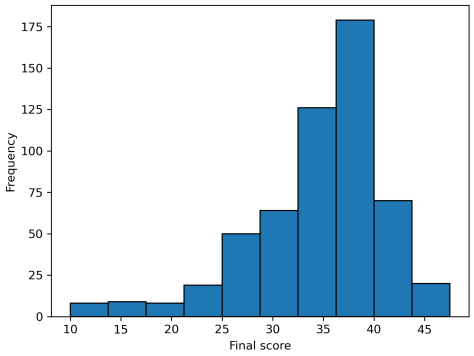
(a) Scenario 1



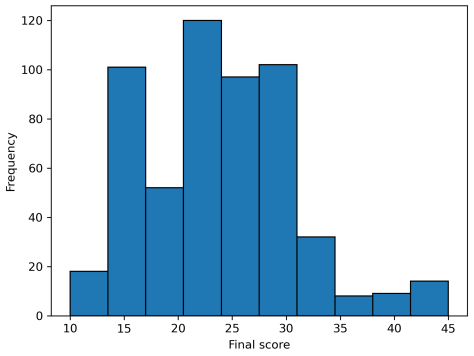
(b) Scenario 2



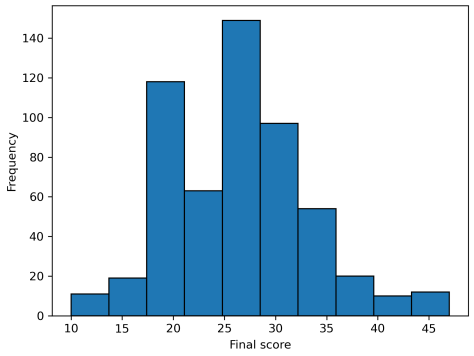
(c) Scenario 3



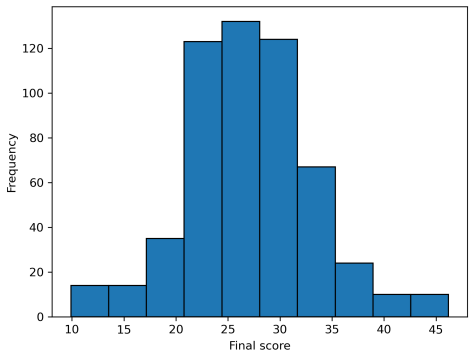
(d) Scenario 4



(e) Scenario 5



(f) Scenario 6



(g) Scenario 7

Figure 5.6: Sensitivity analysis of 7 scenarios

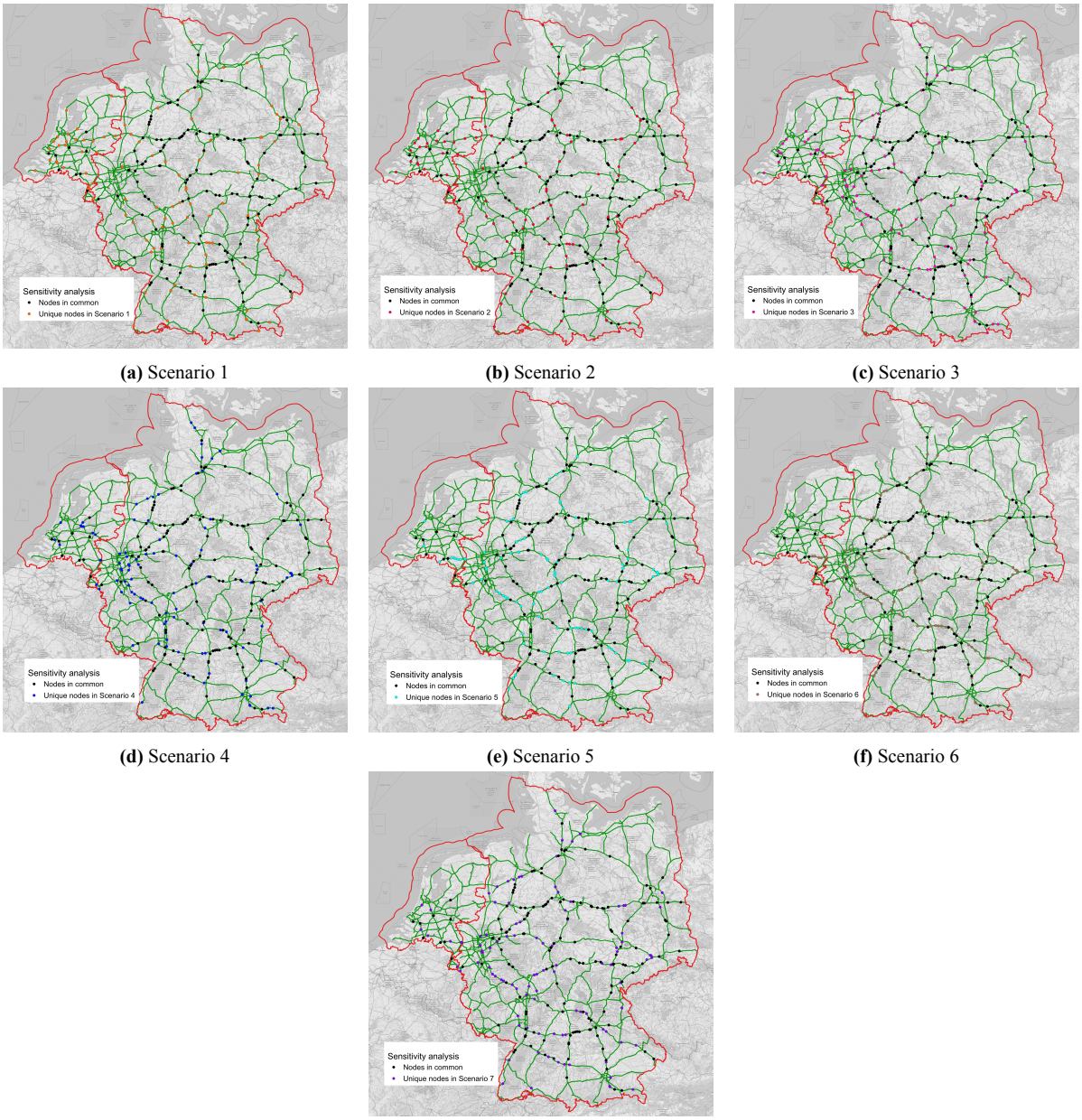
Table 5.1: Sensitivity analysis scenario settings

Scenario/weight	C1	C2	C3
1(Expert Survey)	0.60	0.25	0.15
2	0.60	0.15	0.25
3	0.25	0.60	0.15
4	0.15	0.60	0.25
5	0.25	0.15	0.60
6	0.15	0.25	0.60
7	0.33	0.33	0.33

When comparing the sub-figures in each row, similarities in the distribution patterns can be clearly observed. More precisely, the majority of the final scores in scenarios 1 and 2 are found between 15 and 30, while those in scenarios 3 and 4 predominantly fall between 30 and 40. In scenarios 5 and 6, the bulk of the final scores are distributed more evenly and again cluster between 15 and 30. This phenomenon can be attributed to the fact that each row of the two scenarios is dominated by one criterion. This implies that the value distribution of the dominant criterion would heavily influence the resulting final score. In scenario 7, where all three criteria are deemed equally important, the majority of the final scores are situated within the 20 to 30 range. This falls in the central interval of the final score ranges, and the pattern adheres to a normal distribution.

The top 45% of candidate sites based on the final score were selected in the seven scenarios. Out of the seven scenarios, 250 candidate sites were selected, and among these, 146 were commonly chosen. Although roughly 50% of the candidate sites were commonly selected across all six scenarios, the proportion of shared sites increased when just two scenarios were juxtaposed. For instance, 244 sites were shared between scenarios 1 and 2, 188 between scenarios 1 and 3, and 187 between scenarios 2 and 3, and so on.

From the sensitivity analysis, it can be inferred that varying preferences among the three criteria do not yield significantly different sets of initial filtered candidate sites under the BWM principle. A plausible explanation for this phenomenon might be that certain locations exhibit strong indicators across all three criteria, C_1, C_2, and C_3. In this case study, the metric quality distribution is not uniform. Support for this observation can be found by comparing the sub-figures in Figure 5.7 with the initial candidate sites in Figure 4.9. Notably, all sites in the six scenarios exclude those in the northern NL and the west-south of DE. Nonetheless, such observations pertain specifically to the case where C_1, C_2, and C_3 are the chosen criteria. If more or different criteria are proposed by other stakeholders in future studies, the outcomes may differ.



(a) Scenario 1 **(b)** Scenario 2 **(c)** Scenario 3

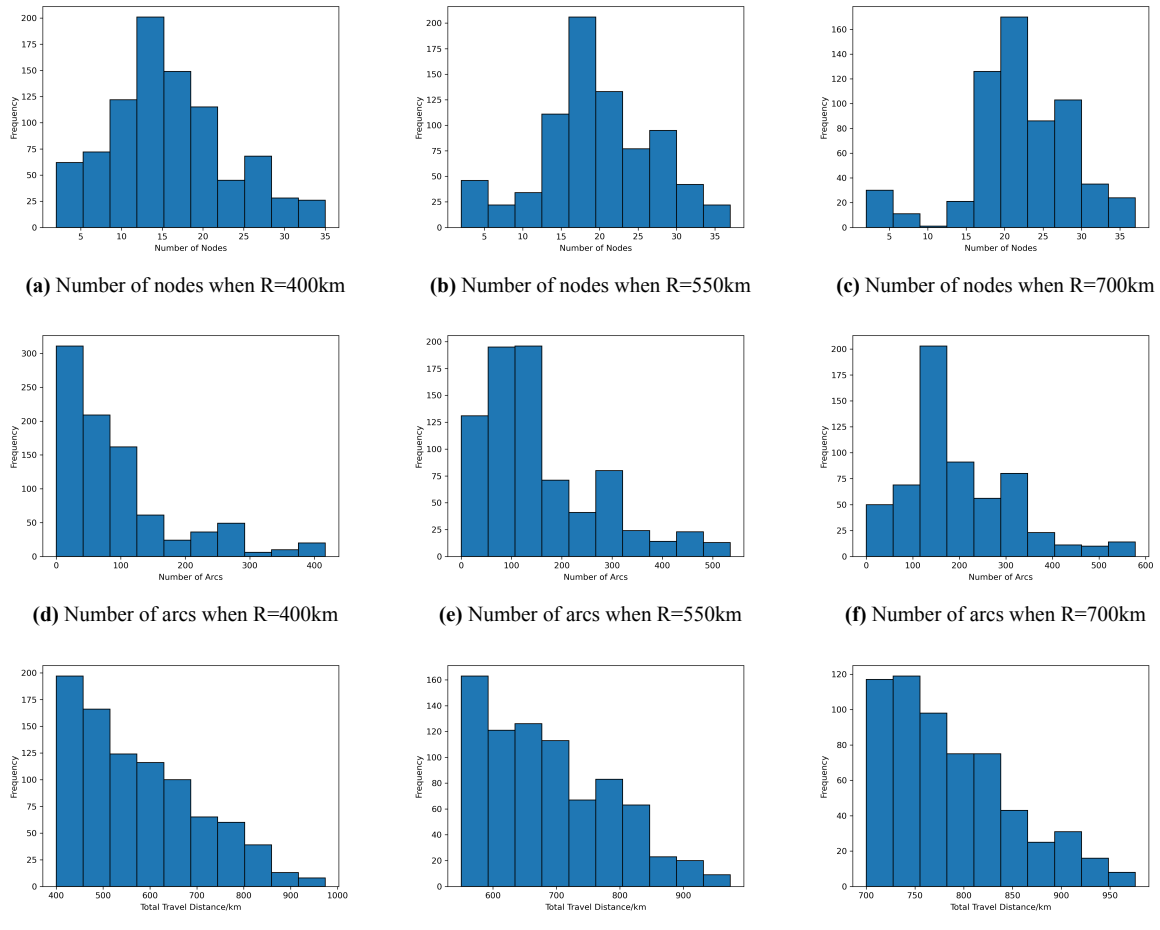
(d) Scenario 4 **(e)** Scenario 5 **(f)** Scenario 6

(g) Scenario 7

Figure 5.7: Candidate sites with 45% top scores in different scenarios

5.2.2. En-route expanded network results

As mentioned in Chapter 3.3, the generation of the en-route expanded network is the pre-processing step for the FRLM optimisation model. The en-route expanded networks generated can vary depending on the range of HDVs used. This is because two factors come into play. Firstly, the set of OD pairs changes with the range of HDVs. Secondly, the range of HDVs is a crucial parameter that affects the algorithm used to generate en-route expanded networks. Figure 5.8 presents the distribution of the number of nodes, arcs, and total distance. It's worth noting that the origin and destination nodes of each OD pair are included in the number of nodes. Furthermore, the adjacent arcs and those that connect the origin and destination nodes of each OD pair are excluded from the number of arcs.



(a) Number of nodes when R=400km **(b)** Number of nodes when R=550km **(c)** Number of nodes when R=700km

(d) Number of arcs when R=400km **(e)** Number of arcs when R=550km **(f)** Number of arcs when R=700km

(g) Total travel distance when R=400km **(h)** Total travel distance when R=550km **(i)** Total travel distance when R=700km

Figure 5.8: Results analysis of the En-route expanded network

To gain a better understanding of the findings from the en-route expanded network, additional indicators have been proposed. These indicators include the average number of nodes, the average number of arcs, the average distance of arcs, the average total distance of OD pairs, and the arc generation rate. Note that the arc generation rate is the average of the OD pair arc generation rate. OD pair arc generation rate is calculated using the number of arcs (without adjacent arcs and the origin-destination arc) divided by the maximum number of arcs that could be generated. Assuming that the maximum number of arcs of OD pair i is $Maxarcs_i$ and the

number of nodes of OD pair i is N_i. Then, the formula is presented as follows. Note that $C_{N_i}^2$ represents the number of choices if choosing 2 elements from N_i elements without order.

$$Maxarcs_i = C_{N_i}^2 - N_i = \frac{{N_i}^2 - 3N_i}{2} \tag{5.1}$$

The results are presented in Table 5.2. As the range of HDVs increases, the number of Origin-Destination (OD) pairs decreases. This results in an increase in the average total distance and the number of nodes, as the OD pairs with a total travel distance lower than the range of HDVs are eliminated. The other indicators related to arcs increase proportionally with the range of HDVs. This is because a higher range generates more connection choices according to the algorithm. In reality, this phenomenon reflects the true nature that drivers with a higher range have more charging options. Therefore, the result aligns with the initial theoretical expectations as well as the real-life situation.

Table 5.2: Results analysis of En-route expanded network for scenarios where R=400km, 550km and 700km

R (km)	Number of ODs	Avg.Number of Nodes	Avg.Number of Arcs	Arc Generation Rate	Avg.Distance of arcs (km)	Avg.Total Distance (km)
400	888	15.80	93.85	72.81%	200.81	576.78
550	788	19.25	153.21	81.54%	247.58	687.26
700	607	21.67	199.29	87.16%	293.05	786.47

5.2.3. FRLM based optimisation results

As mentioned in Chapter 4.2.3, nine scenarios are set based on the level of electric HDV technology development and the penetration rate of on-the-go HDV charging stations. 250 candidate sites served as the input of the model after selecting the top 45% of the initial candidates based on the expert survey. The detailed formation of the nine scenarios is shown in Table 4.5 and the optimisation results of the en-route expanded network based FRLM model is presented in Table 5.3. The number of HDVs' OD trips decreases as the range of HDVs increases from 400km to 700km. This is due to the reason that the OD trips with travel distances lower than the range of HDV would not generate its corresponding en-route expanded network. Hence, more OD trips have been eliminated from the input data as the driving range increases.

As shown in the table, 'ObjVal' stands for the value of the objective function, representing the total number of traffic flows or the number of HDVs covered by the optimized charging network. Essentially, this figure indicates the number of HDVs that can complete their journeys without depleting their batteries due to the provided charging network. Even though the 'ObjVal' for $R = 700km$ is lower than the value when $R = 400km$, it is not accurate to claim that the same number of charging stations serve fewer HDVs when HDVs have an extended range. This is the outcome of technology development that fewer charging stations are needed when HDVs have a higher range. Hence, in order to evaluate the real effectiveness of charging stations, the flow coverage rate is proposed and it is calculated by the number of HDVs being covered divided by the total number of HDVs in the highway network. Similarly, 'No.OD

Table 5.3: Results of the NL and DE HDVs charging network for R ranging from 10 to 50 and P set to be 400km, 550km and 700km

	R=400(Number of ODs=888)				R=550(Number of ODs=788)			
p	ObjVal	Flow coverage rate	No.OD trips covered	OD trip coverage rate	ObjVal	Flow coverage rate	No.OD trips covered	OD trip coverage rate
10	619562.50	30.94%	257	28.94%	635202.50	54.91%	446	56.60%
20	1016250.71	50.75%	404	45.50%	945940.00	81.78%	631	80.08%
30	1228037.50	61.33%	535	60.25%	1085060.00	93.81%	745	94.54%
40	1259158.13	62.87%	561	63.18%	1086176.37	93.90%	748	94.92%
50	1295408.75	64.68%	581	65.43%	1086468.75	93.93%	749	95.05%
	R=700(Number of ODs=607)							
p	ObjVal	Flow coverage rate	No.OD trips covered	OD trip coverage rate				
10	542222.50	91.01%	553	91.10%				
20	569747.69	95.63%	592	97.53%				
30	592761.25	99.49%	604	99.51%				
40	592761.25	99.49%	604	99.51%				
50	592761.25	99.49%	604	99.51%				

trips covered' refers to the number of OD trips that are covered by the charging network, while 'OD trip coverage rate' is the percentage of OD trips that are covered among all the OD trips in the network. It is calculated by the number of covered OD trips divided by the total number of OD trips in the network.

A comparison of the flow coverage rate across scenarios with different ranges R=400km, R=550km and R=700km is presented in Figure 5.9. It is obvious that the flow coverage rate increases as the range of HDVs increases under the same value of P, where P represents the number of charging stations planned to be built. This outcome underscores that as the range of HDVs expands, there's a reduced need for charging stations.

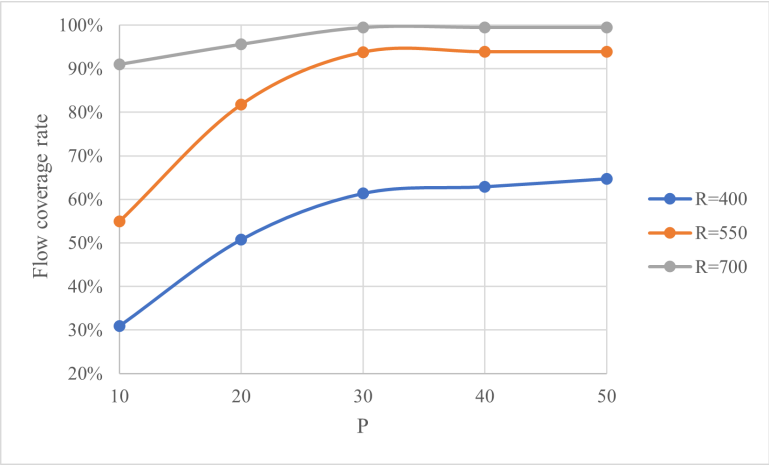


Figure 5.9: Flow coverage rate comparison across with R=400km, R=550km and R=700km

Detailed analyses for scenarios with different ranges where R=400km, R=550km and R=700km are provided in the following article. These analyses encompass the geographical positioning of the optimized charging networks, the demand loads at these charging stations, and the respective load capacity ratios of the stations.

The yellow nodes on the map correspond to charging stations, with each being surrounded by a white circle that represents the annual charging load. The radius of the circle indicates the magnitude of the charging demand – larger circles represent a higher demand for charging. The value is classified into 5 ranges: 0-20000, 20000-40000, 40000-60000, 60000-80000 and 80000-100000 (unit: $Veh/year$). Each range is represented by a circle with different radii. It is calculated by summing the total number of HDVs that stop and charge at a certain charging station in a period of time. The red heatmap underneath each node symbolizes the load capacity ratio for the respective charging station, computed by dividing the load by the station's capacity. A value of 1 signifies that the station's capacity is fully utilized.

Scenarios when R=400km

Compared with the results of scenarios where the range of HDVs is set to be 400km under low technology development assumption, the flow coverage rate and OD trip cover rate are extremely low when 10 charging stations are built. As the number of charging stations increases, the flow coverage rate and OD trip cover rate increase accordingly. When the number of charging stations to be built is $P = 50$, there are still around 40% of the number of HDVs and trips that are not being covered.

The location of the charging networks with 10, 30 and 50 charging stations are presented in Figure 5.10, Figure 5.11 and Figure 5.12 as yellow nodes. With a mere 10 stations slated for construction, the majority are strategically positioned along the A1 and A2 highways situated in central Germany, notably at points $C327$,$C331$ on A1 and $C422$,$C323$ on A2. A few are strategically placed along the A4 highway near Aachen (specifically at $C489$) and on the A61 highway in proximity to Pfeddersheim (at $C415$). As the number of charging stations increases, the charging network expands eastwards along the A1 and A2 highways, while stations radiate north and south from Aachen along the A4 highway. When 10 charging stations are planned to be built, the Netherlands remains devoid of any charging stations. But as the number of charging stations increases, stations begin to dot the Netherlands, primarily along A16, A27, A28 and A67 highways. This is due to the reason that highways in NL are located at the edge of the whole network and the charging stations tend to be located at the central parts of the highway network when fewer charging stations are built. However, comparing the distribution of charging stations in Germany and the Netherlands, the latter sees a more balanced dispersal across various highways. In contrast, Germany's stations appear to be located primarily towards its main highways.

For the annual load of the charging network, when 10 charging stations are planned to be built, the majority of the charging demand is concentrated along A1 and A2 highways in the middle of Germany. Specifically, these areas are centered around stations $C327$,$C331$ on A1, as well as stations $C422$,$C323$ on A2. A smaller demand for charging is observed near the A4 highway, close to Aachen, specifically at station $C489$. As the number of charging stations increases, more areas of charging demand become active within the Netherlands. Moreover,

there is a notable surge in charging demand along the A4 highway, extending towards the northern regions. While the growth in the number of stations leads to increased charging demand along the A1 and A2 highways, the rate of increase is not as significant in comparison.

For the load capacity ratio of the charging network, when $P = 10$, the stations primarily positioned along the A1 and A2 highways exhibit the highest load capacity ratios. As the number of charging stations being built P increases, the load capacity ratios for these stations remain elevated, regardless of the burgeoning number of adjacent stations. For other stations, the load capacity increases as the number of stations increases (e.g., $C489$ close to Aachen). This illustrates the pressing need for charging, as even a network encompassing 50 stations proves insufficient in meeting the charging requirements when the HDVs' range is limited to 400km.

In conclusion, when the number of charging stations P increases under the low technology development assumption, the location of the charging stations tends to spread out to the end of the network. However, the load capacity ratio of the stations could not be reduced as the number of stations increased. This is because even though more charging stations have been built along the highway, it is still not enough to support the total charging demand since HDVs with low range need to charge more frequently.

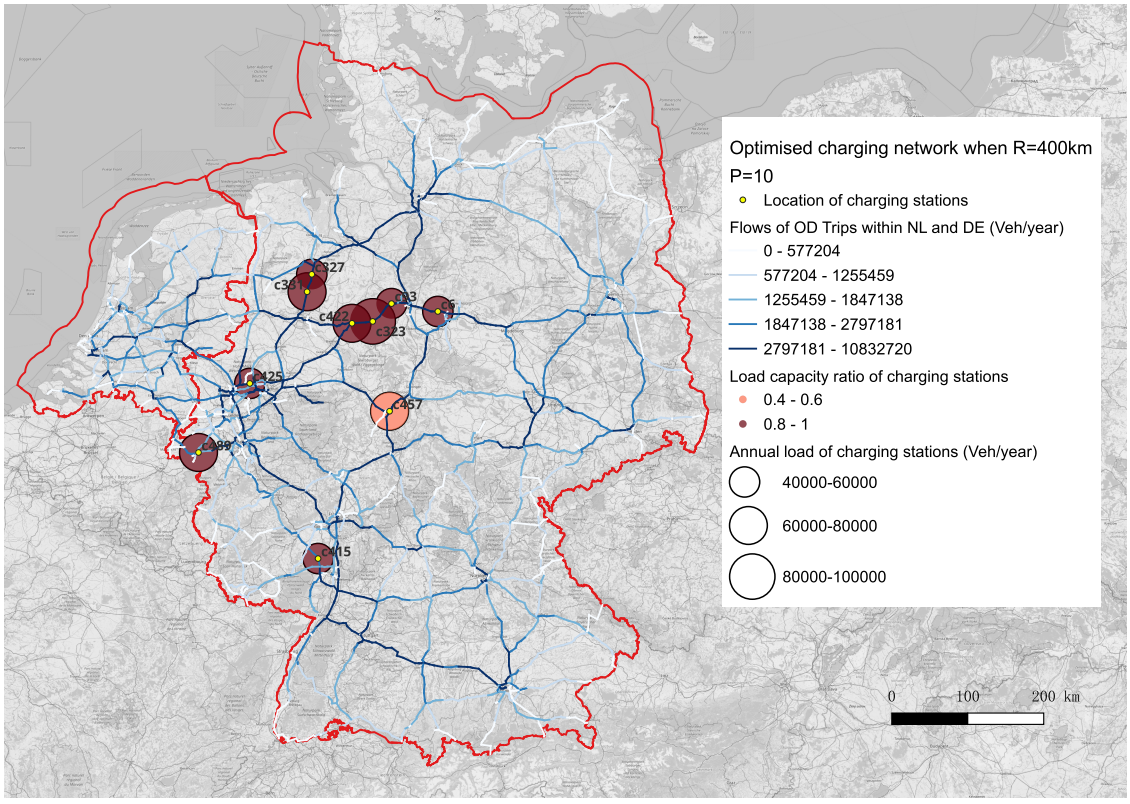


Figure 5.10: Result analysis for scenario 1, where P=10 and R=400km

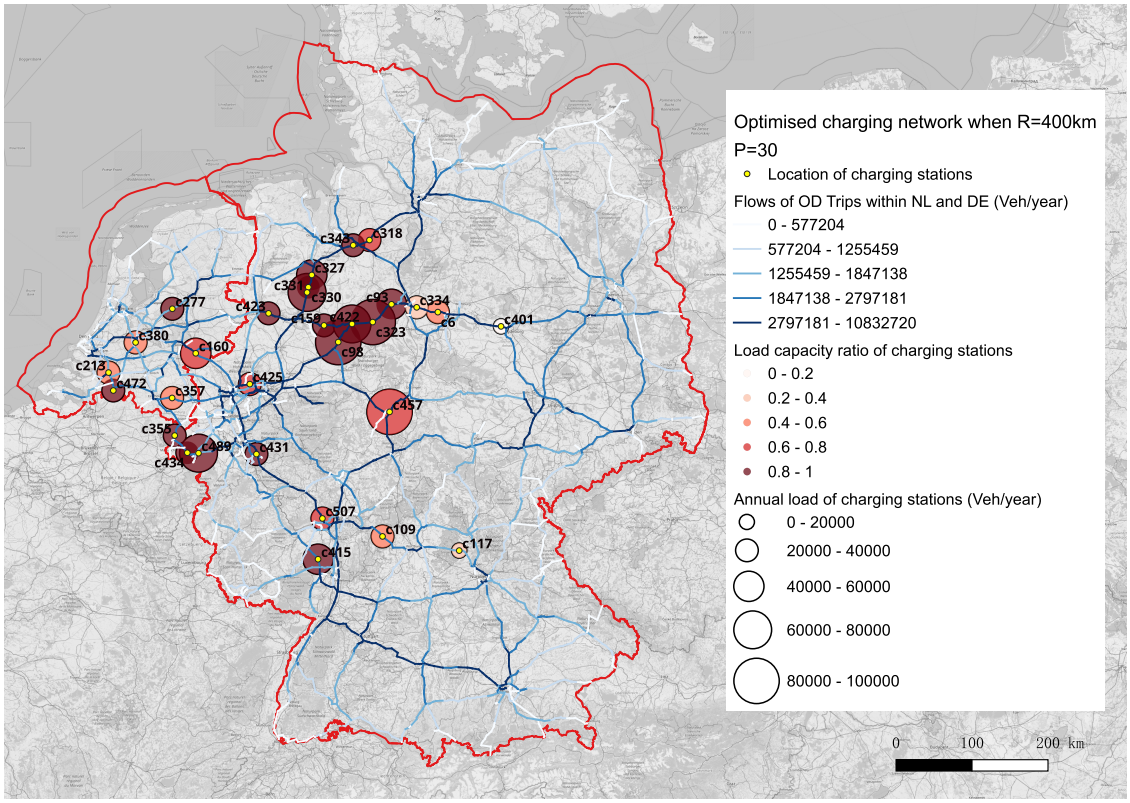


Figure 5.11: Result analysis for scenario 2, where P=30 and R=400km

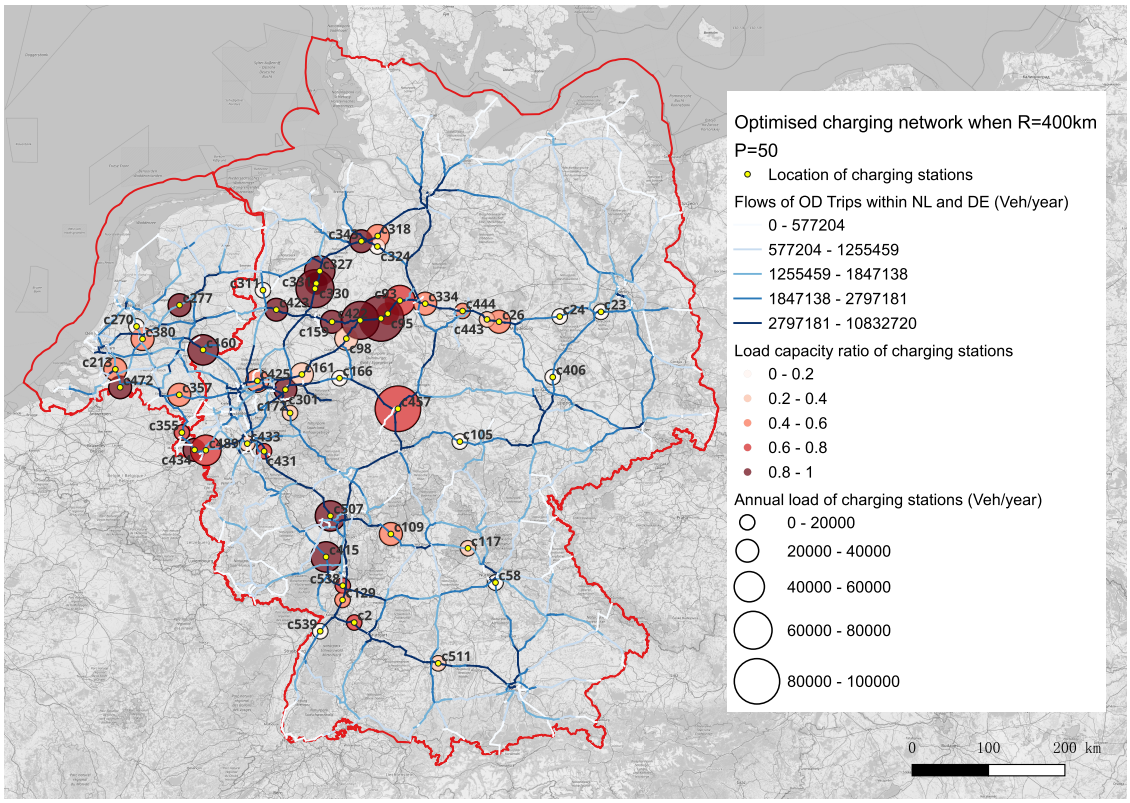


Figure 5.12: Result analysis for scenario 3, where P=50 and R=400km

Scenarios when R=550km

Compared with the results of scenario 4, 5 and 6 where the range of HDVs is set to be 550km under medium technology development assumption, the flow coverage rate and OD trip cover rate is low (around 30%) when 10 charging stations are built. As the number of charging stations increases, the flow coverage rate and OD trip cover rate increase accordingly. When the number of charging stations is 50, most of the charging demand in the network has been covered.

The location of the charging networks with 10, 30 and 50 charging stations are presented in Figure 5.13, Figure 5.14 and Figure 5.15 as yellow nodes. With a mere 10 stations slated for construction, nearly half of the stations are strategically positioned along A2 highways situated in central Germany, notably at points $C422$, $C323$, $C302$ and $C334$ on A2. The other half are strategically placed along the A3 and A61 highway at the south part of the highway network in Germany ($C415$,$C507$,$C109$ and $C117$). All the charging stations are located within Germany. As the number of charging stations increases, more charging stations dot inside the Netherlands along the A16, A27, A28 and A67 highways. In the southern part of Germany, more charging stations appear along A5 ($C8$,$C129$), A8($C545$,$C139$) and extend along A3 highway ($C109$ to $C58$). In the northern part of Germany, stations extend westbound and reach the end of the A2 highway inside Germany($C351$), while more stations appear along the A1 highway ($C330$ to $C84$) which is located the north of A2 highway.

For the annual load of the charging network, when the number of charging stations is 10, the majority of the charging demand is concentrated along A2 highways in the middle of Germany. Specifically, these areas include station $C422$ and $C323$ on A2. A smaller demand for charging is observed along the A3 and A61 highways at the southern part of the highway network in Germany ($C415$,$C507$,$C109$ and $C117$). As the number of charging stations increases, more areas of charging demand become active within the Netherlands. Moreover, there is a notable surge in charging demand along the A8 and A3 highways, extending towards the southern and south-eastern regions respectively.

For the load capacity ratio of the charging network, when $P = 10$, the stations primarily positioned along the A2 highways exhibit the highest load capacity ratios. As the number of charging stations planned to be built P increases, the load capacity ratios for these stations are reduced and the charging pressure is released, due to the burgeoning number of adjacent stations. For other stations along the A5 highway, the load capacity increases as the number of stations increases ($C8$ and $C129$). However, this is due to the reason that these two stations have a low capacity since the charging demand is low.

In conclusion, when the number of charging stations P increases under the medium technology development assumption, the location of the charging stations tends to spread out to the end of the network. Besides, the load capacity ratio of the stations could be reduced as the number of stations increases. This is because more charging stations have been built along the highway, which has helped alleviate the charging demand pressure that previously existed on the charging stations.

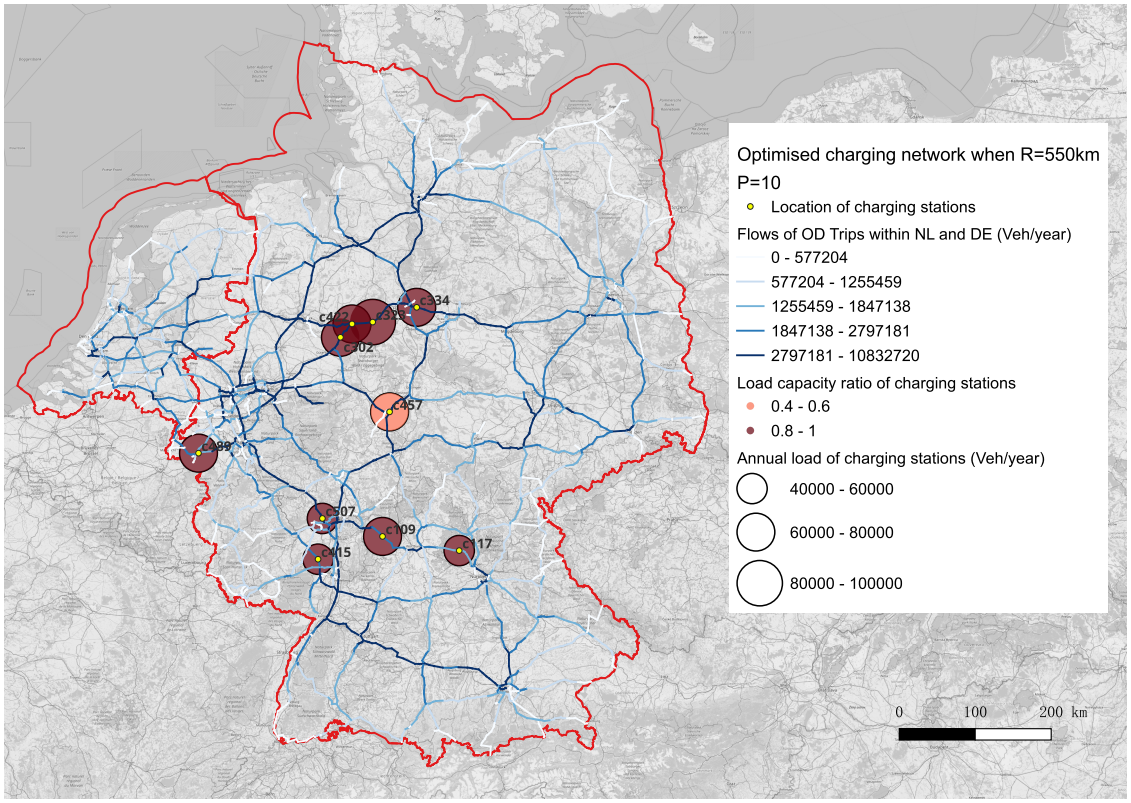


Figure 5.13: Result analysis for scenario 4, where P=10 and R=550km

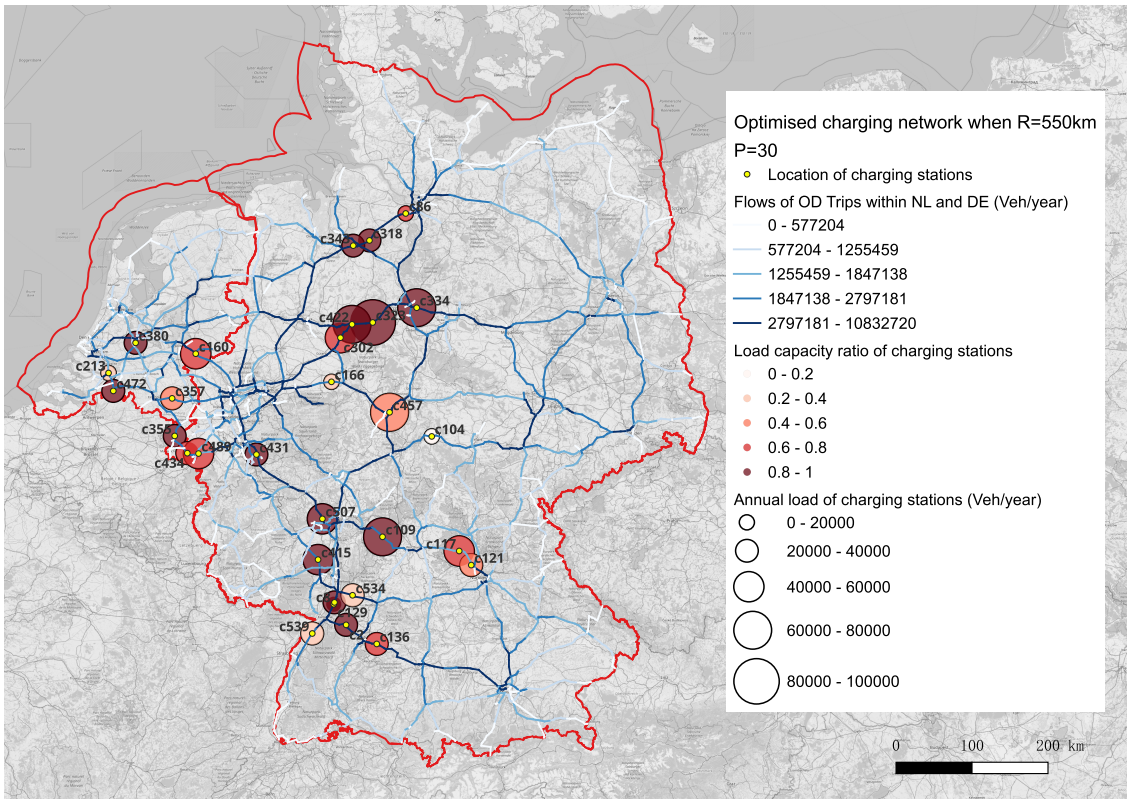


Figure 5.14: Result analysis for scenario 5, where P=30 and R=550km

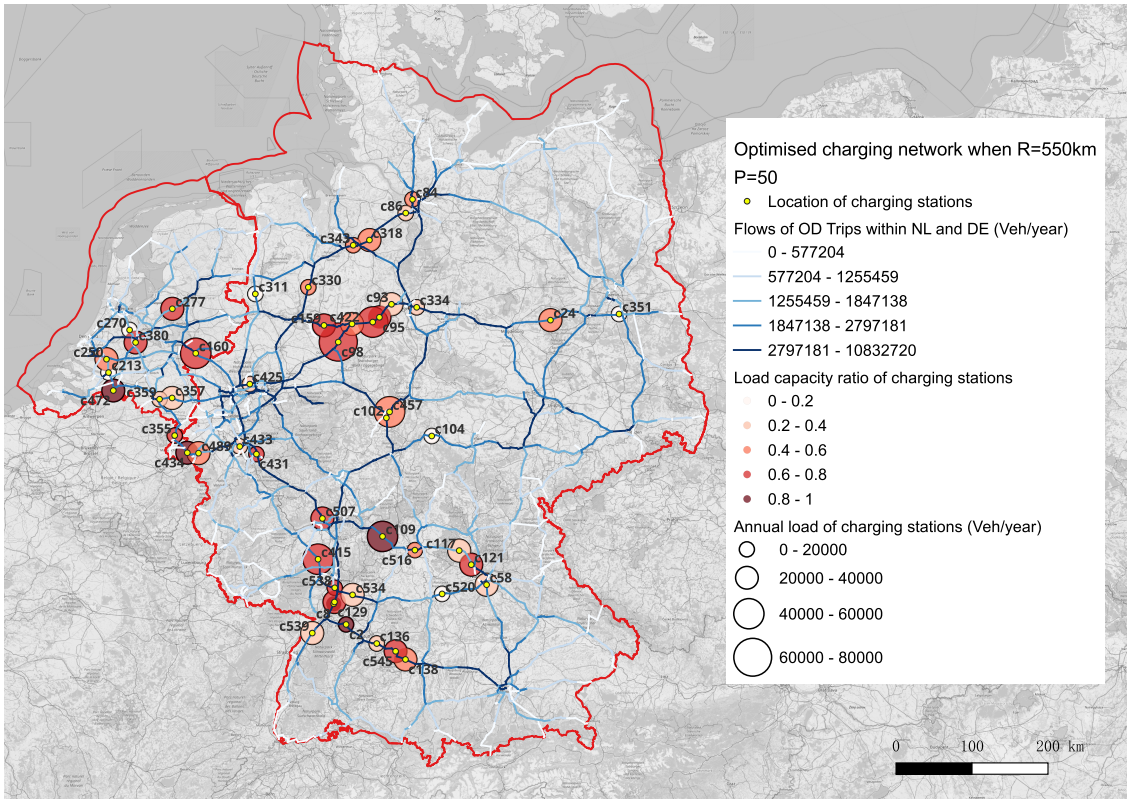


Figure 5.15: Result analysis for scenario 6, where P=50 and R=550km

Scenarios when R=700km

Compared with the results of scenarios where the range of HDVs is set to be 700km under high technology development assumption, the flow coverage rate and OD trip cover rate reach 90% even though only 10 charging stations are built. As the number of charging stations increases to 30, the charging demand is nearly fully covered.

The location of the charging networks with 10, 30 and 50 charging stations are presented in Figure 5.16, Figure 5.17 and Figure 5.18 as yellow nodes. With a mere 10 stations slated for construction, the charging stations are located evenly in different parts of the highway network in Germany. As the number of charging stations increases, more charging stations dot inside the Netherlands. In the southern part of Germany, more charging stations appear along A5 ($C538$) and extend along the A3 highway ($C507$ to $C484$). In the northern part of Germany, stations extend westbound and reach the end of the A2 highway inside Germany($C23$). Surprisingly, the location of charging stations changes as P increases, which does not happen in the previous scenarios when $R = 400$ and $R = 550$. $C442$, $C323$, $C136$, $C138$ which were initially selected when 10 charging stations were planned to be built, remain to be selected when 30 stations, however, are eliminated when 40 stations are.

For the annual load of the charging network, when 10 charging stations are planned to be built, the majority of the charging demand is concentrated along A2 highways in the middle of Germany. Specifically, these areas station $C422$,$C323$ on A2. A smaller demand for charging is observed along the A3 and A61 highways at the southern part of the highway network in Germany ($C507$,$C121$,$C109$ and $C117$). As the number of charging stations increases, the

majority of the charging demands move to the west side of Germany which creates charging station lines from $C2$ to $C439$. Besides, the charging demand is activated in the southern area of the Netherlands.

For the load capacity ratio of the charging network, when 10 charging stations are planned to be built, the stations primarily positioned along the A2 highway($C422$ and $C323$) and along the A3 highway($C117$ and $C121$) exhibit the highest load capacity ratios. As the number of charging stations increases, the high load capacity ratios on the A2 highway are eliminated and moved to the west side of Germany. Unlike scenarios when $R = 550km$, the load capacity rates do not decrease as the number of charging stations increases. This could be explained that OD trips with travel distances higher than 700km are distributed on certain edges of the network and there are not enough options to build charging stations on certain parts of the network.

In conclusion, when the number of charging stations to be built increases under high technology development assumption, the location of the charging stations moves from the center to the edges of the network. Besides, the load capacity ratio of the stations could not be reduced as the number of stations increases. This is due to the uneven distribution of OD trips that leads to charging stations only located on certain parts of the highway network.

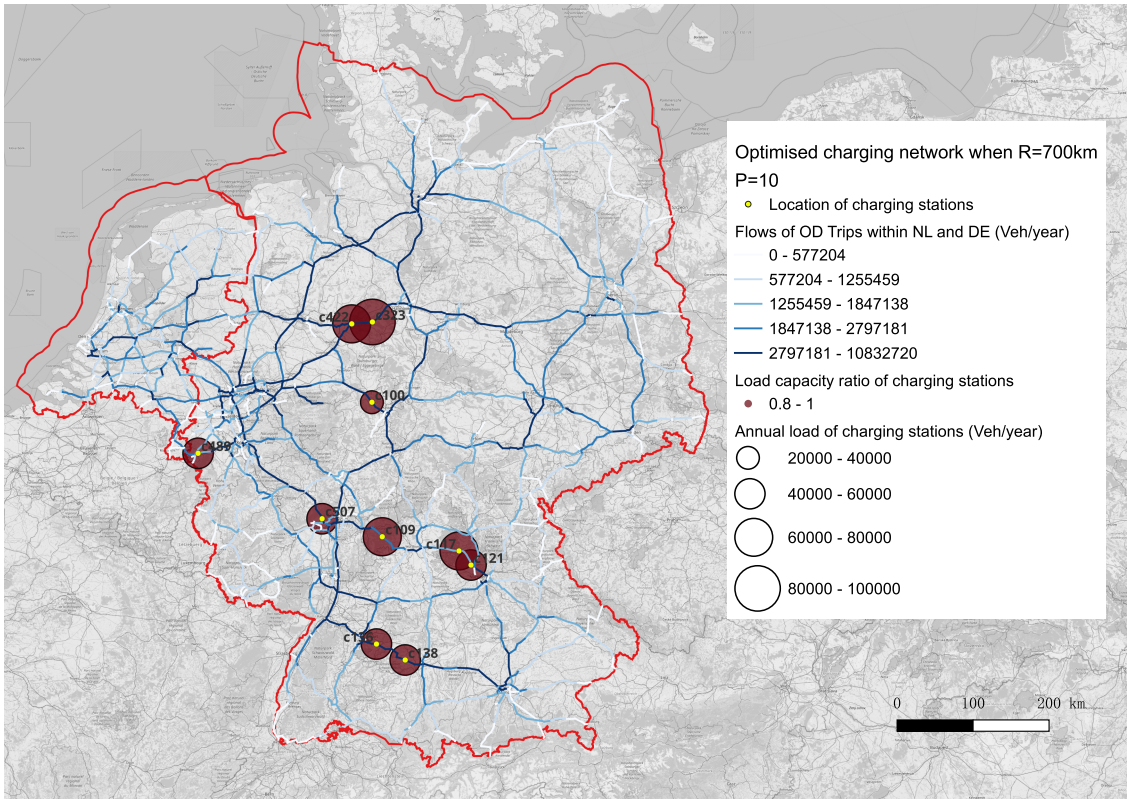


Figure 5.16: Result analysis for scenario 7, where P=10 and R=700km

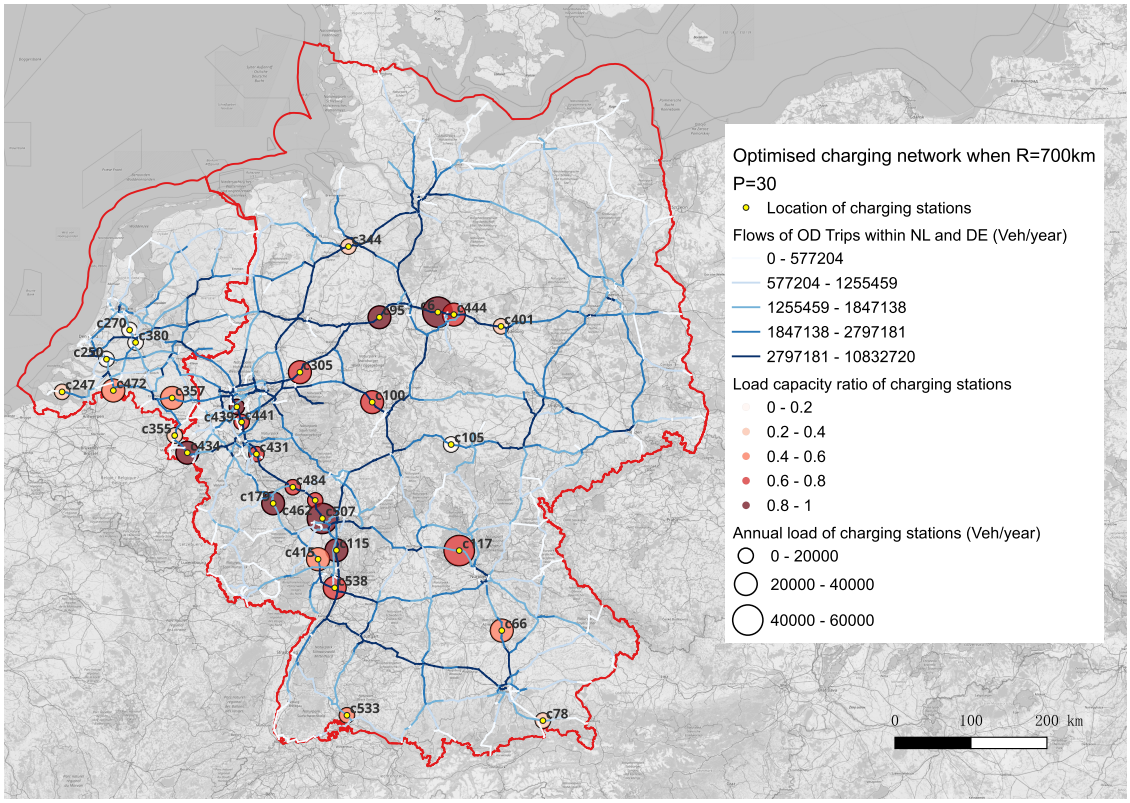


Figure 5.17: Result analysis for scenario 8, where P=30 and R=700km

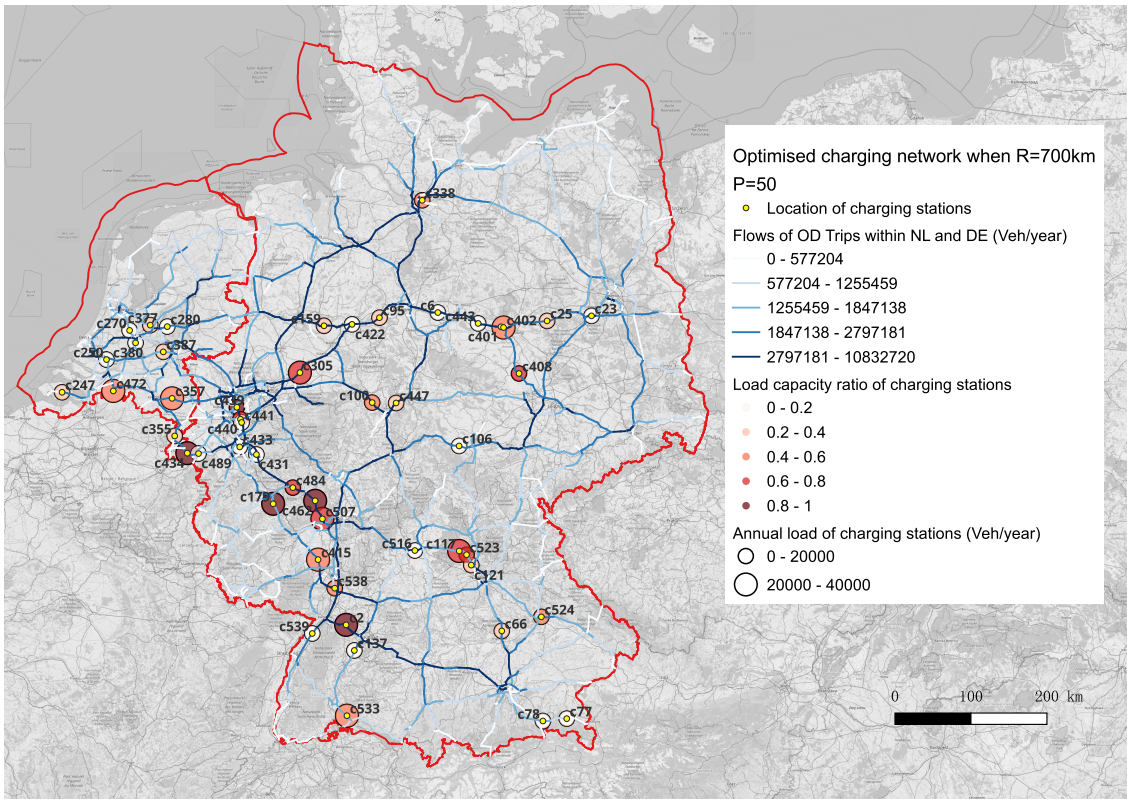


Figure 5.18: Result analysis for scenario 9, where P=50 and R=700km

Conclusion

In scenarios when the driving range is $R = 400km$ and $R = 550km$, the positioning of the charging network radiates from several central locations. This indicates that the optimized locations determined when the number of charging stations to be built is $P = 10$ are consistently chosen even when the number of charging stations increases to 30 or 50. These pivotal locations are predominantly situated around the central sections of the A2, and A3 highway network in Germany ($C422$, $C331$), the A4 highway near Aachen ($C489$) and the A61 highway near Pfeddersheim($C415$). These sections of highways have a high volume of HDVs, which means the optimisation model tends to locate charging stations at the highway sections with the highest traffic flow to capture more charging demand when only a few charging stations are planned to be built.

As the quantity of charging stations expands, additional stations emerge along the A16, A27, A28 and A67 highways in the Netherlands, as well as the extensive locations along the highway of the core locations. Under the medium technology development rate assumption where the range of HDVs is 550km, the incorporation of more stations along these highways alleviates the congestion at the central stations, leading to a corresponding decrease in their load capacity rates. However, under the low technology development rate assumption where the range of HDVs is 400km, the expansion of surrounding charging stations could not release the pressure of the current stations. This is because HDVs with limited driving range need more frequent charging, requiring an increase in charging stations to handle demand without overloading the stations.

For the scenario where $R = 700km$, there's a marked difference. The locations of the charging stations tend to shift to different areas as the number of charging stations increases. Furthermore, these charging stations exhibit a propensity to be distributed towards the periphery of the highway network, unlike the scenarios $R = 400km$ and $R = 550km$ where stations are more centrally clustered. This dispersal can be attributed to the greater driving range of the HDVs in this scenario, which means drivers can travel farther distances without the urgent need for charging. Consequently, the demand for the majority of the charging stations is not as pronounced as in the scenarios with a shorter HDV range. However, certain charging stations, particularly those located on the western side of the highways in Germany, still register high load capacity ratios. This is primarily due to constraints in the size of these stations, which limits their ability to accommodate higher demand.

5.2.4. Performance analysis

As mentioned in Chapter 3.1, one of the reasons for implementing MCDA in the first stage of the methodology is to reduce the computational cost of FRLM optimisation by filtering out candidate sites with low quality. Hence, a performance analysis is conducted when the filtering rate of MCDA is 0%, 35%, 55% and 75%, in order to check the effect of MCDA. Note that when 100% of the initial candidate sites (553 nodes) are treated as inputs, the optimisation gap could hardly reach 0%, hence, a 1% of the MIP gap is set in the Gurobi to obtain the approximate optimisation time.

The analysis is conducted based on the MCDA result of the expert survey and the range of

HDV is set to be 500km and the number of charging stations to be built is 50. The total calculation time includes the pre-processing time of the en-route expanded network, the En-route expanded network construction time and FRLM optimisation time. The results are presented in Table 5.4. Note that the unit of time is in seconds.

The results in Table 5.4 show that the filtering rate of MCDA considerably affects the total calculation time. Specifically, the pre-processing time and the time taken to construct the expanded network increase within an acceptable range when the size of inputs increases. However, the FRLM optimization time is significantly impacted by the volume of MCDA inputs since it accounts for the majority of the total calculation time. In sum, the more candidate sites filtered out during the MCDA stage, the faster the total calculation time for the algorithm. Hence, MCDA in the first stage of the methodology could significantly reduce the computational complexity for the FRLM-based optimisation.

Table 5.4: Performance analysis under different filtering rates of MCDA

MCDA	No. Nodes	Pre-processing		Expanded network construction time	FRLM Optimisation time	Total time
		N	d			
100%	553	118.92	337.71	7.04	1627.5(MIP Gap 1%)	2091.17
65%	360	117.95	260.64	5.04	908.17	1291.8
45%	250	115.30	189.09	2.57	507.18	814.14
25%	140	111.76	127.42	0.96	50.35	290.49

CPU model: AMD Ryzen 7 5800H with Radeon Graphics, instruction set [SSE2|AVX|AVX2]
Thread count: 8 physical cores, 16 logical processors, using up to 16 threads

5.2.5. Benchmark

In order to test the performance of the proposed methodology, the results of objective values and flow coverage rate are compared with the results from other benchmark methodologies including the randomly chosen method, the top criterion selection method and the solely MCDA method. The first method randomly selects candidate sites and considers them as optimal results. This method represents the worst solution for the HDV charging station location problem. The second method selects the top candidate sites based on the ranking of a single criterion. It simulates the most naive solution for the HDV charging station location design. In the case study, three criteria have been selected including the size of the charging station (C_1), the distance from the substation (C_2) and the traffic volume (C_3). Hence, three top criterion selection methods based on C_1, C_2 and C_3 should be tested. The third method selects the top candidate sites based on the ranking of the final score. The exact number of candidate sites being preserved is shown in the column 'P' in Table 5.5. The weight of each criterion comes from the results of the expert survey. In other words, this method is the outcome of the first stage of the proposed methodology (MCDA) without the optimisation step of the second stage of the proposed methodology.

The tests are conducted in a scenario where the range of HDVs is 550km. The results are presented in Table 5.5. The results demonstrate that the proposed methodology yields the highest objective function values and flow coverage rates in comparison to other techniques.

Table 5.5: Performance comparison with three benchmark methods

	Proposed methodology		Randomly chosen		Solely MCDA	
P	ObjVal	Flow coverage rate	ObjVal	Flow coverage rate	ObjVal	Flow coverage rate
10	635202.50	54.91%	69348.75	6.00%	390256.25	33.74%
30	1085060.00	93.81%	300925.00	26.02%	657926.25	56.88%
50	1086468.75	93.93%	411618.75	35.59%	710448.75	61.42%
	Top C1		Top C2		Top C3	
P	ObjVal	Flow coverage rate	ObjVal	Flow coverage rate	ObjVal	Flow coverage rate
10	397500.00	34.37%	91260.00	7.89%	365995.00	31.64%
30	637935.00	55.15%	314531.25	27.19%	455163.75	39.35%
50	831062.50	71.85%	415153.75	35.89%	598582.50	51.75%

Conversely, the method of random selection produces the lowest outcomes. Among the Top criteria methods, the Top C1 strategy, which selects based on the highest P value of 'Size' criteria, outperforms its counterparts. The proposed methodology increases the flow coverage rate 200% better than the randomly chosen method and 50% higher than the Solely MCDA method. This can be attributed, in part, to the predominance of C_1 in the weight as the outcomes of the BWM expert survey. For the Solely MCDA method, it generates results that are lower than the results from Top C1 but higher than Top C2 and C3. In summary, this performance analysis proves the efficacy of the proposed methodology in pinpointing the optimal locations for the charging network. It further validates its capacity to cater to the charging demands of the network more effectively than other naive charging station location selection approaches.

To further analyze the difference between the proposed methodology with other benchmark methods, the scenario where the range of HDVs is 550km is chosen and the results from using solely MCDA method are presented in Figure 5.19, Figure 5.20 and Figure 5.21. Compared the results with Figure 5.15, Figure 5.14 and Figure 5.13, it could be seen that solely MCDA method generates charging stations located more scattered than the results generated by the proposed method. This is due to the reason that FRLM optimisation tends to cover more charging flow in the network, which means choosing locations in the center of the network is more beneficial than selecting locations near the boundary of the network since the highways at the center are more accessible for the OD flows between Germany and the Netherlands.

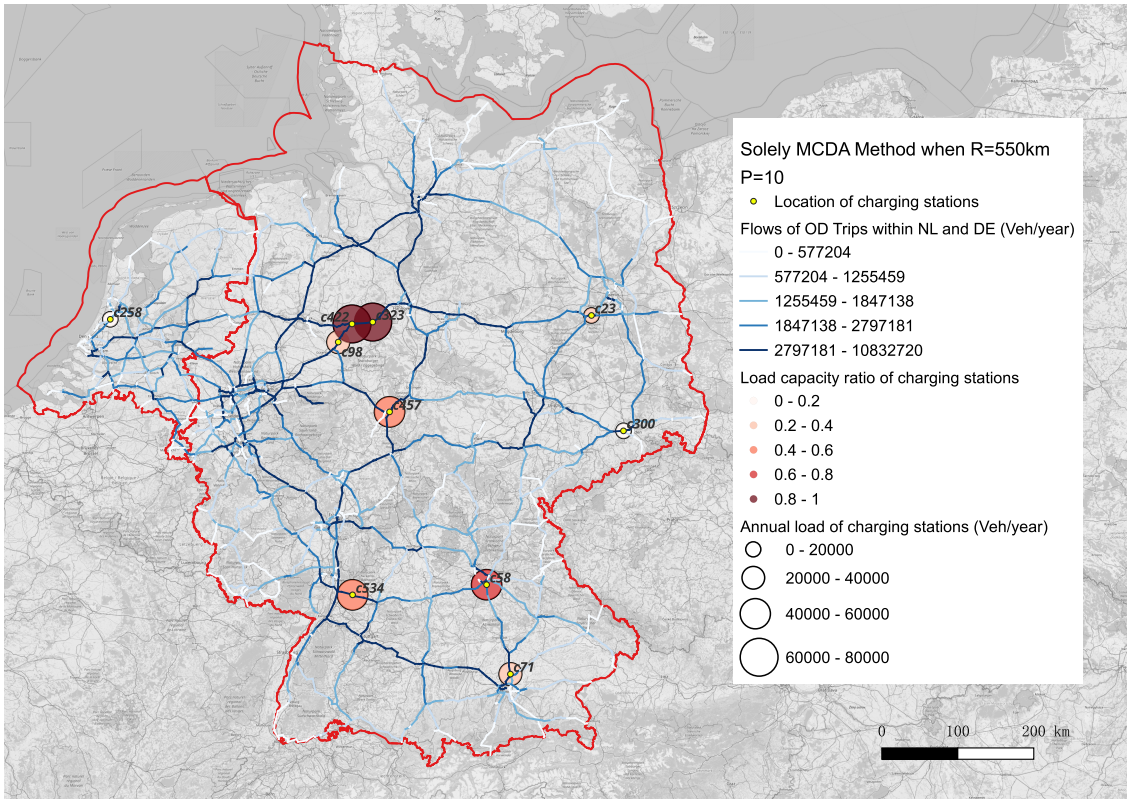


Figure 5.19: Result analysis of the solely MCDA method where P=10 and R=550km

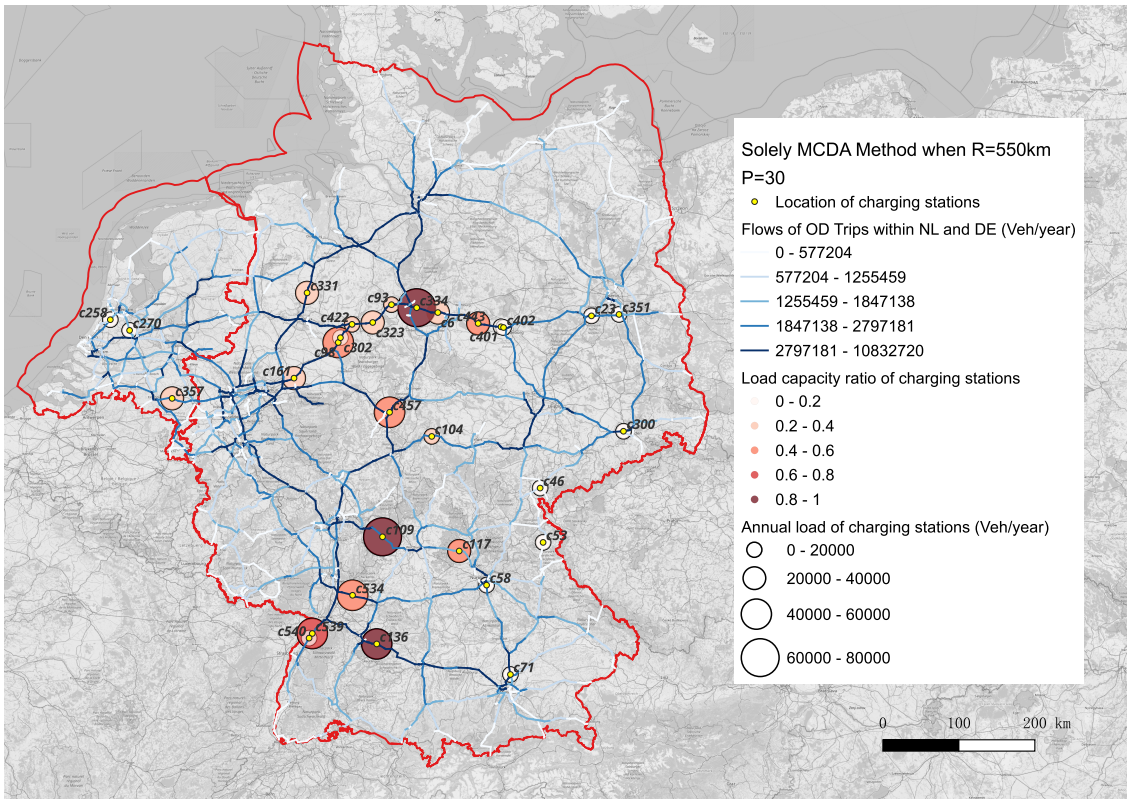


Figure 5.20: Result analysis of the solely MCDA method where P=30 and R=550km

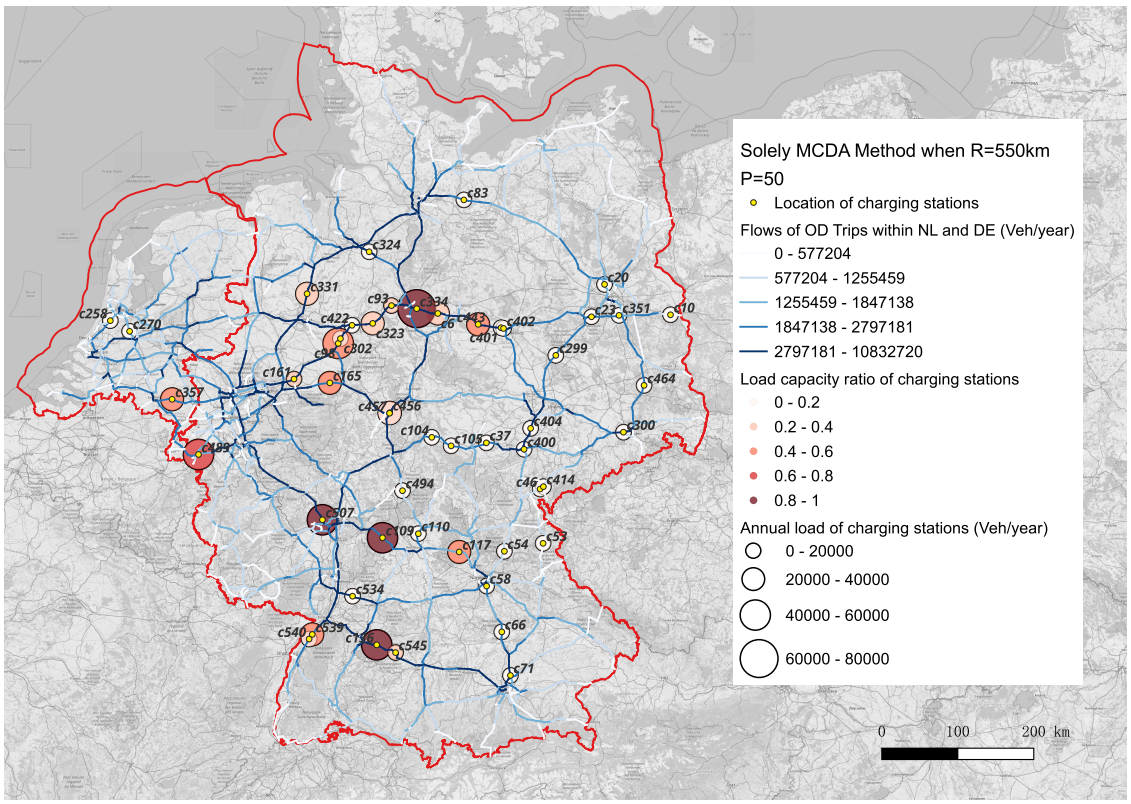


Figure 5.21: Result analysis of the solely MCDA method where P=50 and R=550km

6

Conclusion

This chapter summarizes the research by first answering the research questions. Then, the main findings of this research are highlighted. After that, the contributions of this research are included in terms of scientific contributions and social contributions. Finally, the research limitations are pointed out and future developments are suggested accordingly.

6.1. Main findings

By integrating MCDA with the optimization model, computational time can be reduced up to 85% compared to the optimization model without MCDA as shown in Table 5.4 and the flow coverage rate can be increased up to 50% compared to solely MCDA method according to Table 5.5. This approach combines the benefits of both MCDA and optimization, and its effectiveness has been verified in both a hypothetical toy network and a real-world case study.

A case study has been conducted within the Netherlands and Germany using real-world transport network data and projected traffic flow data in 2030. Nine scenarios have been set based on different combinations of charging station penetration rates and the technology development of the HDV driving range. The results show that in scenarios where the driving range is 400km and 550km, the charging stations tend to be located at the center of the study area where its road section endures high traffic volume. The optimization model's inclination to position charging stations for optimal coverage of charging demand can be attributed to the central highway sections capturing the majority of the origin-destination (OD) flow between Germany and the Netherlands. This makes these sections a priority, especially when planning a limited number of stations. As the penetration rate of HDV charging station increase, new charging stations are built along the highway to which former stations belong and expand to the edge of the highway network. For scenarios where the driving range of HDV is 550km, the incorporation of more stations along these highways alleviates the congestion at the central stations. However, when the driving range of HDV is 400km, the expansion of surrounding charging stations cannot release the pressure of the current stations. This is because HDVs with limited driving range need more frequent charging, requiring an increase in charging stations to handle demand without overloading the stations. Different phenomena have been made in the scenarios where the range of HDV is 700km. Instead of starting with core locations at the center of the transport network and extending radically, the location of the charging stations tends to shift to different areas as the number of charging stations increases. Besides, the layout

of the charging network is more scattered compared with scenarios where the driving range is 400km and 550km. These findings suggest that when drivers have a larger travel range, there's less immediate need for charging. Consequently, the demand for most charging stations isn't as intense as in scenarios with shorter HDV driving ranges.

6.2. Answers to research questions

As mentioned in Chapter 1.4, four sub-questions have been proposed based on the main research question. In this section, the answers for the four sub-questions are first discussed and then a comprehensive answer for the main research question is presented.

Question1: What are the criteria for selecting a potential location for HDV charging station based on multiple criteria decision analysis (MCDA)

Answer: When considering a potential location for an HDV charging station using MCDA, various criteria can be taken into account. According to the literature review, environmental, economic, and social factors are commonly selected as the primary evaluation criteria. For environmental factors, commonly used sub-criteria include distance to water resources, distance to vegetation, and slope of land. In terms of economic factors, construction cost, land cost, and distance to power supply are frequently considered. Regarding social factors, distance to the main road, distance to junctions, and distance to other EVCSs are commonly used sub-criteria.

Question2: What is the most proper MCDA method for selecting charging station locations?

Answer: MCDA is a branch of methods that involves evaluating various alternatives based on multiple criteria to identify the most favorable option(s). MCDA methods could be classified into three categories: outranking methods, utility and value-based methods and multi-objective methods. The main differences among these three categories lie in the way alternatives are evaluated and compared. The most commonly used outranking methods include ELECTRE and PROMETHEE. For utility and value-based methods, AHP, TOPSIS and BWM are popular methods.

In general, BWM stands out from other MCDA techniques due to two key characteristics. First, it requires less comparative data, making it a more streamlined method. Second, it results in more consistent comparisons, implying that it yields more trustworthy outcomes. However, it's not without its drawbacks. For instance, while BWM's reliance on integers simplifies its use, it may lack the flexibility of methods that permit fractional comparisons.

Question3: How to formulate the charging station location problem into an optimization problem?

Answers: Charging station location optimization problem approaches can be classified based on their representation of charging demand, namely the node-based model, flow-based model, and trajectory-based model. Node-based model is widely used in optimal location planning of EVCS due to its simplicity and directness. However, the main drawback of the node-

based model is obvious, which is it assumes charging demand originates solely from specific nodes within the network. To address the limitations of the node-based model, the flow-based model has been proposed by taking into account origin-destination (OD) flows and allowing charging demand to be accommodated during journeys.

In this research, the charging station location optimization problem has several features. First of all, the research focuses on the en-route charging stations along the transport network, which means the charging demand should be expressed by OD flows. Hence, the flow-based model is a more suitable type of model to be formulated. Furthermore, since this research mainly focuses on the location optimisation of HDVs charging stations, it is crucial to take the range of vehicles into account since HDVs usually take on long-distance freight transport. To tackle this issue, the flow refueling location model (FRLM) is suitable compared with other models. By generating combinations of charging stations, the driving range constraint is considered in FRLM model.

To formulate the FRLM-based optimisation model, the En-route expanded network for each OD pair should be generated as the pre-processing step. This is a simplification of generating combinations of charging stations in the former model and it could reduce the computational complexity dramatically. The former FRLM-based model utilizes the expanded network as the input for the model, however, there remains a notable drawback of the conflation of the road network with the charging network. To tackle this issue, the innovative en-route expanded network is introduced in this research.

Once the En-route network has been expanded, mathematical optimization is processed. The objective of the model is to maximize the flow coverage. Constraints of the model include balancing flow in the en-route expanded network, making sure that all the paths with common nodes can make a site active, guaranteeing that the total number of charging stations being built should equal the number being planned and preventing the charging load of each charging station in the network from exceeding its capacity.

Question4: What are the key performance indicators for HDV charging station evaluation?

Answers: The key performance indicators for HDV charging station evaluation could be classified into global indicators and local indicators. Global indicators refer to the indicators that could reflect the comprehensive performance of the charging network. In contrast, local indicators are the indicators that only reflect certain charging stations in the network. In this research, the total number of traffic flows being covered and the flow coverage rate are two global indicators. The coordinates of the charging station (regard as a node), the annual load of the charging station and the load capacity ratio of charging stations belong to local indicators.

The total number of traffic flows being covered and the flow coverage rate reflect the service supply ability of the charging network. The higher these two indicators, the better the charging network in terms of satisfying the charging demand. The coordinates reflect the location of the charging station, more information could be derived by referring to the road network, for example, the highway that the charging station belongs to and the distance to the nearest

charging station. The annual load is calculated by summing the total number of HDVs that stop and charge at a certain charging station in a year. This is a useful indicator that can help us understand the charging demand that a particular station can handle in a year. Besides, the charging stations with relatively high annual loads could be regarded as key locations in the transport network since they support more OD flows compared with other locations with lower annual loads. The last local indicator is the load capacity ratio, which is computed by dividing the load by the station's capacity. A value of 1 signifies that the station's capacity is fully utilized. The indicator shows the current service capacity of each charging station. Stations with low capacity utilization at present have more potential for future growth. On the other hand, stations that are already highly utilized may reach slow charging loads in the future. This would require the construction of new charging stations nearby or the expansion of existing ones.

Main research question: How to optimize the location of the En-route HDVs charging network?

Answers: In order to optimize the location of the En-route HDVs charging network, an innovative methodology that integrates MCDA with mathematical optimization is proposed. The proposed methodology consists of two steps. In the first step, initial candidate sites are found based on current infrastructure. Then, these initial candidate sites are ranked and filtered based on the MCDA principle. An expert survey has been conducted to obtain the weight of these three criteria. For the first time, the BMW has been used as the MCDA method to calculate weight. It requires less comparative data and offers higher consistency in comparisons, unlike other similar MCDA methods such as TOPSIS and AHP. In the second step, the optimal location for the HDV en-route charging network is selected using an FRLM-based optimization model. An innovation has been made during the pre-processing step: The construction of the en-route expanded network. It is built based on the original expanded network to tackle its drawback of the conflation of the road network with the charging network. Besides, a capacity constraint is added to the FRLM-based optimisation model for the first time. This helps to fill in the gap where HDVs have higher requirements in charging station capacity.

6.3. Contributions

In this section, conclusions on the scientific and practical contributions of this research are proposed and discussed.

6.3.1. Scientific contribution

First of all, this study systematically reviewed the current literature on the electric vehicle charging station location problem, drawing the following conclusions and corresponding knowledge gaps.

The first knowledge gap is about methodologies on charging station location problems. Existing literature employs either MCDA or optimisation models solely to solve the charging station location problem. The drawback of MCDA is its inability to account for the range constraints of electric vehicles, while the shortcomings of using optimization models include the

high computational complexity and lack of consideration of multiple criteria.

The second knowledge gap is about related works on en-route HDVs charging station location problems. The majority of literature on charging station location problems concentrates on passenger vehicles, with only a few studies focusing on freight vehicles such as trucks or HDVs. Compared to passenger vehicles, freight vehicles have longer travel distances, higher driving ranges, and require a power supply system and charging station capacity with higher specifications. Besides, existing literature lacks real-world verification of HDV charging station location methodologies that utilize national-scale transport network and traffic flow data.

The knowledge gaps found in the literature review have been filled by proposing an innovative integration of MCDA with an FRLM-based optimisation model and verifying the proposed methodology in a real-world highway network within the Netherlands and Germany using real-world transport network data and projected traffic flow data in 2030. The proposed methodology's performance was evaluated through this case study, and the results show that it can reduce computational time by up to 85% when compared to the optimization model without MCDA. Additionally, the flow coverage rate can increase up to 50% compared to using MCDA alone. This real-world case study verifies the effectiveness of the proposed methodology and proves its potential to be applied to charging station design and construction industries.

6.3.2. Practical contribution

This research offers valuable insights and inspiration for various stakeholders in the process of HDV en-route charging station design, construction and usage. The stakeholders who could benefit from this research include the governments, the charging station design and construction companies and the charging station users.

The presented methodology equips governments with an actionable strategy for HDV electrification infrastructure planning. By identifying and ranking initial candidate sites for charging station sites based on existing infrastructure, governments can ensure efficient resource allocation and minimize redundancy. The capacity constraint consideration ensures that the infrastructure developed meets the heightened demands of HDVs, thereby preventing bottlenecks and service interruptions. Overall, this research provides a precise blueprint for governments, streamlining the transition to electrified HDVs, aiding in carbon emission reduction, and aligning with the EU's goals of carbon neutrality by 2050.

Companies that are involved in the infrastructure and logistics sectors, stand to benefit immensely. The proposed methodology in this research provides a framework for determining optimal charging station locations. The MCDA steps embedded in the methodology consider various criteria, taking into account inputs from various stakeholders. Such inclusivity not only ensures a comprehensive strategy but also boosts cooperation between the entities involved. Furthermore, the insights from the case study are particularly enlightening. With varying assumptions regarding charging station penetration rates and HDV driving range technological advancements, companies can glean invaluable information, enabling them to design adaptive construction strategies.

The research offers tangible solutions to everyday challenges for the end-users, primarily the HDV drivers. The proposed methods aim at maximizing the flow coverage rate. This ensures that a majority of the charging demands of users are met efficiently. The implications of this are profound, especially for long-distance freight HDV drivers, as it directly addresses and alleviates charging anxiety, and consequently increases the efficiency of road freight transport in the future.

6.4. Limitation

In the second stage of the proposed methodology, the en-route expanded network based FRLM optimisation model is formulated based on several assumptions. Some of the assumptions over-simplified the situation in reality, hence becoming limitations of the optimisation model.

One of the key assumptions is that all HDVs possess identical driving ranges, overlooking the diversity of ranges found among actual vehicles. This assumption will lead to an overestimation or underestimation of charging demand in the optimisation model if the actual average driving range of HDVs is higher or lower than the hypothetical driving range. To address this limitation, a multi-class approach could be adopted wherein HDVs are categorized based on their driving ranges, battery capacities, or specific makes and models. By creating distinct categories, the model could then account for the different charging needs of each class. Furthermore, machine learning or advanced statistical methods could also be used to predict and incorporate the distribution of different ranges into the model. Incorporating these adaptations ensures a more representative and effective charging infrastructure that caters to the diverse needs of all HDVs on the road.

The second simplification is the assertion that trips sharing the same OD pairing will adhere to uniform charging decisions, neglecting the possibility of varied charging strategies among HDVs embarking on identical routes. This will lead to the restriction of optimal solution space in the optimisation model. To tackle this issue, it's essential to incorporate variability into the model. By considering factors such as driver preferences, vehicle battery state, and real-time traffic or charging station congestion, a more dynamic charging strategy can be formulated. Integrating probabilistic or stochastic models can capture the diverse charging behaviors and decisions of HDVs on identical routes, ensuring a more realistic representation in the optimization process.

The model also glosses over the intricacies of charging patterns, presuming an even distribution of HDV arrivals and omitting queuing realities, which becomes problematic when considering real-world peak charging times and the conventional "first come, first served" charging sequence. This assumption will lead to over-concentration of the charging station location in the optimisation model. To overcome the oversight of even HDV arrival distribution and queuing, the model could integrate time-dependent variables or simulations. By utilizing real-world data on HDV traffic patterns and charging station usage, the model can anticipate peak and off-peak charging periods. Incorporating a queueing theory-based approach will allow for a more accurate depiction of waiting times and service rates at charging stations. By simulating these dynamics, the model can better account for real-world charging patterns and optimize infrastructure to cater to actual demand fluctuations and queuing behaviors.

Lastly, the model's premise that HDVs consistently pursue the shortest return routes does not account for potential detours, which drivers might undertake to sidestep congestion or to access alternative destinations. To address the limitation of assuming HDVs always take the shortest return routes, the model could incorporate dynamic route planning algorithms that factor in real-time traffic data, road closures, and other unforeseen events. By integrating GPS data and traffic prediction tools, the model can account for route variations that drivers may choose based on current road conditions or personal preferences. Additionally, feedback loops from drivers or fleet management systems can be used to update and refine route preferences over time, ensuring the model remains adaptive and reflects actual driving behaviors.

Beyond the assumptions made, the model's intrinsic formulation presents its own set of limitations. While the objective function of the model focuses on maximizing the flow coverage rate, it inadvertently sidelines the network coverage rate. This setting may neglect the charging demand for users who travel in remote places on highway networks with low OD flows and only focus on road users on highway network sections with high OD flows, which could cause equity issues. To tackle this issue, it is possible to adopt a multi-objective optimization approach where both flow coverage and network coverage rates are optimized simultaneously. This ensures that while major traffic arteries are serviced, remote areas aren't left behind.

In terms of infrastructure planning, the model rigidly stipulates an exact count for charging stations, bypassing the nuances of varying construction costs associated with different stations; this highlights a potential avenue for introducing budgetary constraints in future renditions. A dynamic cost estimation module can be integrated, accounting for location-specific costs. Rather than dictating a strict station count, the model should be optimized to work within a defined budget, taking into account the varied costs of different station tiers.

Lastly, the capacity designation for each charging station, as per the model, is solely predicated on its physical dimensions, failing to incorporate pivotal elements like electricity capacity, thereby necessitating a broader perspective on capacity considerations. To address the limited viewpoint on charging station capacity, it's essential to consider both the physical and electrical dimensions. Integrating real-time electricity grid data can ensure stations have a consistent power supply without overwhelming local infrastructure. Furthermore, differentiating between peak and off-peak power availability can aid in scheduling HDV charging during periods of lower grid demand.

6.5. Future research

To address the limitations of existing research, future research directions are considered from two main viewpoints: refining the optimization model and broadening the case study's scope.

Refining the en-route expanded network based FRLM optimisation model is crucial for enhancing its accuracy, applicability, and efficiency. The promising directions for future development of the model are concluded as follows.

- **Multi-objective Optimization**: Current models can be expanded upon by introducing a multi-objective optimization approach. Here, the objective function would be twofold: to maximize both the flow coverage rate and network coverage rate concurrently. Em-

ploying Pareto-based solutions can help identify optimal locations, striking a balance between efficiency and equity.

- **Incorporation of Additional Constraints**: As the models become more complex and closer to real-world scenarios, it would be beneficial to introduce constraints reflecting the realities of infrastructure development and usage. For instance, accounting for the total construction cost associated with charging stations and integrating constraints reflecting the capacity limitations related to electricity consumption.
- **Considering diverse factors for en-route expanded network generation**: The expanded network can be enhanced by weighing in multiple variables. For example, each trip is free to set a different driving range, each OD pair could have multiple route choices, charging and queuing times are considered during the charging strategy, etc.

While the current case study provides a foundational understanding, future research can look at diverse geographies, varying urban and rural landscapes, and differing levels of infrastructure development. This would ensure a more holistic understanding of the model's applicability and effectiveness. Furthermore, refining the MCDA component is crucial. Enriching the expert panel to encompass a broader set of stakeholders would enhance the robustness of the evaluations. Moreover, while the study presently focuses on three evaluation criteria for charging stations, there's potential to delve into a wider range of criteria, from environmental implications to user convenience. Such an expanded and refined approach not only promises academic depth but also equips us with tools better suited for diverse real-world applications.

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A

Source Code Example

1. The en-route expanded network generation

```
# Starting generate expanded network:
# Define Arcs and nodes

class Arc:
    def __init__(self, origin, destination, distance, trip):
        self.origin = origin
        self.destination = destination
        self.distance = distance
        self.trip = trip
        self.show = [origin, destination, distance, trip]

class Node:
    def __init__(self, ID, trip):
        self.InArc  = []
        self.OutArc = []
        self.ID = ID
        self.trip = trip

    def addInArc(self, Arc):
        self.InArc.append(Arc)

    def addOutArc(self, Arc):
        self.OutArc.append(Arc)

# Start generating set of nodes in expanded network
Node_set = {}

for key in N:
    Node_trip_set = []
    trip = key
    for nodeID in N[key]:
        ID = nodeID
        node = Node(nodeID,trip)
        Node_trip_set.append(node)

    Node_set[key] = Node_trip_set

# Start generating set of arcs in expanded network
```

```
Arc_set = {}
# Set the range of the HDV:
Range = 100 # Could be adjusted

for key in N:
    Arc_trip_set = []
    trip = key
    # 1. Connect adjacent nodes:
    for i in range(len(N[key])-1):
        origin = N[key][i]
        destination = N[key][i+1]
        distance = d[key][i]
        arc = Arc(origin, destination, distance, trip)
        Arc_trip_set.append(arc)

        Node_set[key][i].addOutArc(arc)
        Node_set[key][i+1].addInArc(arc)


    # 2. Connect source node to other nodes:
    for index, value in enumerate(N[key][2:], start=1):
        origin = N[key][0]
        distance = d_ex_S[key][index]
        if distance <= Range:
            destination = value
            arc = Arc(origin, destination, distance, trip)
            Arc_trip_set.append(arc)

            Node_set[key][0].addOutArc(arc)
            Node_set[key][index+1].addInArc(arc)

    # 3. Connect other nodes to target node:
    for index, value in enumerate(N[key][:-2]):
        origin = value
        distance = d_ex_T[key][index]
        if distance <= Range:
            destination = N[key][-1]
            arc = Arc(origin, destination, distance, trip)
            Arc_trip_set.append(arc)

            Node_set[key][-1].addInArc(arc)
            Node_set[key][index].addOutArc(arc)


    # 4. Connect the middle nodes:
    for index1, value1 in enumerate(N[key][1:], start=1):
        for index2, value2 in enumerate(N[key][index1+2:-2], start=index1
            +2):
            distance = round(sum(d[key][index1:index2]),1)
            if distance <= Range:
                origin = value1
                destination = value2
                arc = Arc(origin, destination, distance, trip)
                Arc_trip_set.append(arc)

                Node_set[key][index1].addOutArc(arc)
```

```
                Node_set[key][index2].addInArc(arc)

    # 5*. X_{st}: Connect the O-node to D-node
    origin = N[key][0]
    destination = N[key][-1]
    distance = df['shortest_distance'][key]
    arc = Arc(origin, destination, distance, trip)
    Arc_trip_set.append(arc)

    Arc_set[key] = Arc_trip_set
```

2. Parameter setting of the en-route expanded network based FRLM model

```
# Parameters
f = df_filtered['od_trip_generation'].tolist()
p = 50 # Number of on-the-go charging stations to be built

# Sets

#  Q
Q = list(range(len(df_filtered)))

#  N
#N_set = set(network.nodes())
N_set = set(chargers_S1['Node Name'])
N_set = [str(element) for element in N_set]

# N+^ q
for key in N:
    N[key] = [str(element) for element in N[key]]

# A+^q: Set of arcs in expanded network for each trip q
A_ex = {}
for key in Arc_set:
    arc_list = []
    for arc in Arc_set[key]:
        arc_list.append((arc.show[0],arc.show[1]))

    A_ex[key] = set(arc_list) # Unique the list, delete the repetitive
       elements
    A_ex[key] = [(str(x),str(y)) for x , y in A_ex[key]]

# Set of s-t  arcs
A_od = [('o' + str(i), 'd' + str(i)) for i in range(len(df))]

'''
# A^ q
A = {}
def contains_s_or_t(s):
    return 's' in s or 't' in s

# Remove tuples if one of the string elements contains 's' or 't'
A = {key: [t for t in tuples if not any(contains_s_or_t(e) for e in t)]
   for key, tuples in A_ex.items()}
'''

# Q_i:
Q_trip = {}
for key in N:
    N[key] = [str(element) for element in N[key]]

for node in N_set:
    Q_trip[node] = []
    for key, node_list in N.items():
        if node in node_list:
            Q_trip[node].append(key)

# J_1 & J_2, for j|(i,j) \in A^q
```

```
J_1 = {} # j (i,j) in A^q
J_2 = {} # j (j,i) in A^q

for q in Q:
    for i in N[q]:
        j_set = []
        for tuple in A_ex[q]:
            if tuple[0] == i:
                j_set.append(tuple[1])

        J_1[q,i] = j_set

for q in Q:
    for i in N[q]:
        j_set = []
        for tuple in A_ex[q]:
            if tuple[1] == i:
                j_set.append(tuple[0])

        J_2[q,i] = j_set

# *** Capacity=10000000 by default
Cap = {}
Area_per_truck = 19*(3.3+4.5)
Batch_coefficient = 8*60/45
# for i in N_set:
#    Cap[i] = 100000000

for i in N_set:
    area = chargers_S1.loc[chargers_S1['Node Name'] == i, 'Area'].values
       [0]
    number_chargers = (area/3)/Area_per_truck
    capacity = number_chargers*365
    Cap[i] = round(capacity)
```

```
model = Model('FRLM_modified')

x = {}
for q in Q:
    for (i,j) in A_ex[q]:
        x[q, i, j] = model.addVar(vtype=GRB.BINARY, name=f"x_{q}_{i}_{j}")

y = {}
for i in N_set:
    y[i] = model.addVar(vtype=GRB.BINARY, name=f"y_{i}")

# Objective Function
model.setObjective(quicksum(f[q] * (1 - x[q, A_od[q][0], A_od[q][1]]) for
    q in Q), GRB.MAXIMIZE)

# Constraints
for q in Q:
    for i in N[q]:
        model.addConstr(
            quicksum(x[q, i, j] for j in J_1[q,i]) -
            quicksum(x[q, j, i] for j in J_2[q,i]) ==
            (1 if 'o' in i else (-1 if 'd' in i else 0)),
            name=f"flow_balance_{q}_{i}"
        )

for i in N_set:
    for q in Q_trip[i]:
        model.addConstr(
            quicksum(x[q, j, i] for j in J_2[q,i]) <= y[i],
            name=f"station_{i}_{q}"
        )

model.addConstr(quicksum(y[i] for i in N_set) == p, name="num_stations")

#for i in N_set:
#    model.addConstr(
#        quicksum(f[q]*x[q, j, i] for q in Q_trip[i] for j in J_2[q, i])
    <= Cap[i],
#        name="capacity"
#        )


for i in N_set:
    model.addConstr(
        quicksum(f[q] * quicksum(x[q, j, i] for j in J_2[q, i]) for q in
           Q_trip[i])
         <= Cap[i],
        name="capacity"
        )

# Set the MIP gap parameter
# model.Params.MIPGap = 0.01  # Set the MIP gap to 1%

# Start the timer
start_time = time.time()
```

```
53
54 # Solve the model
55 model.optimize()
56
57 # Calculate the elapsed time
58 elapsed_time = time.time() - start_time
59
60 # Output the results
61 if model.status == GRB.OPTIMAL:
62     print("Optimal solution found:")
63     for q in Q:
64         for (i, j) in A_ex[q]:
65             print(f"x_{q}_{i}_{j} =", abs(x[q, i, j].x))
66     for i in N_set:
67         print(f"y_{i} =", abs(y[i].x))
68 else:
69     # Print model status
70     status_code = {
71         GRB.LOADED: 'LOADED',
72         GRB.OPTIMAL: 'OPTIMAL',
73         GRB.INFEASIBLE: 'INFEASIBLE',
74         GRB.INF_OR_UNBD: 'INF_OR_UNBD',
75         GRB.UNBOUNDED: 'UNBOUNDED',
76         GRB.CUTOFF: 'CUTOFF',
77         GRB.ITERATION_LIMIT: 'ITERATION_LIMIT',
78         GRB.NODE_LIMIT: 'NODE_LIMIT',
79         GRB.TIME_LIMIT: 'TIME_LIMIT',
80         GRB.SOLUTION_LIMIT: 'SOLUTION_LIMIT',
81         GRB.INTERRUPTED: 'INTERRUPTED',
82         GRB.NUMERIC: 'NUMERIC',
83         GRB.SUBOPTIMAL: 'SUBOPTIMAL',
84         GRB.INPROGRESS: 'INPROGRESS',
85         GRB.USER_OBJ_LIMIT: 'USER_OBJ_LIMIT'
86     }
87     print(f"Model status: {status_code.get(model.status, 'UNKNOWN')}")
```