MSc thesis in Transport, Infrastructure, and Logistics

Combination of Static and Dynamic Charging Facilities for Road Freight Electrification

Inez

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Inez: *Combination of Static and Dynamic Charging Facilities for Road Freight Electrification* (2024)

The work in this thesis was carried out in the:

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Preface

Philippians 4:13 (NIV):
"I can do all this through Him who gives me strength."

As a child, I always dreamed of becoming a fashion designer. Who would have thought that life would lead me down a completely different path into the world of transport and logistics? If you had told me back then that I would end up analyzing charging infrastructure for heavy-duty freight vehicles, I would not have believed it. Yet, here I am, not only immersed in this field but also genuinely enjoying it. Sometimes life has a funny way of guiding us toward the unexpected, and I am grateful for where this journey has taken me. His strength has carried me through the challenges and uncertainties, and I am beyond grateful for the opportunities and experiences He has given me.

My time at TU Delft has taught me more than I could have imagined. It has challenged me intellectually, pushed me out of my comfort zone, and broadened my perspective on what it means to contribute to the world. The opportunity to study how technology and innovation can drive sustainable solutions in such a critical sector has opened my eyes to the endless possibilities ahead.

I would like to express my sincere gratitude to my supervisors, Prof. dr. ir. Lóri Tavasszy, Dr. ir. Mahnam Saeednia, and Dr. ir. Maria Nogal Macho, for their invaluable guidance and support throughout this research process. Their expertise, patience, and feedback were important in shaping this work. They have not only guided me through the technical aspects of my thesis but also provided endless support beyond the academic sphere. Whether it was advice on navigating challenges or just a word of encouragement when things got tough, they were always there for me, and for that, I am truly thankful. I would also like to thank Ximeng Liao, my PhD supervisor, for the insights provided during the development of the mathematical models used in this study.

Furthermore, I am thankful for the support of my family and friends, whose encouragement helped me stay focused and motivated throughout this journey. This thesis is a testament to the unexpected turns life can take—and the joy that can be found along the way.

– Inez, October 2024

Summary

The purpose of this master's thesis is to explore and develop an optimal configuration of Electric Road Systems (ERS) and static charging infrastructure for the electrification of heavy-duty road freight transport. The study addresses the growing need for sustainable freight transport solutions, focusing on minimizing the environmental impact while maintaining operational efficiency. The research objective is to provide a model that integrates both static and dynamic charging or ERS methods, aiming to minimize the total cost of ownership and operational costs for freight trucks while considering varying levels of ERS adoption.

The primary objective of the thesis is to develop a model that identifies the optimal combination of dynamic and static charging stations for heavy-duty electric trucks. This model aims to minimize the overall infrastructure and operational costs while covering the maximum possible demand for charging along key transport routes. The main research question driving the study is: *"How to determine a configuration of dynamic and static charging stations for heavy-duty vehicles that achieves the most demand coverage within a limited budget, considering different acceptance levels of ERS among stakeholders?"*

The research identifies significant challenges in the existing studies, which typically focus on either static or dynamic charging infrastructure but rarely address the combined use of both systems. This work aims to fill that gap by proposing a comprehensive, integrated approach that balances the costs and benefits of both systems.

Methodology

The research employs a combination of literature review, mathematical modeling, and a case study validation. The literature review focuses on existing ERS technologies and the trade-offs between dynamic and static charging infrastructures. A bi-level optimization model is developed, representing both government decisions (upper-level problem) and user responses (lower-level problem). The government focuses on minimizing infrastructure costs for charging networks, while users aim to minimize their transportation costs, optimizing their routes and charging behaviors. The model is applied to real-world data from the Netherlands, optimizing the placement of charging facilities on highways while considering user demand and technology acceptance rates. The model is validated through simulations and a case study to test its effectiveness in real-world scenarios.

Key findings

1. **Trade-offs Between ERS and Static Charging:** ERS and static charging are complementary rather than mutually exclusive. ERS proves to be economically favorable on high-traffic routes by reducing battery size requirements and eliminating

the downtime associated with static charging. Static chargers serve as necessary infrastructure in low-traffic areas or where ERS deployment is impractical. As ERS adoption increases, the demand for static chargers decreases, leading to infrastructure and operational cost savings of up to 22-25%.

2. **Impact of ERS Adoption on Network Design:** Higher ERS adoption rates reduce the need for static chargers and make the ERS network more cost-effective. For example, with ERS installation costs exceeding €900,000 per kilometer, static charging becomes more favorable. The model demonstrates that traffic density plays a key role in determining the priority for electrifying certain highway segments.

3. **Case Study Results for the Netherlands:** The model suggests that prioritizing high-traffic corridors for ERS deployment, such as the Randstad area, is the most efficient strategy. The Netherlands' case study found that electrifying 80% of the country's highways with ERS would provide significant cost savings. Strategic placement of static chargers in less dense areas supports network resilience, and this combined approach maximizes both coverage and cost-efficiency.

4. **Policy and Investment Recommendations:** To optimize infrastructure investments, policymakers are advised to prioritize routes with higher freight traffic for ERS deployment, while static chargers should complement ERS in areas where installation is less feasible. Additionally, a focus on reducing ERS installation costs through public-private partnerships and technological innovation is critical to making ERS a viable long-term solution.

Conclusion and Recommendations

The thesis concludes that a combined ERS-static charging infrastructure is the an cost-effective solution for electrifying freight transport, particularly for heavy-duty electric trucks. The results indicate that an integrated network of ERS and static charging stations can lead to significant cost savings, reduce reliance on large battery sizes, and support environmental goals like the Paris Agreement. Furthermore, the flexibility of the model allows it to be adapted to various countries, making it an essential tool for global infrastructure planning.

For future research, the thesis recommends exploring the resilience of the combined charging network under scenarios such as infrastructure failures or extreme weather conditions. Additionally, further studies should focus on the operational challenges of static chargers, such as queuing and peak demand periods, to refine infrastructure deployment strategies.

This research offers valuable insights into optimizing the transition to electric freight transport and underscores the importance of strategic, cost-effective deployment of ERS and static charging systems. The findings provide actionable recommendations for governments, policymakers, and private stakeholders involved in electric road system projects.

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Introduction

1.1. Background

Freight transport is essential to the global economy and a major contributor to environmental degradation. Billions of tons of cargo are transported by road every year [27]. Road freight transport alone is responsible for approximately 8% of global CO_2 emissions from energy-related activities, a figure projected to double by 2050 due to economic growth in Asia, Africa, and Latin America [31]. Despite constituting only 5% of the vehicles on European roads, heavy-duty vehicles, including trucks, account for about 28% of the EU's CO_2 emissions from road transport [76]. Compounded by a 3% annual increase in freight activity, driven by rising e-commerce and global trade, this trend significantly exacerbates environmental impacts [58]. The persistent rise in emissions is alarming and highlight the urgent need for comprehensive strategies to reduce the carbon footprint. This urgency has motivated stakeholders across various sectors to actively seek and implement effective solutions.

In line with the Paris Agreement's objective for global carbon emissions to reach net zero by 2050 [34], there is a pressing call for action. The key solution to this is renewables. According to [34], for the next 15 years we need to drive huge leaps in clean energy innovation and have huge declines in the use of fossil fuels such as coal, oil, and gas. In reaching this, many solutions has been explored to substitute fossil fuels in transport, such as using hydrogen, electric power, and biofuels. While hydrogen and biofuels present promising alternatives, they face significant hurdles in terms of production efficiency, infrastructure development, and overall scalability. Hydrogen, for instance, requires substantial energy input for production and lacks a widespread refueling infrastructure [49]. Biofuels, on the other hand, compete with food production and can contribute to deforestation [72]. In contrast, electric vehicles (EVs) have emerged as the most viable and mature solution due to their advanced technology, growing infrastructure, and immediate impact on reducing emissions [52] [40].

EVs provide substantial environmental advantages, including zero tailpipe emissions, reduced air pollution, and enhanced air quality, alongside significant long-term cost savings. The initial high investment required for electric trucks is offset by the lower cost of electricity compared to gasoline, resulting in reduced operating and maintenance expenses. Furthermore, the EU government actively supports the widespread adoption of EVs, notably through tax subsidies for adopters and a robust plan to expand charging infrastructure. For instance, there is a target to establish approximately 2 million static charging stations in the Netherlands alone. These initiatives are expected to drive increased adoption of EVs, both for passenger cars and freight transport.

Electric trucks offer several environmental benefits but face substantial challenges that limit their practicality in long-haul freight operations. One of the primary limitations is the driving range constraint imposed by the substantial weight and cost of their battery packs. These large and heavy batteries not only consume valuable space but also diminish the available payload capacity, thereby impacting the overall vehicle cost. As a result, long-haul operations require larger batteries to reduce the frequency of charging stops, which in turn further reduces the load quantity that can be carried. Moreover, the cost of batteries escalates with size, making larger batteries significantly more expensive. Additionally, the infrastructure for charging for heavy duty trucks is not yet fully implemented, often leading to long charging time at charging stations. The inherent downtime required for charging, severely disrupts delivery schedules and reduces overall productivity. For instance, current technology limits heavy-duty electric truck range to approximately 200-300 kilometers under full load before needing a recharge — considerably less than diesel trucks, which can cover upwards of 1,000 kilometers on a single tank. Furthermore, the increased weight of the batteries can reduce the payload capacity by as much as 10-15%.

These factors contribute to the low adoption rates of EVs among freight companies. The high operational costs associated with the current limitations of EV technology—such as heavy batteries, frequent charging needs, and extended downtime—deter widespread use. These challenges underscore the necessity for solutions that not only lower operational costs but also ensure safety and reliability. Addressing these issues is critical for making electric trucks a viable and competitive option in the freight transport industry, fostering broader acceptance and aligning them with sustainability goals.

1.2. ERS as a solution

Electric Road Systems (ERS), also known as dynamic charging, offer a promising solution to the significant challenges faced by electric trucks in freight transport. ERS technology involves embedding conductive rails, overhead powerlines, or inductive charging systems into roadways, allowing vehicles to charge directly while in motion. As vehicles drive over the electrified sections, the energy is captured by the receiver coils in the vehicles, inducing voltage that charges the batteries in real time. This technology allows vehicles to charge continuously while in motion, eliminating the need for frequent stops at static charging stations.

ERS deliver transformative benefits for sustainable transportation by merging economic savings, environmental gains, and enhanced operational efficiency. Compared to traditional battery-only solutions, ERS proves to be more cost-effective due to its facilitation of large-scale battery downsizing, thus reducing both vehicle and infrastructure costs [14] [61]. Economically, ERS can significantly reduce the total cost of ownership for electric vehicles. Börjesson et al. [10] reported that ERS implementation could cut these costs by 20-30%, primarily through savings in battery and fuel expenses. Additionally, Coban, Rehman, and Mohamed [13] estimated societal cost savings of 15-25% compared to conventional fuel-based systems, with long-term operational and maintenance savings justifying the high initial investments. Connolly [14] highlighted that ERS could also reduce road maintenance costs by up to 15%, enhancing the overall economic viability. These financial advantages make ERS an attractive investment for both public and private sectors, potentially accelerating the transition to electric transportation.

Environmentally, Domingues-Olavarría et al. [23] projected that a full-scale ERS implementation in Denmark could reduce CO2 emissions from road transport by up to 40%, contributing substantially to national climate targets. In Sweden and Germany, large-scale ERS deployment could integrate up to 80% of renewable energy into the transport sector, as indicated by Olovsson et al. [59]. These environmental benefits are critical for meeting global climate goals and reducing the carbon footprint of transportation. Technologically, ERS enhances the efficiency and reliability of electric vehicles. Soares and Wang [68] demonstrated that wireless power transfer (WPT) technology in ERS could achieve energy transfer efficiencies of over 90%, minimizing energy loss. Operationally, ERS provides a constant power supply, reducing the need for large onboard batteries and mitigating range anxiety. Nordin, McGarvey, and Ghafoori [57] estimated that ERS could extend the lifespan of vehicle batteries by up to 40% and reduce vehicle downtime by 30% [55].

These studies collectively affirm the benefits and significant future potential of ERS. However, despite the compelling evidence presented, this technology remains in its nascent stages, with widespread adoption and pilot project implementation still evolving. Sweden's Smartroad Gotland, the world's first public wireless electric road for heavy-duty vehicles, demonstrated dynamic wireless power transfer, providing 100 kW to trucks at 80 km/h and withstanding -23°C, proving its suitability for harsh climates. However, challenges like consistent energy transfer and infrastructure integration remain [25] [28]. Sweden also plans to convert part of the E20 motorway into a permanent electrified road by 2025, aiming to extend up to 3,000 km by 2035. This project highlights logistical and economic hurdles, including road wear and high initial costs [51] [53]. France's A10 highway project aims to reduce CO2 emissions by 86% with a 2 km dynamic charging stretch, showcasing potential but also needing further technological advancements [24]. These pilot projects represent ongoing efforts to scale up the implementation of ERS to broader applications.

The ongoing development of ERS projects as new technology raises doubts among various stakeholders, including users, investors, and government bodies. Successful deployment requires concerted collaboration among all parties, including truck manufacturers. However, this situation presents a classic "chicken and egg" dilemma: manufacturers are hesitant to invest extensively in trucks equipped with pantographs or receiver coils without clear commitments to ERS infrastructure development and demonstrated customer demand. Conversely, investors and ERS developers are reluctant to allocate significant funds to ERS without a guaranteed market large enough to justify the costs. Therefore, customer acceptance becomes a critical factor in the viability of ERS. A high adoption rate among users would justify further expansion of ERS infrastructure due to increased demand, whereas low user interest would suggest a scaled-back approach to minimize financial risks.

When aiming for larger-scale implementation of Electric Road Systems (ERS), it is crucial to explore the optimal network structure of chargers, determining the most effective arrangement of dynamic and static charging facilities to optimize both investment and operational efficiency. According to Hou et al. [33], a mixed network of dynamic and static chargers, strategically placed along major transport routes and urban areas, can maximize coverage while minimizing costs. Additionally, a well-planned network design for ERS could minimize redundant installations and enhance cost-effectiveness [62]. Properly balancing the placement of ERS and static chargers can significantly reduce unnecessary expanses of static infrastructure.

Existing studies have focused on optimizing location and distribution for either static or dynamic charging systems independently. For instance, methodologies for designing electrical infrastructure supporting both dynamic and static charging have been developed, highlighting their potential to enhance efficiency and facilitate large-scale implementation [16]. Location optimization methods for fast-charging stations have also been proposed, considering user demands, electrical distribution network sizing, and traffic conditions [11][15]. Additionally, integrated approaches combining static plug-in charging stations with dynamic charging lanes have shown promising improvements in charging efficiency and convenience [70]. However, a comprehensive optimization model that simultaneously addresses the deployment of both ERS and static charging stations still needs to be explored.

1.3. Problem description

1.3.1. Research gap

Current research primarily focuses on the deployment and scalability of ERS, neglecting the real-world coexistence with static charging infrastructure. This scope overlooks the potential synergies and challenges inherent in integrating ERS with static charging stations. Considering different rates of ERS acceptance adds another layer of complexity to this issue. Previous research posits ERS as a viable alternative, suggesting significant government investment. However, practical uptake among electric truck users may be limited due to the novelty of the technology, associated costs, and other deterrents. Consequently, it is critical to consider technology adoption when designing networks to ensure that investments are precisely targeted and align with actual user needs and behaviors.

A deeper exploration into the optimal configuration of ERS and static charging could enhance significant cost efficiencies in infrastructure investment. However, this integrated approach remains underexplored, representing a gap in current research. Addressing this gap could influence future investment decisions and policy development in the EV sector.

1.3.2. Research questions and objective

The objective of the study is to develop a model that produce the optimal configuration of dynamic and static charging facilities for heavy-duty trucks while minimizing cost, given different ERS acceptance from various stakeholders. This research aims to enhance existing studies by integrating both dynamic and static charging methods into the analysis, offering insights for future EV infrastructure investments and policy development, thereby providing insights into optimal infrastructure deployment strategies for decarbonizing freight transportation.

The research objective can be achieved by the following main research question:

"How to determine a configuration of dynamic and static charging stations for heavy-duty vehicles that has the most demand coverage within a limited budget, taking into account varying acceptance levels of ERS among different stakeholders?"

The main research questions can be answered by the following sub-questions:

1. What are the key trade-offs between ERS and static charging for heavy-duty truck electrification?
2. Which modeling approaches are most suitable for developing a model that optimizes the configuration of dynamic and static charging stations, and how can this model be effectively developed and validated?
3. How does different ERS adoption rate impact the ERS network design?
4. What is the optimal configuration of ERS and static charging stations for heavy-duty electric trucks in the context of a specific case study?
5. What considerations and recommendations can be given to different stakeholders in the ERS project based on the case study?

1.3.3. Research scope

The research scope encompasses a detailed investigation into the primary areas of interest, ensuring a comprehensive understanding of the subject matter. This section outlines the key components and boundaries of the study, providing a clear framework for the research activities. The scope is defined by the following points:

- **Charging infrastructure**: This study utilizes a conductive ERS with a pantograph as the type of dynamic charging. For static charger, only Level 3 chargers are considered, which are high-power DC fast chargers with capabilities exceeding 50 kW.
- **Modality**: The research focuses primarily on heavy-duty trucks used for road freight transport, specifically battery electric vehicles (BEVs). Diesel and hydrogen-powered vehicles are not included in this study.

- **Data and Network**: All data, including distances between cities, demand levels, and highway connections, are assumed fixed throughout the modeling time-span, ensuring a consistent framework for analysis.

1.4. Research approach

In this section, the methods to answer the research questions are explained. The methodologies to answer the sub-questions are summarized in Table 1. There are three methods in the study: literature review, mathematical modeling and simulation, and case study validation.

Sub-RQ	Method	Detail
1	Literature review	Analyze existing research to identify and compare the trade-offs associated with static and dynamic charging systems.
2	Literature review, mathematical modeling	Conduct a thorough literature review to identify existing models and develop a mathematical model optimizing charging infrastructures based on model in the previous research.
3	Model application and validation	Apply the developed model to evaluate its performance under varying ERS adoption rates and analyze how these differences impact the optimal configuration of the charging network.
4	Model application and validation	Apply the developed model to a specific case in the Netherlands, analyzing data to identify optimal charging network configurations
5	Result analysis	Examine the case study results to draw insights and formulate practical recommendations for stakeholders involved in ERS projects

Table 1.1: Research methods per sub-research question

Figure 1.1 depicts the structured research workflow guiding the study, ensuring systematic analysis and reliable insights.

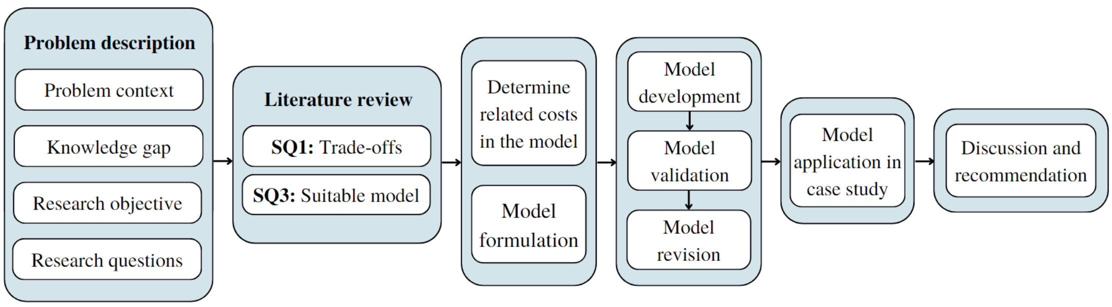


Figure 1.1: Research workflow

1.5. Report outline

This thesis is organized into seven chapters. Chapter 1 introduces the background, problem statement, and research objectives. Chapter 2 reviews the existing literature on ERS and static charging infrastructure, identifying key knowledge gaps. Chapter 3 presents the bi-level optimization model used to determine the optimal configuration of ERS and static chargers. Chapter 4 describes the data used for the model, while Chapter 5 explains the modeling approach, including the methods used for optimization. Chapter 6 presents the results of the model, focusing on the cost trade-offs and optimal configurations for the Netherlands' highway network. Finally, Chapter 7 discusses the policy implications, limitations. Finally, the Conclusion summarizes finding and suggests future research directions.

2

Literature Review

The literature review provides a comprehensive analysis of existing research and theoretical frameworks pertinent to the study. This section synthesizes key findings, identifies prevailing trends, and highlights gaps in the current knowledge base, establishing a foundation for the present research.

2.1. Overview of Electric Road Systems

The shift towards electrification in transport highlights the need for high-power charging infrastructure to complement home chargers and ensure HDEVs match the convenience of diesel refueling. HDEVs in Europe typically have a 200-300 km range, which may decrease with heavy loads, underscoring the necessity for accessible public high-power stations [35]. HDEV adoption faces hurdles like longer charging times, high energy requirements, and the lack of suitable infrastructure, with most stations designed for passenger cars and providing only 250-350 kW. However, HDEVs require stations capable of delivering over 350 kW, up to 1 MW, for rapid 30-45 minute recharges [36].

2.1.1. Different types of ERS

ERS can be broadly categorized into three types based on the method of power transfer: overhead conductive, ground-based conductive, and inductive (wireless) systems. Each system has unique characteristics and implementation requirements, which are explored below.

Overhead conductive systems

Overhead conductive or catenary systems utilize overhead wires to supply electricity to vehicles equipped with pantographs, enabling power transfer through a direct and constant connection between the vehicle and the energy source [62]. Pantographs can be positioned on top, on the side, or beneath the vehicle [67]. The most common placement is on top of the vehicle, with overhead wires as seen in trolleybuses and trams. However, a significant challenge with top-mounted pantographs is their height requirement. The transmitting power lines are placed high, limiting their use to tall vehicles such as trucks, buses, and trams, making them less attractive for standard passenger vehicles [67].

An alternative placement for transmitting power lines is on the side of the road, as proposed by Honda. In this setup, the pantograph's mechanical arm extends from the side of the vehicle to slide along a conductive rail on the road barrier for charging [67]. For future planning, where ERS is intended for both trucks and passenger cars, side-mounted power lines are preferable. This configuration can accommodate a wider range of vehicles, enhancing the system's overall utility and attractiveness.

Despite being the most mature ERS technology to this date, ERS catenary system has its own advantages and disadvantages. The primary advantage of this system is its proven technology and reliability. Studies by Min [54] highlight the successful implementation of overhead ERS in Sweden's eHighway project, demonstrating significant reductions in carbon emissions and operational costs for heavy-duty trucks [3]. However, overhead systems face challenges related to infrastructure aesthetics and compatibility with existing road networks. Maintenance of overhead lines and ensuring continuous power supply in adverse weather conditions are additional concerns [82].

Ground-based conductive system

Similar to the overhead catenary system, ground-based conductive systems require constant and direct contact between the power source and the vehicle's conductive arms through conductive rails embedded in the road surface [62]. In operation, the vehicle aligns with the electrified track, and a mechanical arm directly extends from beneath the vehicle to connect with the electrified rail.

This system is straightforward and compatible with various vehicle types, including heavy goods vehicles, light goods vehicles, and passenger cars. Moreover, the technology is well-developed. However, the ground-level placement of the rails poses safety risks for motorcyclists [67]. Additionally, this system is highly susceptible to weather conditions such as water and snow. When the rail is covered by snow or debris, power transfer efficiency can be significantly compromised. Ensuring reliable contact between the vehicle and the conductive rail under varying weather and road conditions remains a technical challenge.

Inductive (wireless) system

Inductive ERS utilize electromagnetic fields to wirelessly transfer power from coils embedded within the road to receivers on the vehicle. This system can transfer power over varying air gaps, eliminating the need for physical contact and offering significant safety and convenience benefits [62]. The invisibility of the coils enhances the aesthetic appeal of this system and makes the system less susceptible to weather conditions. Unlike overhead catenary systems, which are limited to large vehicles only, inductive ERS can be used by all types of electric vehicles, including passenger cars, making them more versatile for widespread implementation.

However, inductive wireless systems face key challenges. The installation costs are significantly higher due to the extensive work required to embed the coils within the road. Additionally, the efficiency of power transfer is slightly lower compared to conductive systems. While conductive systems can achieve 95% efficiency and above, inductive systems range from 70% to 95%. This lower efficiency is attributed to the air gap between the power supply coils and the receiver coils [67]. Despite these challenges, inductive ERS systems continue to be a major focus of research due to their potential benefits.

2.1.2. ERS Implementation

ERS are still in the early stages of development, primarily focused on research and small-scale implementations in specific corridors and pilot projects. However, global progress in ERS deployment is advancing, with key projects in Sweden showcasing the technology's potential. Table 2.1 provides a summary of ERS projects implemented worldwide. For instance, Michigan is introducing a public wireless in-road EV charging system in Detroit, developed in collaboration with Electreon and partners [74]. Despite these advancements, ERS technology has yet to be implemented at scale.

Name	**Location**	**Length (km)**	**ERS type**
E16	Sweden	2	Overhead lines
eRoadArland	Sweden	2	Conductive rail
Evolution Road	Sweden	1	Conductive rail
Smartroad Gotland	Sweden	2	Inductive wireless
ELISA	Germany	5	Overhead lines
FESH	Germany	5	Overhead lines
eWayBW	Germany	4	Overhead lines
Detroit	Michigan, USA	-	Inductive wireless

Table 2.1: Implemented ERS projects worldwide [29] [74]

Several pilot projects in Sweden are designed primarily for research purposes, aimed at understanding how to build, operate, and maintain ERS. Implementing ERS in real-world settings helps uncover practical challenges. For example, according to [29], the first procurement and early phases of implementation led to higher-than-expected costs due to unforeseen complexities. In these pilot projects, no extensive road planning was required given their small scale, though typical road planning for larger projects would take between 1 and 3 years.

One notable Swedish project, the 2 km Smartroad Gotland, is the first inductive ERS for heavy-duty vehicles. It successfully demonstrated Dynamic Wireless Power Transfer (DWPT) by charging a 40-ton truck and a 12.5-meter bus, achieving 100 kW charging at speeds of 80 km/h, and operating reliably even in extreme temperatures as low as -23°C [29].

In contrast, the three ERS projects in Germany use a catenary line system, a technology long employed in railways. These projects also focus on researching technical aspects related to vehicles, road infrastructure, and energy grids. Given the maturity of the catenary system in rail transport, the technical challenges for these ERS implementations are considered relatively low [29].

While pilot projects have proven the benefits of ERS, realizing its full potential depends on addressing key research areas such as integration into urban and regional planning and ensuring scalability for future expansion. Research is needed to explore how ERS can be seamlessly incorporated into existing and future transportation networks, including the impact on traffic flow, road design, and its interaction with other charging infrastructures. As ERS technology continues to evolve, ongoing research will be essential to assess its scalability and readiness for large-scale implementation.

2.2. Trade-offs between ERS and Static Chargers

The introduction of ERS has sparked research into whether it is superior to static chargers and what trade-offs exist between the two technologies. Understanding these trade-offs helps determine the optimal conditions for investing in each and the key factors to consider in decision-making. Both approaches present distinct advantages and challenges in terms of cost, convenience, technological efficiency, and user behavior. Understanding these trade-offs is essential to developing an integrated and scalable solution for widespread EV adoption.

Cost and Infrastructure Investment

ERS requires substantial upfront investment, as it involves embedding charging technology directly into roadways. This makes large-scale deployment costly and complex, particularly in urban areas where infrastructure modifications are both expensive and disruptive [46][70]. While continuous charging during travel may justify the investment for long-haul routes, the significant initial cost limits ERS implementation to high-use corridors [21]. In contrast, static chargers provide a more cost-effective and scalable option [70]. However, widespread deployment is still necessary to alleviate range anxiety, especially in areas with limited charging infrastructure [46]. Therefore, the decision between ERS and static chargers must balance the immediate cost advantages of static systems with the long-term operational benefits of ERS.

Range, Charging Convenience, and User Experience

A major advantage of ERS is its ability to provide continuous, on-the-go charging, which significantly reduces range anxiety and eliminates the need for frequent stops [46] [70]. The smaller batteries advantage from using dynamic charging depends on the availability of ERS infrastructure, which is typically limited to specific routes. In contrast, static chargers increases travel time and potentially inconveniencing drivers, particularly on long journeys [66]. While fast-charging stations can reduce some of the downtime associated with static chargers, they become less efficient at higher states of charge and do not eliminate the need for larger battery capacities [66].

Technological Efficiency and Operational Impact

ERS faces challenges in maintaining efficient energy transfer between the road and the vehicle at varying speeds, introducing complexities that may affect overall performance [46][70]. Additionally, ERS must be compatible with a wide range of vehicles, further complicating its implementation [46]. On the other hand, static chargers benefit from a stable connection, resulting in higher charging efficiency [70]. However, frequent use of fast-charging stations can lead to diminishing returns, and over-reliance on them may shorten long-term battery life [46]. While ERS offers the potential for a more seamless charging experience, static chargers are more technologically mature and reliable to this date.

Battery Size and Energy Management

ERS supports the use of smaller batteries by providing continuous charging during travel, which is particularly beneficial for long-haul journeys [21]. This allows for lighter vehicles and greater payload capacity, making ERS especially attractive for heavy goods vehicles and long-distance freight operations. In contrast, static chargers require larger batteries to cover the longer gaps between charging stops [21]. For long trips, especially in areas with sparse charging infrastructure, EVs may need oversized batteries, which increase costs and reduce efficiency [21]. However, strategically placed high-capacity static chargers can help minimize the need for excessively large batteries.

2.3. ERS stakeholder acceptance

The widespread adoption of ERS faces several barriers, particularly during the early stages of the technology. Not all trucks will adopt ERS immediately due to the high costs and required investments in compatible components. Trucks without ERS compatible components will continue to rely on static charging stations, emphasizing the importance of a versatile charging infrastructure. The system's benefits—economic, environmental, and social—are acknowledged, but transitioning current systems has proven challenging due to market inertia and dependence on established technologies [9]. Without a clear government plan to to build ERS, vehicle manufacturers are hesitant to produce ERS-compatible vehicles, further limiting market growth [71].

There are significant barriers to ERS adoption, including technological, financial, and market domains. Technological uncertainties and the high costs of infrastructure create challenges [9]. Additionally, market dynamics further hinder adoption. In Sweden, established business relationships favoring conventional technologies, combined with a lack of awareness and understanding of ERS, have slowed its adoption rate [9]. Financially, the gradual expansion of ERS infrastructure discourages investment in compatible vehicles, leading to low utilization rates and reducing the cost-effectiveness of public investments in the system [71]. Similar barriers are observed in the broader context of EV adoption. Studies from the Netherlands highlight key obstacles such as price sensitivity and driving range limitations, which are also relevant to ERS adoption [8].

Several key drivers influence the adoption of ERS. For road freight companies, the relative advantages of ERS—such as cost savings, operational efficiency, and sustainability—play a critical role in shaping their adoption intentions [48]. Technological advancements, including improvements in driving range and charging infrastructure, are also significant. For instance, studies show that reducing the distance between charging stations and shortening recharge times can significantly boost the adoption of static chargers [8]. Additionally, word of mouth becomes a powerful driver, particularly in later stages of adoption. While initial uptake may be slow, adoption tends to accelerate as more users embrace the technology [8]. This S-shaped adoption curve indicates that as technical advancements meet consumer expectations and charging infrastructure becomes more accessible, the rate of ERS adoption will increase substantially [8].

Survey data from the United States indicates that lifestyle factors, environmental awareness, and safety concerns regarding ERS networks play a significant role in shaping public willingness to adopt the technology [41]. The research also emphasizes the importance of time savings, with individuals more likely to adopt ERS if it offers exclusive electrified lanes and tangible benefits, such as reduced travel times [41]. These findings highlight the need to address consumer concerns and preferences through targeted strategies that build public trust and increase confidence in ERS.

2.4. Regulatory aspect regarding ERS

Current regulations regarding static chargers and ERS address various aspects, including infrastructure placement, standardization, and technological innovation, all aimed at facilitating a smooth transition to electric trucks. The current and future regulations are elaborated in this section.

2.4.1. Regulations regarding static chargers

In the European Union (EU), directives like the Alternative Fuels Infrastructure Regulation (AFIR) mandate the development of fast-charging infrastructure along the Trans-European Transport Network (TEN-T) corridors. These regulations set strict targets for the deployment of high-power chargers at regular intervals along major transport routes. By 2025, fast chargers of at least 150 kW must be available every 60 km, with a requirement to scale up to 600 kW by 2027—critical for supporting the growing electric truck fleet [6][4].

Equity and accessibility are also key considerations in static charging infrastructure regulations. In the UK, policies require new developments with parking facilities to include charging points, while mobile charging stations are proposed to fill gaps in underserved regions [32]. Dynamic pricing models further enhance affordability by offering lower rates during off-peak hours, reducing grid strain and making charging more accessible to truck operators [32].

The Dutch regulatory framework showcases the role of government incentives in accelerating public charging infrastructure. Initiatives like the Electric Transport Green Deal 2016-2020 have supported the installation of high-capacity fast-charging stations, with some reaching up to 350 kW to facilitate long-haul transport [1].

2.4.2. Regulations regarding ERS

European regulations for ERS remain in the early stages of development. Under the AFIR, ERS is recognized as an emerging technology, though it lacks the same mandatory deployment targets imposed on static charging infrastructure [4]. The recognition of ERS as "emerging" has been criticized as overly cautious, given that comparable technologies like hydrogen have received more assertive regulatory support despite similar levels of technological readiness

[4]. To support ERS development, European standardization bodies, such as CEN-CENELEC, are working on establishing technical standards for various ERS technologies, including both conductive and inductive systems [4].

In terms of funding, ERS implementation faces significant financial challenges due to its high infrastructure costs. The Eurovignette Directive, which allows EU member states to charge for road use, has been amended to permit the inclusion of ERS infrastructure costs in road tolls, providing a potential funding mechanism for broader ERS deployment [4]. In Germany, pilot projects for ERS are being funded as part of national road infrastructure initiatives, and future legislation may provide further clarification on how to incorporate ERS costs into toll systems [4].

One notable regulatory challenge facing ERS is ensuring interoperability and cross-border consistency. The European regulatory environment underscores the importance of integrating ERS into the TEN-T network to enable seamless travel across different countries. A unified billing system, potentially modeled on the European Electronic Toll Service (EETS), is also considered essential for ensuring consistent user experiences across borders [4]. However, the possibility of fragmented ERS implementations, where different countries adopt varying technologies, remains a significant obstacle to the system's broader rollout [4].

2.5. Charging stations network design

The design of ERS networks plays a crucial role in determining their adoption potential. Studies comparing dense infrastructure networks, which involve multiple short routes, with corridor-based designs, which focus on longer segments, reveal that each configuration presents different benefits and challenges [5]. Corridor designs tend to be more efficient for long-haul transport, attracting longer trips and contributing more significantly to reducing carbon emissions. However, dense networks offer greater route flexibility, making them more attractive to a larger number of users in the early stages of adoption [5]. Policymakers face a critical trade-off between the immediate adoption potential offered by dense networks and the long-term environmental benefits of corridor designs. This suggests that a phased approach, where investments start with dense networks and gradually expand to corridors, might be the most effective strategy for maximizing ERS market growth [5].

Since a huge number of charging infrastructures are needed, both dynamic and static charging, more research around charging network design is needed. As an instance, [65] uses a mathematical approach with a path-constrained network equilibrium model to optimize the location of electrification roads, aiming to minimize total travel time within a limited construction budget. The numerical experiments done validate the model's effectiveness and explore the impact of variables like charging efficiency, battery size, and comfortable range of the system. On the other hand, a Geographic Information System (GIS)-based model is used by [60] to calculate potential charging station locations by employing user- and destination-based approaches. In this research, optimal charging station locations are determined by minimizing walking distances while ensuring extensive coverage of electric energy demand, which is further applied in the southern Germany case study. Moreover, [43] develops two mixed integer linear programming (MILP) models to optimize the location of charging stations along intercity highways, aiming to minimize detour mileage within budget constraints. The first model is based on the original node-link network topology, incorporating path and subpath activation indicators to reflect the utilization of paths and subpaths. The second model utilizes a station-subpath metanetwork topology, which simplifies routing and charging decisions into a two-phase process, enhancing computational efficiency for large-scale problems. Results indicate both models are effective, with the metanetwork-based approach offering computational advantages for larger problems. MILP is also used by [42], [45], and [81]to solve the origin-destination shortest distance-based flow-capturing location model (FCLM). Arc cover model is used in [80] to locate battery exchange stations to serve tourism transport.

The paper by Chen, Liu, and Yin [12] investigates the deployment of both stationary and dynamic chargers along traffic corridors. The study develops a charging-facility-choice equilibrium model that analyzes how drivers select between these two types of charging facilities. The research optimizes deployment strategies under two scenarios: public provision, where a government agency develops infrastructure to minimize social costs, and private provision, where competing companies build and operate infrastructure to maximize profits. Numerical experiments using empirical data explore the competitiveness of charging lanes, showing that dynamic charging lanes can attract drivers and generate revenue in both public and private contexts. Results highlight the potential of dynamic charging lanes, especially for vehicles with higher values of time, such as commercial fleets. This study contributes to the literature by offering a first-of-its-kind comparison between stationary and dynamic charging infrastructure within the framework of user equilibrium and infrastructure deployment planning.

Several other methods are explored by [39], exact methods like branch and bound, as used in [79], and mixed integer linear programming to heuristic algorithm due to computational complexity. The paper evaluates various algorithms and mathematical models such as greedy algorithms, genetic algorithms, Non-Dominated Sorting Genetic Algorithm (NSGA-II), Particle Swarm Optimization (PSO). Each of these methods has its strengths and weaknesses. Greedy algorithms are simple and can provide quick solutions but may not always reach the global optimum. Genetic algorithms and NSGA-II are powerful for complex, multi-objective problems but require careful design and can be computationally intensive. PSO and its variants offer a balance between exploration and exploitation, providing efficient solutions for a wide range of problems. The choice of method depends on the specific requirements of the location optimization problem, including the complexity of the dataset, the number of objectives to be optimized, and computational resource constraints. Moroever, [39] highlights the transition towards heuristic methods, which, despite not always yielding the ideal solution, provide reasonably accurate solutions efficiently. The review emphasizes the need for models that consider both road network accessibility and electric distribution grid impacts to develop sustainable charging station location strategies.

3

Model Specification

In this thesis, the objective is to determine the optimal configuration of static chargers and ERS. To achieve this, we will employ an optimization model that strategically integrates both charging technologies. Optimization models provides a systematic and quantifiable approach to decision-making. These models allow us to identify the most efficient allocation of resources, balancing various objectives such as cost, time, and environmental impact. By using an optimization model, we can ensure that the deployment of static chargers and ERS is done in a manner that minimizes overall transport costs for users while also reducing the infrastructure costs invested by the government. This approach will allow us to assess the most efficient and cost-effective solutions for supporting electric vehicle infrastructure.

3.1. Model characterization

3.1.1. Road segments

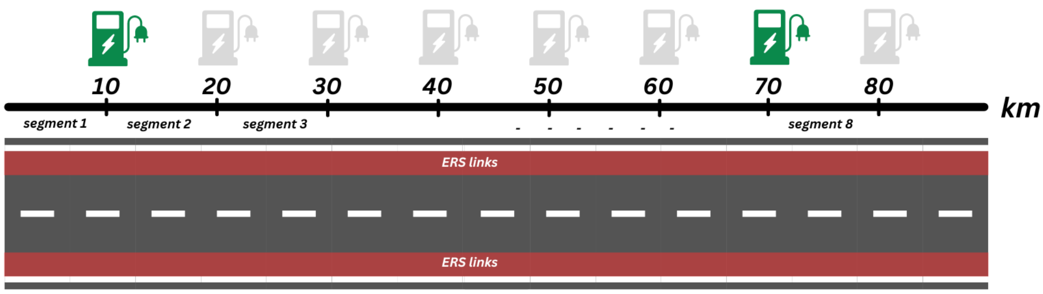


Figure 3.1: Road segments visualization

In the model, roads are divided into segments, each 10 kilometers in length. At the end of each segment, there is the potential for a static charging station to be installed, as illustrated in Figure 3.1. This segmentation approach is designed to streamline the modeling process;

rather than considering a continuous range of potential charging station locations—which would be computationally intensive—charging stations are considered every 10 kilometers. The 10-kilometer interval was chosen because it aligns well with the government's initial guideline of having at least one charging station every 60 kilometers, making it a practical representation of potential charging locations. Additionally, ERS can be installed along the same highway links, offering a complementary solution to the static charging stations.

3.1.2. Network representation

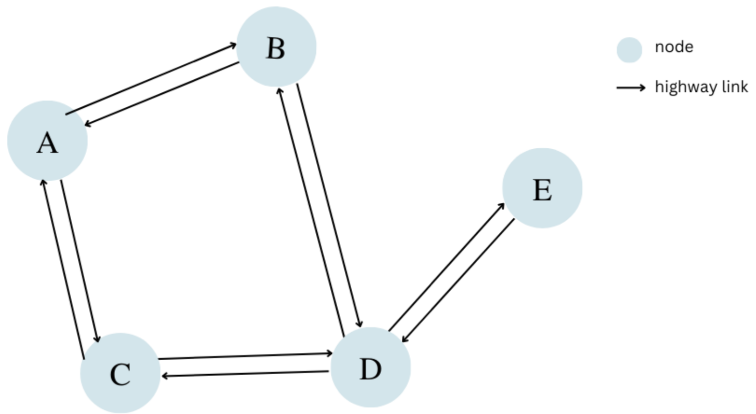


Figure 3.2: Network example visualization, consist of nodes and bi-directional highway connections

In this thesis, the transportation network is illustrated by representing cities as nodes and connecting highways as bidirectional links. As shown in Figure 3.2, the example includes five cities interconnected by ten highway links. For a hypothetical journey from node A to node E, we evaluate three strategic charging options:

- **Large Battery Capacity:** This option equips vehicles with large batteries that can complete the journey without recharging, suitable for distances up to 300km. While this avoids charging delays, it also introduces higher costs and reduced payload capacity due to the significant weight of the batteries. This approach becomes impractical for longer distances due to the exponential increase in battery size and cost.
- **DC Fast Charging Stations:** By installing DC fast charging stations along the route, vehicles can recharge mid-journey. This configuration uses standard Battery Electric Vehicles (BEVs) but introduces additional time costs for charging stops, which need to be integrated into overall trip cost calculations.
- **Electric Road Systems:** Installing ERS along certain highway segments represents a more significant initial investment compared to static chargers but offers considerable benefits. It allows vehicles to charge while driving without necessitating large on-board batteries, thereby eliminating charging stops and reducing the journey time and operational costs for users. However, it requires vehicles to be equipped with specific technologies such as pantographs or receiver coils, which limits its use to specially equipped BEVs.

Each option presents unique benefits and challenges, necessitating a comprehensive analysis to determine the optimal integration of static and dynamic charging systems to minimize both infrastructure and operational costs. The analysis will focus on the optimal placement and quantity of charging facilities and the appropriate length of ERS to efficiently meet traffic needs. This approach aims to strategically locate these assets to maximize investment efficiency and operational effectiveness.

3.2. Bi-level optimization

In the literature review, various types of optimization models have been explored, including single objective optimization, bi-level optimization, and multi-objective optimization. Each of these models has its own advantages and suitable applications. However, for our specific problem of optimizing the combination of static chargers and ERS, a bi-level optimization model stands out as the most suitable.

A bi-level optimization model involves two interrelated levels of optimization problems, where the solution to the upper-level problem depends on the solution to the lower-level problem. In this thesis, the bi-level optimization can be represented as the following:

- **Upper-Level Problem:** This represents the government's perspective, focusing on minimizing the infrastructure costs associated with installing and maintaining static chargers and ERS. The government needs to decide on the optimal locations and number of these installations to achieve cost efficiency.
- **Lower-Level Problem:** This captures the users' perspective, aiming to minimize their transport costs. Users will optimize their travel routes and charging behaviors based on the infrastructure provided by the government.

The bi-level optimization model is particularly well-suited for addressing this problem because it accurately reflects the hierarchical decision-making process observed in real-world scenarios.

Figure 3.3 depicts the iterative process of the bi-level optimization model. At the upper level, the government makes strategic decisions about where to build charging infrastructure based on the routes commonly used by travelers. These decisions are influenced by the need to optimize the locations and types of charging stations to meet the projected demand while minimizing infrastructure costs. In response to these government decisions, users at the lower level optimize their travel routes to minimize their individual costs, including both travel and charging expenses.

The routes selected by users provide feedback to the government, which can then re-evaluate and adjust the charging infrastructure to better align with actual usage patterns. This feedback loop—where the government continually re-optimizes infrastructure placement based on usage and costs, and users, in turn, adjust their routes based on the newly developed infrastructure and their travel costs, creating an iterative process.

The dynamic interaction between government decisions and user responses ensures that the charging infrastructure evolves to meet real-world demands effectively, balancing costs

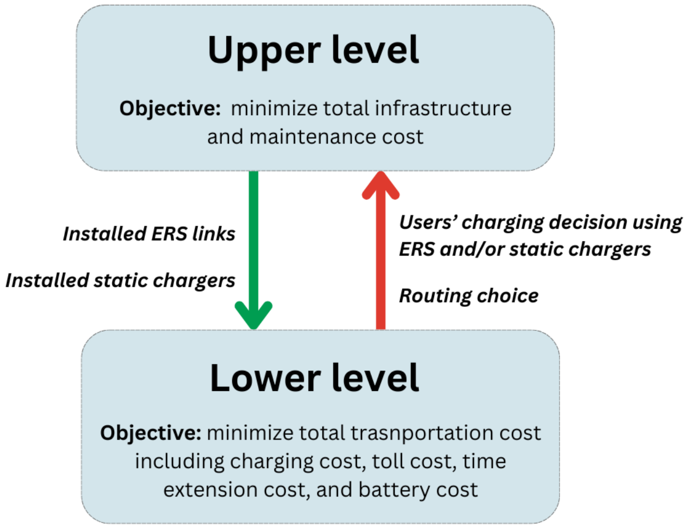


Figure 3.3: Bilevel optimization scheme

and user needs over time. By incorporating real-world constraints and data, such as traffic patterns, energy consumption, and user preferences in routing, the model can provide insights about the optimal number of chargers need to be installed to satisfy EV trucks charging needs while minimizing costs.

3.2.1. Assumption and simplification

The subsection on model assumptions and simplifications outlines the foundational premises and necessary reductions in complexity that underpin the study's analytical framework. By clearly stating these assumptions and simplifications, this section ensures transparency and facilitates an understanding of the model's limitations and applicability. The key assumptions and simplifications are as follows:

- **Electric Road Systems type:** The study focuses exclusively on conductive ERS, either overhead or side pantograph. This type of ERS is considered the most advanced in terms of development, making it the chosen model for this study.
- **Vehicle types:** The model only considers battery electric trucks (BETs) used for road freight transport. Personal vehicles and alternative fuel vehicles, such as diesel or hydrogen trucks, are excluded. The adoption of ERS technology among BETs varies, with some vehicles equipped with pantographs and others not, reflecting different levels of adoption.
- **Highway electrification:** Electrified highway lanes are divided into two sections. The first section operates as a regular highway for all vehicles, regardless of pantograph presence. The second section, equipped with ERS, is exclusively for vehicles with pantographs actively charging. When not charging, these vehicles revert to using the regular highway lane. Only vehicles with pantographs can charge on ERS lanes.

Additionally, highway electrification must cover the entire length of the highway; it is not feasible to install ERS on only a portion of a single highway link.

- **Toll pricing:** Vehicles charging via ERS benefit from a subsidized toll price per kilometer, incentivized by government subsidies to encourage ERS adoption. Vehicles that are not using ERS pay the standard toll price per kilometer.
- **Battery capacities:** For simplification, two battery capacity categories are used:
  - Battery size for BETs with receiver coils for pantograph (vehicle type 1)
  - Battery size for BETs without receiver coils for pantograph (vehicle type 2)
- **Highway electrification scope:** All highways are considered eligible for electrification, with no limitations on implementing ERS lanes.
- **Charging and energy consumption rates:** Charging rates for both ERS and static chargers, as well as energy consumption rates, are predetermined and constant. Although, in reality, energy consumption varies due to factors such as vehicle weight, speed, and road elevation, these variables are not accounted for in the model.
- **Charging station time:** The time each vehicle spends at a charging station is based on the kWh required to reach full battery capacity. It is assumed all vehicles charge to full capacity, despite real-world behavior where drivers might charge only enough to reach their destination.
- **Starting battery capacity:** All vehicles are assumed to start their journey from the depot with a full battery. The model considers only one-way trips; return trips are not included.
- **Electricity cost:** The cost of electricity per kWh is assumed constant. Users of ERS receive a partially subsidized electricity cost as part of the government's initial efforts to promote ERS technology.
- **Pantograph adoption rate:** The percentage of BETs equipped with pantographs is a parameter. The study analyzes different adoption rates to assess their impact.
- **Discount rate for future costs:** Future costs are discounted using a fixed discount rate.
- **Cost timeline:** All costs are projected to occur in the year 2030, with a model timespan of one year.

3.3. Model formulation

The model formulation section details the mathematical and logical structures that define the sets, parameters, variables and decision variables that are going to be modeled using bi-level optimization algorithm. Moreover, the detailed optimization objectives and constraints will be elaborated.

The formulation starts with the sets and indices to represent the problem, which are listed as follows:

- $\mathcal{N}$: a set of nodes in the network representing set of cities. The individual city is represented with $i \in \mathcal{N}$
- $\mathcal{A}$: a set of links connecting pairs of nodes, representing a unidirectional highway road with several links. The link is denoted as $(i, j) \in \mathcal{A}$
- $\mathcal{Q}$: a set of traffic demand from origin $o \in \mathcal{N}$ to destination $d \in \mathcal{N}$, denoted as (o, d)
- $\mathcal{V}$: a set of truck types where $v = 1$ is trucks with receiver coils and $v = 2$ is trucks without the receiver coils. $\mathcal{V} = \{1, 2\}$
- $\mathcal{S}$: a set of potential static charging station locations $s \in \mathcal{S}$ that are set every certain distance called segment length, along the highway link $(i, j) \in \mathcal{A}$. Potential static charging location s is denoted as $s \in \mathcal{S}_{i,j}$

The following part enumerates the parameters integral to the model, each of which holds the input data for the model, shaping the outcomes. The parameters included in the models are:

- dr: Discount rate for future cost *[-]*
- efE: Transfer efficiency when charging using ERS *[-]*
- efS: Transfer efficiency when charging using a static charger *[-]*
- len: Segment length, which is the distance between each potential static charger location in S. The length is constant of 10km. *[m]*
- t: Time spent as vehicle downtime when charging using static charger to recharge vehicle type 2 battery until full capacity *[hour]*
- $tollE$: Toll price a vehicle has to pay after using ERS charger *[€/km]*
- $tollS$: Toll price a vehicle has to pay when using battery or when not charging using ERS *[€/km]*
- vot: Value of travel time which is related to translate the t in monetary value *[€/hour]*
- B_v: The battery capacity of vehicle type $v \in \mathcal{V}$. This set consist of B_1 being the vehicle with receiver coils for pantograph, and B_2 being the vehicle without receiver coils. *[kWh]*
- Cb: Battery price of the vehicle *[€/kWh]*
- Cd: Catenary cost to install ERS on the highway link *[€/km]*
- Ce: Charging cost using ERS *[€/kWh]*
- Csc: Chagring cost when using static charging stations *[€/kWh]*
- Sc: Installation cost of a static charging station *[€/unit]*
- veh_1: Number of vehicle of type 1. This is calculated after each iteration of lower level model. *[-]*

- ywd: Number of trips a vehicle have in a year *[trips/year]*
- α: Percentage of type 1 vehicle, which has pantograph *[-]*
- β: Truck energy consumption rate while driving on a highway *[kWh/km]*
- γ: Penalty to be paid in case in case if there is not enough charging station available, which results in unfulfilled charging demand. In order to reach the destination, the vehicle is forced to reload the battery without an actual charging station available, calculated as a penalty *[-]*
- η_{max}: Maximum battery level that the vehicle effectively can use, represented by a percentage of full battery capacity *[-]*
- η_{min}: Minimum battery level that the vehicle need to have, represented by a percentage of full battery capacity *[-]*
- μ_{ers}: Annual operation and maintenance cost rate of the installed ERS. This value is a percentage of the whole investment of the installed ERS *[-]*
- μ_{ers_use}: Maintenance cost for parts reparation and replacement, which is represented by a cost per km per vehicle using the ERS charger *[€/km.v]*
- μ_{sc}: Maintenance cost for parts reparation and replacement, which is represented by a cost per km per vehicle using the static charger *[€/unit.year]*
- μ_{sc_use}: Maintenance cost for parts reparation and replacement, which is represented by a cost per charger unit per vehicle using the static charger *[€/unit.v]*
- τ_{batt}: Operational life of vehicle battery *[years]*
- τ_{ers}: Operational life of ERS infrastructure *[years]*
- τ_{sc}: Operational life of static charger *[years]*
- ϕ: Charging rate of ERS on the vehicle *[kWh/km]*

The variables used in the optimization model are outlined in the following part. These variables are essential for defining the decision-making framework and for solving the optimization problem effectively. The key variables in the model are:

- $bl^{(o,d)}_{v,(i,j),s}$: Positive continuous variable denoting battery level of each vehicle v that travels from origin o to destination d at location s on link (i,j) *[kWh]*
- $cl^{(o,d)}_{v,(i,j),s}$: Positive continuous variable denoting the power consumed to recharge trucks of type $v \in \mathscr{V}$ traveling on link $(i,j) \in \mathscr{A}$ for demand $(o,d) \in \mathscr{Q}$ at the end of segment $s \in S_{ij}$ *[kWh]*
- $Ecl^{(o,d)}_{v,(i,j),s}$: Amount of kWh added to vehicle type v to finish a trip from origin o to destination d while there is no charging station at location s on link (i,j) to fulfil this demand. When there are insufficient charging stations to meet the demand, vehicles are compelled to draw additional energy, measured in kilowatt-hours (kWh), to ensure they can reach their destination, calculated as a penalty.

- $f^{(o,d)}_{v,(i,j)}$: Positive continuous variable denoting the number of trucks of type $v \in \mathscr{V}$ traveling on link $(i,j) \in \mathscr{A}$ for demand $(o,d) \in \mathscr{Q}$

Apart from the variables written above, the following part lists the decision variables that represent the choices to determine the optimal solution. The decision variables in the model are:

- x^s_{ij}: Binary variable stating 1 if a static charging station is established at location s in link (i,j), and 0 otherwise $\quad x^s_{ij} \in \{0,1\}$
- y_{ij}: Binary variable stating 1 if ERS is implemented on the link (i,j) $\quad y_{ij} \in \{0,1\}$
- $r^{(o,d)}_{v,(i,j),s}$: Binary variable that equals to 1 if trucks type $v \in \mathscr{V}$ traveling on link $(i,j) \in A$ for demand $(o,d) \in Q$ use the static charging to recharge at the end of segment $s \in S_{ij}$, and 0 otherwise $\quad r^{(o,d)}_{v,(i,j),s} \in \{0,1\}$
- $\pi^{(o,d)}_{(i,j)}$: Binary variable that equals to 1 if vehicles type 1 traveling on link (i,j) for demand (o,d) use ERS for recharging. The charging activity using ERS happens from the start until the end of the link. $\quad \pi^{(o,d)}_{(i,j)} \in \{0,1\}$
- $w^{(o,d)}_{v,(i,j)}$: Binary variable whether vehicle type v traveling with origin-destination (o,d) choose to travel through the link (i,j) to reach the destination $\quad w^{o,d}_{v,(i,j)} \in \{0,1\}$

3.3.1. Lower-level optimization model

The objective function of the lower-level optimization model aims at minimizing the total transportation cost of each trips paid by the logistic company, including travel extension time due to charging using a static charger, toll cost, charging cost, and battery cost. These individual components of the lower-level objective function can be represented as follows:

- **Travel time extension cost due to static charging**: When a vehicle opts to charge using a static charger, it must stop and charge until the battery reaches full capacity. This stop incurs a cost associated with vehicle downtime, which is reflected in the travel time extension cost. This cost is calculated by multiplying the number of times the vehicle charges using static chargers by the time required to fully charge the battery and by the value of travel time in euros. The value of travel time encompasses various costs, including operational expenses, driver wages, and potential delays in delivery schedules.

$$\sum_{(o,d)\in\mathscr{Q}} \sum_{v\in\mathscr{V}} \sum_{(i,j)\in\mathscr{A}} \sum_{s\in\mathscr{S}} t \cdot vot \cdot r^{(o,d)}_{v,(i,j),s} \cdot Q^{(o,d)} \tag{3.1}$$

- **Toll cost**: Toll costs are incurred when using highways. However, in the initial stages of ERS implementation, the government may offer subsidies on toll costs to encourage ERS adoption. Therefore, the toll cost per kilometer for vehicles using ERS is lower than the standard toll rate for driving on highways without ERS. This toll cost is calculated by multiplying the toll rate per kilometer by the highway length, and by the variable

$\pi_{(i,j)}^{(o,d)}$ for vehicles using ERS, or $\left(1-\pi_{(i,j)}^{(o,d)}\right)$ for those not using ERS.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\left\{tollE\cdot\pi_{(i,j)}^{(o,d)}\cdot d_{ij}\cdot w_{v,(i,j)}^{(o,d)}\cdot Q^{(o,d)}+\sum_{v\in\mathcal{V}}\left[tollS\cdot\left(1-\pi_{(i,j)}^{(o,d)}\right)\cdot d_{ij}\cdot w_{v,(i,j)}^{(o,d)}\cdot Q^{(o,d)}\right]\right\} \tag{3.2}$$

- **Cost of electricity**: This cost refers to the charging expense, which differs between using an ERS and a high-power static charger. It is calculated based on the amount of energy (kWh) required to fully charge the vehicle's battery, multiplied by the respective rate for ERS or static charging, and a variable indicating the charging method used.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\left[Ce\cdot cl_{1,(i,j),s}^{(o,d)}\cdot\pi_{(i,j)}^{(o,d)}\cdot Q^{(o,d)}+\sum_{v\in\mathcal{V}}\left(Csc\cdot cl_{v,(i,j),s}^{(o,d)}\cdot r_{v,(i,j),s}^{(o,d)}\cdot Q^{(o,d)}\right)\right] \tag{3.3}$$

- **Battery cost**: The larger the battery, the higher the vehicle's cost. Consequently, vehicles equipped with ERS technology tend to have a lower purchase price due to their smaller batteries. The battery cost is determined by multiplying the price per kWh by the battery capacity specific to each vehicle type and the number of vehicles. Overall, the number of trips in the dataset is divided by the number of trips of a vehicle per year (*ywd*) to determine the total number of trucks.

  Furthermore, the modeling is conducted over a one-year period, while the vehicle battery, static chargers, and ERS infrastructure have different lifespans. To account for these varying lifespans, the Equivalent Annual Cost (EAC) is used. EAC represents the annual cost of owning, operating, and maintaining an asset over its entire lifespan, allowing for the comparison of net present values and amortized annual costs across different infrastructures with varying service periods.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{v\in\mathcal{V}}\frac{Cb\cdot B_v\cdot f_{v,(o,j)}^{(o,d)}}{ywd}\cdot ann_{batt} \tag{3.4}$$

$$ann_{batt}=\frac{dr}{1-(1-dr)^{-\tau_{batt}}} \tag{3.5}$$

The costs involved in the **total transportation cost** can be combined as lower-level optimization equation, denoted as follows:

$$\begin{aligned}\min_{\mathbf{r},\pi}\ &\sum_{(o,d)\in\mathcal{Q}}\sum_{v\in\mathcal{V}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\left(t\cdot vot\cdot r_{v,(i,j),s}^{(o,d)}\cdot Q^{(o,d)}\right)+\sum_{(o,d)\in\mathcal{Q}}\sum_{v\in\mathcal{V}}\sum_{(i,j)\in\mathcal{A}}\frac{Cb\cdot B_v\cdot f_{v,(i,j)}^{(o,d)}}{ywd}\cdot ann_{batt}\\&+\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\left[tollE\cdot\pi_{(i,j)}^{(o,d)}\cdot d_{i,j}\cdot w_{v,(i,j)}^{(o,d)}\cdot Q^{(o,d)}+\sum_{v\in\mathcal{V}}tollS\cdot(1-\pi_{(i,j)}^{(o,d)}\cdot d_{ij}\cdot w_{v,(i,j)}^{(o,d)}\cdot Q^{(o,d)}\right]\\&+\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\left[Ce\cdot cl_{1,(i,j),s}^{(o,d)}\cdot\pi_{(i,j)}^{(o,d)}\cdot Q^{(o,d)}+\sum_{v\in\mathcal{V}}\left(Csc\cdot cl_{v,(i,j),s}^{(o,d)}\cdot r_{v,(i,j),s}^{(o,d)}\cdot Q^{(o,d)}\right)\right]\end{aligned} \tag{3.6}$$

The lower-level objective function is subject to the following **constraints**:

- Flow conservation constraints, they imply that the number of trucks of all types leaving node i if node i is the origin equals to the total number of trucks that shall leave o, if node i is the destination then the total number of trucks that enters d is the number of trucks that shall be received at d, and the trucks getting into a node and leaving a node is equal for all other nodes.

$$\sum_j \sum_v f_{v,(i,j)}^{(o,d)} - \sum_j \sum_v f_{v,(j,i)}^{(o,d)} = \begin{cases} N_{(o,d)} & \text{if } i = o \\ -N_{(o,d)} & \text{if } i = d \\ 0 & \text{otherwise} \end{cases} \quad \forall i \in \mathcal{N}, (o,d) \in \mathcal{Q} \tag{3.7}$$

- Guarantee that the battery level of any vehicle $v \in V$ does not exceed the maximum level and does not drop below the minimum level of battery, respectively.

$$bl_{v,(i,j),s}^{(o,d)} \leq \eta_{min} \cdot B_v \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q} \tag{3.8}$$

$$bl_{v,(i,j),s}^{(o,d)} \geq \eta_{max} \cdot B_v \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q} \tag{3.9}$$

- At the start of the trip, all vehicles begin with their batteries fully charged.

$$bl_{v,(o,j),s}^{(o,d)} \leq B_v \qquad \forall (o,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q}, v \in \mathcal{V} \tag{3.10}$$

$$cl_{v,(o,j),s}^{(o,d)} = 0 \qquad \forall (o,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q}, v \in \mathcal{V} \tag{3.11}$$

- Determine the battery level for all vehicles across all links and segments. This constraint specifies that the battery level of a vehicle type v entering segment s of link (i,j) is equal to the battery level from the previous segment of the link, minus the battery consumption, which is a function of the distance traveled (i.e., segment length), plus any recharging that occurs.

$$bl_{v,(i,j),s}^{(o,d)} = bl_{v,(i,j),s-1}^{(o,d)} - \beta \cdot d_{ij} \cdot w_{v,(i,j)}^{(o,d)} + cl_{v,(i,j),s}^{(o,d)} + Ecl_{v,(i,j),s}^{(o,d)} \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q}, v \in \mathcal{V} \tag{3.12}$$

- Calculate the recharging quantity for vehicles of type 2, which can only utilize static charging stations.

$$cl_{2,(i,j),s}^{(o,d)} \leq B_2 \cdot r_{2,(i,j),s}^{(o,d)} \cdot x_{ij}^s \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q \tag{3.13}$$

- Calculate the recharging quantity for vehicles of type 1, which have the option to recharge using both static charging stations and the ERS.

$$cl_{1,(i,j),s}^{(o,d)} \leq B_1 \cdot r_{1,(i,j),s}^{(o,d)} \cdot x_{ij}^s + \phi \cdot \pi_{(i,j)}^{(o,d)} \cdot len \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in \mathcal{Q} \tag{3.14}$$

- The vehicle flow cannot exceed the total number of traffic trips, and whenever there is a flow on a link, there must be at least one vehicle operating on that link.

$$w_{v,(i,j)}^{(o,d)} \leq f_{v,(i,j)}^{(o,d)} \leq Q^{(o,d)} \cdot w_{v,(i,j)}^{(o,d)} \qquad \forall (i,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in \mathcal{Q} \tag{3.15}$$

- Ensure that the proportion of the fleet consisting of vehicles of type 1 meets or exceeds the specified acceptance rate. Therefore, limiting the number of vehicle type 2.

$$f_{2,(o,j)}^{(o,d)} \leq (1-\alpha) \cdot \sum f_{v,(o,j)}^{(o,d)} \qquad \forall (o,j) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q} \tag{3.16}$$

- Ensure that recharging can only happen at charging stations that are open or ERS that are installed, respectively.

$$\pi_{(i,j)}^{(o,d)} \leq y_{ij} \qquad \forall (i,j) \in \mathscr{A}, (o,d) \in \mathscr{Q} \tag{3.17}$$

$$r_{v,(i,j),s}^{(o,d)} \leq x_{ij}^{s} \qquad \forall (i,j) \in \mathscr{A}, s \in \mathscr{S}_{ij}, (o,d) \in \mathscr{Q} \tag{3.18}$$

- Ensure that the total number of vehicles aligns with the number of trips for all OD pairs.

$$\sum f_{v,(o,j)}^{(o,d)} = Q^{(o,d)} \qquad \forall (o,j) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q} \tag{3.19}$$

- Ensure that all vehicles depart from the origin node and reach the destination node.

$$\sum w_{v,(i,d)}^{(o,d)} = 1 \qquad \forall (i,d) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q} \tag{3.20}$$

$$\sum w_{v,(o,i)}^{(o,d)} = 1 \qquad \forall (o,i) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q} \tag{3.21}$$

- Domain values of the variables and decision variables

$$r_{v,(i,j),s}^{(o,d)}, \pi_{(i,j)}^{(o,d)}, w_{v,(i,j)}^{(o,d)} \in \{0,1\} \qquad \forall (i,j) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q}, s \in \mathscr{S}_{ij} \tag{3.22}$$

$$bl_{v,(i,j),s}^{(o,d)}, cl_{v,(i,j),s}^{(o,d)}, Ecl_{v,(i,j),s}^{(o,d)}, f_{v,(i,j)}^{(o,d)} \geq 0 \qquad \forall (i,j) \in \mathscr{A}, v \in \mathscr{V}, (o,d) \in \mathscr{Q}, s \in \mathscr{S}_{ij} \tag{3.23}$$

3.3.2. Upper-level optimization model

In the upper-level model, the benefits are also included as cost reductions when determining which infrastructure should be built. This approach is grounded in the understanding that governments create infrastructure to benefit society, which in turn generates a form of societal surplus that can be considered a return on investment. Essentially, when the government invests in public infrastructure like ERS or static chargers, the benefits extend beyond the direct financial costs; they also encompass broader societal gains. In this context, user surplus—representing the cost savings and efficiencies that users experience when utilizing the infrastructure—can be considered a benefit for the government. Although users directly benefit from reduced costs, these individual gains contribute to broader societal benefits. This is why societal gain is factored into the decision-making process.

By incorporating these cost savings, such as reductions in charging time, battery costs, and tolls, into the government's calculations, the model ensures that infrastructure investments are evaluated not only on their financial cost but also on their potential to generate surplus for society. This holistic approach aligns with the government's goal of promoting sustainability and economic growth, recognizing that public infrastructure projects should deliver long-term societal benefits that outweigh the initial capital and operational costs. In this way, the model captures the full scope of the government's role in enhancing societal welfare through strategic infrastructure investment.

The objective function for the upper-level mathematical aims at minimizing the total cost of installing ERS in highway links, installing static charging stations, and maintenance costs for the installed ERS and static charging stations. The individual components of the upper-level objective function are denoted as follows:

- **ERS installation cost**: The cost of ERS installation is calculated by multiplying the installation price per kilometer by the length of the electrified highway and the binary variable y_{ij}, which indicates whether a particular highway segment is selected for electrification. As previously mentioned, this cost is further adjusted by an annuity factor to determine the amortized annual cost of the infrastructure, accounting for the discount rate applied to future expenses.

$$\sum_{(i,j)\in\mathscr{A}} Cd \cdot d_{ij} \cdot y_{ij} \cdot ann_{ers} \tag{3.24}$$

$$ann_{ers} = \frac{dr}{1-(1-dr)^{-\tau_{ers}}} \tag{3.25}$$

- **ERS fixed maintenance cost**: The fixed maintenance cost is independent of usage frequency. This cost encompasses annual operational expenses as well as regular inspections and adjustments. The maintenance rate is expressed as a percentage of the total installation cost.

$$\sum_{(i,j)\in\mathscr{A}} Cd \cdot d_{ij} \cdot y_{ij} \cdot \mu_{ers} \tag{3.26}$$

- **ERS variable maintenance cost**: This cost is directly influenced by the frequency of use. Increased usage accelerates wear and tear on components, leading to a shorter lifespan and necessitating more frequent replacements, adjustments, and maintenance. The cost is calculated by multiplying the maintenance rate per kilometer of use by the frequency of use and the length of the electrified highway.

$$\sum_{(o,d)\in\mathscr{Q}} \sum_{(i,j)\in\mathscr{A}} \pi_{(i,j)}^{(o,d)} \cdot \mu_{ers\_use} \cdot d_{ij} \cdot Q^{(o,d)} \cdot w_{v,(i,j)}^{(o,d)} \tag{3.27}$$

- **Static charging station installation cost**: This cost is determined by multiplying the number of installed static charging stations by the installation cost per station. Additionally, an annuity factor is applied, incorporating the discount rate over the lifespan of the static chargers to calculate the amortized annual cost.

$$\sum_{(i,j)\in\mathscr{A}} \sum_{s\in\mathscr{S}} Sc \cdot x_{(i,j)}^{s} \cdot ann_{sc} \tag{3.28}$$

$$ann_{sc} = \frac{dr}{1-(1-dr)^{-\tau_{sc}}} \tag{3.29}$$

- **Static charger fixed maintenance cost**: Similar to ERS lanes, static chargers require regular maintenance, periodic inspections, and operational expenses over time. The maintenance cost is calculated as an annual rate applied to the total installation cost of the static chargers.

$$\sum_{(i,j)\in\mathscr{A}} \sum_{s\in\mathscr{S}} Sc \cdot x^{s}_{(i,j)} \cdot \mu_{sc} \tag{3.30}$$

- **Static charger variable maintenance cost**: Frequent use makes static chargers susceptible to wear and tear, which incurs additional costs. These costs are calculated by multiplying the cost per usage by the number of uses per year.

$$\sum_{(o,d)\in\mathscr{Q}} \sum_{(i,j)\in\mathscr{A}} \sum_{s\in\mathscr{S}} \sum_{v\in\mathscr{V}} r^{(o,d)}_{v,(i,j),s} \cdot \mu_{sc\_use} \cdot Q^{(o,d)} \tag{3.31}$$

- **Penalty cost**: To ensure that all charging demand is met and to avoid a shortage of charging stations, a penalty cost is incorporated into the model. This penalty cost is set to be exceedingly high, at 10^{12}, reflecting large enough value compared to the substantial expense associated with ERS installation.

  The decision variable $Ecl^{(o,d)}_{v,(i,j),s}$ is introduced to mitigate the risk of infeasible solutions that may arise if the model fails to establish an adequate number of charging stations. This variable is heavily penalized in the objective function to deter reliance on this charging mode as a preferred strategy, ensuring it is used only as a last resort to maintain model viability.

  In the model, the value of Ecl must be carefully monitored to ensure it remains at zero in the optimal solution, thereby guaranteeing that all demand is adequately fulfilled.

$$\sum_{(o,d)\in\mathscr{Q}} \sum_{(i,j)\in\mathscr{A}} \sum_{s\in\mathscr{S}} \sum_{v\in\mathscr{V}} \gamma \cdot Ecl^{(o,d)}_{v,(i,j),s} \tag{3.32}$$

- **(-) Charging time saving when using ERS**: When building infrastructure, the government considers not only the financial investment but also the broader benefits it can provide. Installing ERS can accelerate the adoption of electric vehicles by offering significant advantages to users, thereby helping the government achieve its goal of zero emissions more rapidly, particularly in freight transport. One of the key benefits for users of ERS is the elimination of vehicle downtime associated with static charging. This cost saving is factored into the government's upper-level objective value because it incentivizes users or logistics companies to adopt ERS and electric vehicles, thus contributing to the larger goal of decarbonizing freight logistics.

  The cost saving is calculated by multiplying the number of ERS uses by the time that would have been spent charging using static chargers. This calculation represents the efficiency gained by using ERS instead of static chargers. For vehicle type 1, the time saved is given by $\left(t \cdot \frac{B_1}{B_2}\right)$, accounting for the difference in battery capacity. This is calculated as a negative term in the objective function because it represents a benefit rather than a cost.

$$\sum_{(o,d)\in\mathscr{Q}} \sum_{(i,j)\in\mathscr{A}} \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)} \cdot vot \cdot t \cdot \frac{B_1}{B_2} \tag{3.33}$$

- **(-) Battery saving cost**: There are several reasons why battery cost is considered a benefit for the government in the objective function. Firstly, the smaller battery size of ERS-compatible vehicles is one of the key factors that makes them attractive to companies. A smaller battery not only reduces the vehicle's overall weight but also lowers the purchase price, resulting in significant cost savings. Additionally, the lighter battery allows for the possibility of carrying a larger payload, which enhances operational efficiency.

From the government's perspective, promoting smaller batteries aligns with sustainability goals. Smaller or fewer batteries mean a reduced environmental footprint, less hazardous material to process, and decreased waste generation, which supports key objectives like lowering greenhouse gas emissions and promoting a circular economy. The reduced demand for large-scale battery recycling also eases the burden on environmental management systems, further justifying the inclusion of battery cost as a benefit for the government.

This figure is further adjusted by applying an annuity factor to determine the amortized annual cost.

$$\frac{veh_1 \cdot (B_2 - B_1) \cdot Cb}{ann_{batt}} \tag{3.34}$$

- **(-) Charging cost saving**: In this model, the cost of charging via ERS is lower than that of static chargers. In addition to initial government incentives during the early adoption phase, ERS benefits from more efficient use of grid resources. This reduced cost makes ERS an attractive option for users, encouraging adoption. The cost savings from ERS charging are calculated by taking the difference between the static charger price and the ERS price per kWh and multiplying it by the total kWh required for all vehicles.

$$cl^{(o,d)}_{v,(i,j),s} \cdot \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot (Csc - Ce) \tag{3.35}$$

- **(-) Toll cost saving**: Similar to the savings in charging costs, the toll cost when using ERS is also lower than that of a regular highway, due to government subsidies. The toll cost savings from ERS can be calculated by taking the difference between the toll rates of a standard highway when not using ERS and an ERS-equipped highway when using ERS, then multiplying that by the distance traveled along the highway. This calculation also includes a variable that accounts for whether the ERS-equipped highway is part of the user's chosen route. These toll savings further incentivize the use of ERS.

$$\sum_{(o,d)\in\mathcal{Q}} \sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot (tollS - tollE) \cdot d_{ij} \cdot w^{(o,d)}_{1,(i,j)} \cdot Q^{(o,d)} \tag{3.36}$$

Combining the components stated above, the upper-level objective function minimizing the

total infrastructure cost can be written as:

$$\min_{\mathbf{x},\mathbf{y}} \sum_{(i,j)\in\mathscr{A}} Cd\cdot d_{ij}\cdot y_{ij}\cdot\left(ann_{ers}+\mu_{ers}\right)+\sum_{(o,d)\in\mathscr{Q}}\sum_{(i,j)\in\mathscr{A}}\pi^{(o,d)}_{(i,j)}\cdot\mu_{ers\_use}\cdot d_{ij}\cdot Q^{(o,d)}\cdot w^{(o,d)}_{v,(i,j)}+$$
$$\sum_{(i,j)\in\mathscr{A}}\sum_{s\in\mathscr{S}} Sc\cdot x^{s}_{(i,j)}\cdot\left(ann_{sc}+\mu_{sc}\right)+\sum_{(o,d)\in\mathscr{Q}}\sum_{(i,j)\in\mathscr{A}}\sum_{s\in\mathscr{S}}\sum_{v\in\mathscr{V}} r^{(o,d)}_{v,(i,j),s}\cdot\mu_{sc\_use}\cdot Q^{(o,d)}+$$
$$\sum_{(o,d)\in\mathscr{Q}}\sum_{(i,j)\in\mathscr{A}}\sum_{s\in\mathscr{S}}\sum_{v\in\mathscr{V}}\gamma\cdot Ecl^{(o,d)}_{v,(i,j),s}-\sum_{(o,d)\in\mathscr{Q}}\sum_{(i,j)\in\mathscr{A}}\pi^{(o,d)}_{(i,j)}\cdot Q^{(o,d)}\cdot w^{(o,d)}_{v,(i,j)}\cdot vot\cdot t\cdot\frac{B_1}{B_2}-$$
$$\frac{veh_1\cdot(B_2-B_1)\cdot Cb}{ann_{batt}}-\sum_{(o,d)\in\mathscr{Q}}\sum_{(i,j)\in\mathscr{A}}\pi^{(o,d)}_{(i,j)}\cdot(tollS-tollE)\cdot d_{ij}\cdot w^{(o,d)}_{1,(i,j)}\cdot Q^{(o,d)}-$$
$$cl^{(o,d)}_{v,(i,j),s}\cdot\pi^{(o,d)}_{(i,j)}\cdot Q^{(o,d)}\cdot(Csc-Ce) \tag{3.37}$$

The objective function is subject to the following constraints:

- Domain values of the decision variables

$$x^{s}_{ij}, y_{ij}\in\{0,1\} \tag{3.38}$$

4 Data

This section provides a detailed account of the information and datasets used in this study. It encompasses the sources, types, and characteristics of the data, ensuring a realistic foundation for analysis and modeling. This section aims to enhance the transparency and reproducibility of the research by clearly defining the data parameters, including the values of the parameters, the freight transport and geographical data, and the costs related to the problem.

4.1. Freight data

The dataset utilized is derived from the paper by Daniel Speth et al. [69]. The dataset encompasses European road freight transport data, including traffic flows, Origin-Destination (OD) matrix, highway links, and distance metrics.

The freight demand data is a critical component, encompassing truck traffic flows between the specified regions. This dataset includes road freight flows in tons for the year 2030, as well as truck traffic flows in the number of vehicles for the same year. Each origin-destination pair is identified by unique IDs and names, along with the shortest path between regions within the European highway network. The dataset is focused, containing directed transport flows between significant origin and destination pairs within the Netherlands, Belgium, Germany, and Luxembourg. In this study, only dataset from the Netherlands is used due to complexity and high computational time.

Data processing involved several critical steps to ensure the dataset's relevance and accuracy. The original ETISplus data from 2010 was updated using Eurostat data to reflect projections for 2030. Freight volumes were converted to the number of vehicles using an average loading factor of 14 tons per truck. This conversion methodology follows the approach detailed in the study by Ximeng et al. [44]. Routes were determined using the NetworkX library's implementation of Dijkstra's algorithm, ensuring optimal paths within the E-road network.

The freight demand data presented in table 4.1 has been converted into truckflow units using

	Overig Groningen	Noord-Friesland	Noord-Drenthe	...
Overig Groningen	0	174232	155153	...
Noord-Friesland	160633	0	170415	...
Noord-Drenthe	393712	94023	0	...
...	...	...	...	

Table 4.1: Freight transport origin-destination trips between regions

the payload factor method described by Ximeng et al. [44]. This data is represented as the number of trips traveling from the origin to the destination, formatted into an Origin-Destination (OD) matrix.

4.2. Network data

The network data includes detailed information about the European highway (E-road) network, essential for modeling and optimizing freight transport routes and infrastructure requirements. This data comprises nodes and edges, with the model including relevant nodes and edges for the specified regions. Each node has a unique ID, geographical coordinates (longitude and latitude), and the associated NUTS-3 region. Each edge connects two nodes and includes attributes detailing whether it was manually added and the length of the edge in kilometers.

Distance data

The distance data includes the distance from the origin region to the E-road network, the shortest path distance within the E-road network, and the distance from the E-road network to the destination region. These distances are calculated using Dijkstra's algorithm to ensure optimal routes, with the total distance representing the sum of these components, from the origin region center to the destination region center. The total transport route from the center of origin and destination point is represented in table 4.2 in unit kilometer.

	Overig Groningen	Noord-Friesland	Noord-Drenthe	...
Overig Groningen	0	75	30	...
Noord-Friesland	75	0	105	...
Noord-Drenthe	30	105	0	...
...	...	...	...	

Table 4.2: Distance data between centers of regions

Highway data

The highway data is represented in a binary format, indicating the presence or absence of direct highway connections between cities or regions. In the binary matrix, a value of 1 signifies a direct connection, meaning there is a highway link between two cities, while a value of 0 indicates no direct connection.

The structure of this data involves listing all relevant cities or regions as nodes and then determining the pairs of nodes that have direct highway connections, which example can be seen in table 4.3. In this matrix, the rows and columns represent the different regions, and the presence of a highway connection is indicated by a 1 at the intersection of the respective row and column.

	Overig Groningen	**Noord-Friesland**	**Noord-Drenthe**	...
Overig Groningen	0	1	1	...
Noord-Friesland	1	0	0	...
Noord-Drenthe	1	0	0	...
...	...	...	...	

Table 4.3: Highway connections data between regions

This dataset provides a robust foundation for analyzing and optimizing the infrastructure needs for electric road systems and charging stations, aiding in the strategic planning for future road freight transport in the Netherlands. The synthetic nature of the data ensures a comprehensive and consistent representation of the European road freight landscape, critical for developing effective optimization models.

4.3. Parameters data

Parameters related to ERS

In this research, the parameters concerning ERS are analyzed, emphasizing the installation costs, electricity charges, toll prices, and maintenance expenses associated with ERS infrastructure.

- **Installation Cost:** The initial installation cost of the catenary conductive ERS, chosen for its cost-effectiveness relative to inductive systems, is estimated between 0.7 to 1.1 million euros per kilometer [20] [13]. For this study, a conservative estimate of 0.5 million euros per kilometer is applied for a single-direction installation, resulting in a total of 1 million euros for bi-directional lanes.

- **Electricity Charging Price:** The national average electricity rate for ERS in the Netherlands is approximately €0.36 per kWh [56]. Although regional variations exist, a constant rate of €0.36 per kWh is utilized in this model for uniformity and simplification of calculations.

- **Toll Price:** Toll rates for HGVs in the Netherlands vary based on environmental characteristics, with cleaner trucks incurring lower tolls. While specific rates are pending finalization, an estimated toll rate of €0.15 per kilometer, based on rates from Germany and Belgium, serves as a benchmark [30]. For BETs, which are considered cleaner, a reduced rate of €0.10 per kilometer is assumed [44].

- **Charging efficiency:** The catenary system of ERS has been demonstrated to incur lower energy losses during battery charging compared to standard static charger [20].

Consequently, this model adopts a charging efficiency of 95% to reflect these improved performance metrics.

- **Maintenance Cost:** The annual maintenance and operating costs of the ERS are projected to be between 1% and 2.5% of the initial capital outlay [19] [73]. Maintenance includes routine inspections and, dependent on usage, variable costs for repairs and component replacements are estimated at €0.07 per vehicle-kilometer [18].

- **Discount Rate and Infrastructure Lifetime:** The ERS infrastructure is assumed to have a service life of 30 years [18], considering the potential for up to 35 years as suggested by [63]. Financial calculations employ a discount rate of 1.6% to normalize investment costs over this period [18].

- **Charging rate**: According to Schaap [67], the charging power of an ERS equipped with a catenary system can achieve up to 500 kW, while a rail system can deliver up to 240 kW. Given a vehicle speed of 80 km/h, this study assumes a charging rate of 3 kW per kilometer traveled for ERS within the model.

These financial assumptions are integral to the model, ensuring a comprehensive evaluation of the economic feasibility and sustainability of ERS deployment within the freight transport sector. In summary, the values of the paramaeters related to ERS can be depicted in table 4.4.

Parameter	**Symbol**	**Value**	**Unit**
Installation cost	Cd	500000	€/km
Electricity charging cost	Ce	0.36	€/kWh
Toll rate	toll_e	0.1	€/km
Fixed maintenance cost	μ_{ers}	2	%
Variable maintenance cost	$\mu_{\text{ers\_use}}$	0.07	€/v.km
Charging efficiency	ef_e	0.95	
Discount rate	dr	1.6%	
Charging rate	ϕ	3	kWh/km
Infrastructure lifetime	τ_{ers}	30	years

Table 4.4: Parameter values related to ERS

Parameters related to static chargers

In this study, we evaluate the costs and operational parameters associated with DC fast chargers, which are elaborated as follows:

- **Installation Cost:**DC fast chargers, essential for charging battery electric trucks (BETs), represent the most expensive static charger type due to the need for high-voltage equipment and specialized maintenance. The installation costs for a DC fast charger stand at approximately €100,000, with total investment potentially reaching €200,000 per unit [50].

- **Electricity Charging Cost:** The average rate for using a DC fast charger in the Netherlands is €0.73 per kWh, adopted for this model, with observed prices typically ranging from €0.64 to €0.82 per kWh. Price examples include €0.69 per kWh at a 50 kW Fastned station in Oeienbosch, €0.83 per kWh at a 150 kW Shell station in Arnhem, and €0.65 per kWh at a 62.6 kW Vattenfall station in Groningen. These variations are influenced by factors such as energy market fluctuations, bulk energy purchases by operators, and distinct pricing strategies by charging networks [75].

- **Toll Cost:** For comparative purposes, the estimated toll rate for vehicles using ERS is approximately €0.15 per kilometer traveled.
- **Charging Efficiency:** DC fast charging is noted for its higher efficiency, with typical energy losses around 10%. Consequently, this model assumes a charging efficiency of 90% for DC fast chargers [37].
- **Recharge Time:** Charging times are significantly reduced with DC fast charging; for example, a truck equipped with a 500 kWh battery can achieve a 10% to 80% charge in less than an hour using a 350 kW charger. For a truck with a maximum battery capacity of 1000 kWh, full charging is achievable within two hours [22, 26]. This analysis utilizes a charging duration of one hour for trucks with up to 220 kWh battery capacity.
- **Lifetime and Maintenance Cost:** The expected lifetime of a DC fast charger is 5-6 years with a usage rate of ten cars per day, achieving 90% reliability. This estimate is based on the B10 lifetime of the DC-DC converter, which can vary with component quality [7]. The annual maintenance cost for these chargers, based on studies from California, is approximately 10% of the initial investment. Maintenance includes operational and monitoring costs, with variable expenses introduced for replacing shorter-lived components such as the cooling system (5-7 years) and cables and connectors (2-3 years) at a rate of €0.5 per vehicle per charge [26].

To provide a clear and structured overview of the financial and operational parameters associated with DC fast chargers, table 4.5 summarizes the values.

Parameter	**Symbol**	**Value**	**Unit**
Installation cost	Sc	200000	€/km
Electricity charging cost	Csc	0.73	€/kWh
Toll rate	toll_s	0.15	€/km
Fixed maintenance cost	μ_{sc}	10	%
Variable maintenance cost	μ_{sc_use}	0.5	€/v
Charging efficiency	ef_s	0.90	
Charging time	*recharging_time*	1	hour
Infrastructure lifetime	τ_{sc}	6	years

Table 4.5: Parameter values related to DC fast static charger

Parameters related to vehicles

Furthermore, the parameters related to the vehicle are explored as the following:

- **Battery Cost:**

  Figure 4.1 illustrates the decline in EV battery prices from 2010 to 2030, developed by IEA [38]. The dotted line projects future costs, suggesting that by 2030, prices will stabilize at around €80 per kWh. Furthermore, Lutsey [47] projects in his study that by 2030, battery prices will decrease to approximately 80-90 USD per kWh. In this study, battery cost of €80 per kWh is used.

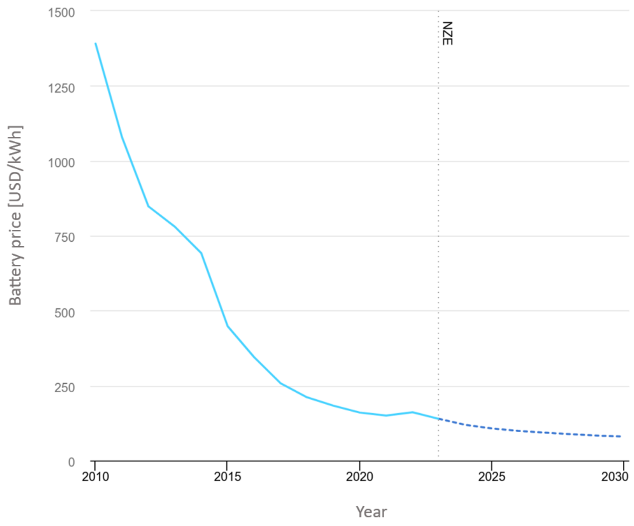


Figure 4.1: Battery price prediction [38]

- **Value of Travel Time:** This metric quantifies the economic impact of transport time extensions due to charging with static chargers. It accounts for the driver's hourly wage and vehicle downtime, collectively assumed to be €38 per hour.

- **Battery Capacities:** The model incorporates 2 battery capacities based on average travel distances: 80 and 220 kWh for short-haul freight transport in the Netherlands.

- **Consumption Rate:** According to research, the energy consumption at the wheels for regional delivery trucks is projected to decrease from 1.6 kWh/km in 2020 to 1.45 kWh/km by 2030. For long-haul trucks, it is expected to reduce from 1.95 kWh/km in 2020 to 1.15 kWh/km in 2030. This model adopts the lower average rate of 1.6 kWh/km for 2030 [2].

- **Number of Operations and Battery Life Cycle:** The lifespan of a truck's battery is estimated to be approximately 8 years. For the purposes of this model, it is assumed that each truck operates 250 days per year [77].

In summary, the parameter values of the vehicles can be concluded in table 4.6.

Parameter	Symbol	Value	Unit
Battery cost	Cb	80	€/kWh
Value of travel time	vot	38	€/hour
Battery capacities	*battery_capacities*	{80, 220}	kWh
Minimum battery level	*min_battery*	10	%
Maximum battery level	*max_battery*	90	%
Energy consumption rate	β	1.6	kWh/km
Battery lifespan	*life_time*	8	years
Number of operations	*ywd*	250	trips/year

Table 4.6: Parameter values related to vehicles

5

Modeling Approach

This section discusses the design and implementation of the solution methodology for solving large-scale instances of the bi-level optimization model introduced in Section 3. Initially the model is solved with exact approach of mixed integer linear problem using Gurobi. Secondly, due to the complexity of the problem, metaheuristics approach is used.

5.1. Exact approach

In this study, a bi-level optimization approach is employed to determine the optimal configuration of dynamic and static charging facilities for heavy-duty trucks. This method effectively captures the hierarchical decision-making process involving infrastructure investment decisions by the government and route optimization by freight operators.

The optimization modeling is conducted using Python, leveraging the Gurobi solver. Gurobi is a powerful mathematical optimization solver widely recognized for its efficiency in solving large-scale linear and mixed-integer programming problems. Its ability to handle extensive datasets and provide robust solutions makes it a suitable choice for the initial phase of our model implementation.

One significant limitation of Gurobi is its inability to directly solve non-linear optimization problems. To address this, the initial phase of the modeling involves simplifying the equations and linearizing the non-linear components. This process ensures that Gurobi can effectively solve the problem on a small scale, providing an initial feasible solution that serves as a basis for further refinement.

The initial modeling approach and the sequence of the algorithm are illustrated in Figure 5.1.

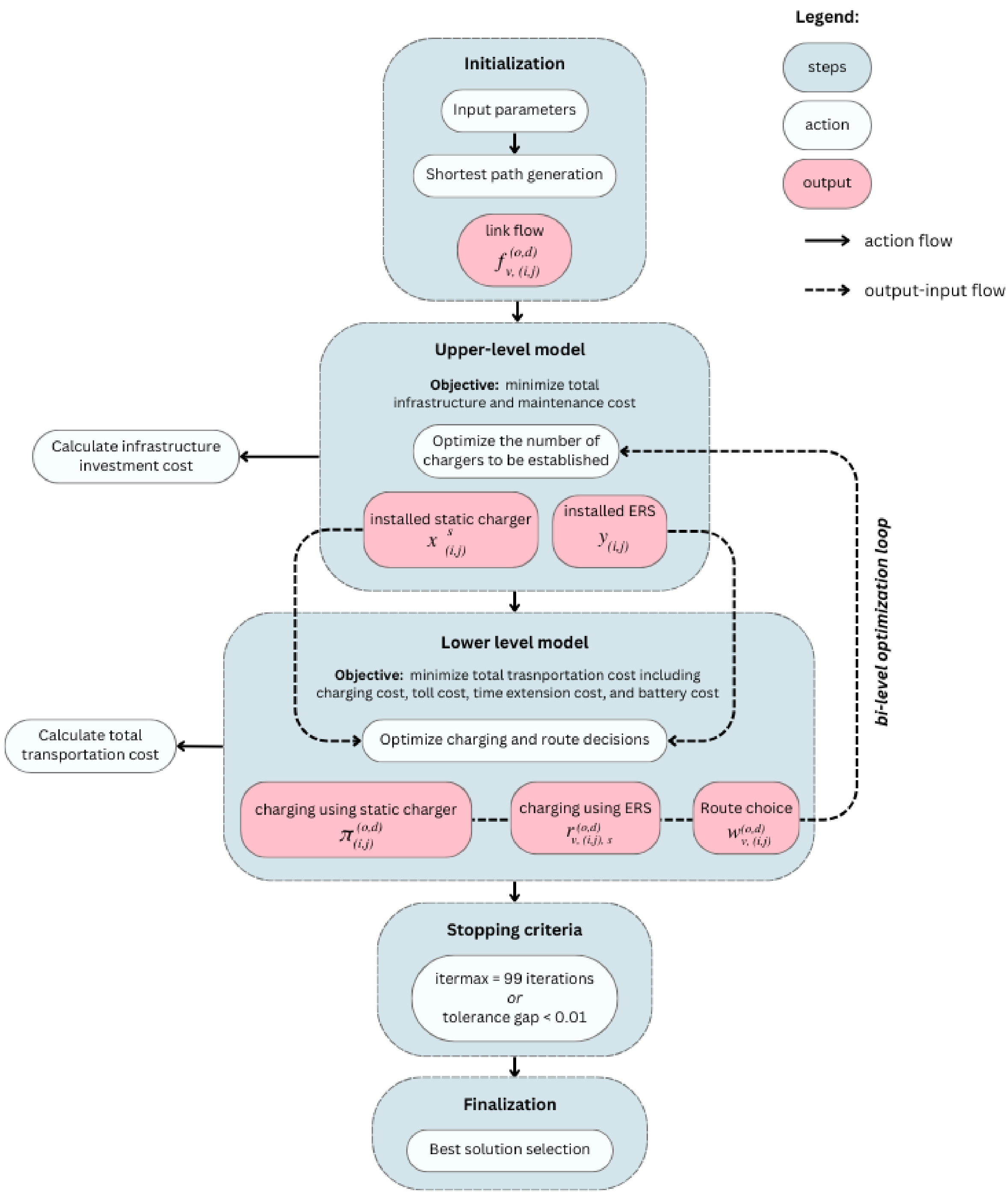


Figure 5.1: Flowchart of bi-level optimization model

The procedure of the algorithm are explained below with an example of 2 OD pairs which are (A,E) and (B,E).

1. **Initialization**

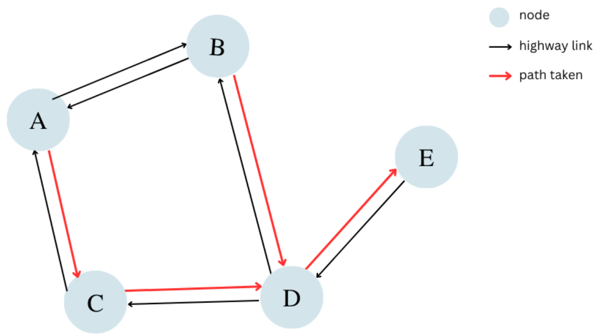


Figure 5.2: Vehicles choose route that has shortest distance to the destination

The modeling process begins with the initialization phase, where the necessary parameters and datasets are loaded. This includes the traffic flow data, distances, highway connections, and costs associated with both ERS and static chargers. During initialization, vehicle routing is determined based on the shortest path from their origin to destination, regardless of the battery level. At this stage, no charging points or electrified links are established. This setup provides a baseline routing scenario to be refined in subsequent steps.

2. **Upper level: Allocation of chargers**

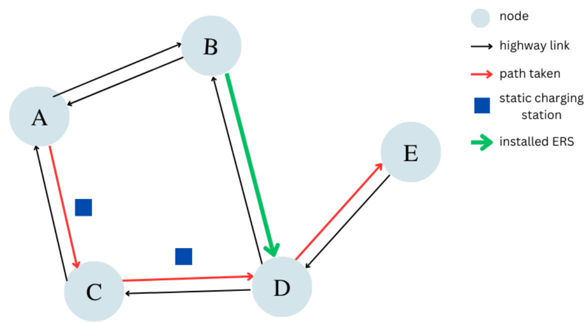


Figure 5.3: Charging stations established based on the charging needs of the vehicles and the lowest cost

At the upper level, the primary goal is to allocate the charging infrastructure optimally. This involves determining the locations and capacities of both static and dynamic charging stations. The battery constraints and other constraints regarding the charging stations are introduced. Based on the vehicle routing determined in the initialization phase, charging stations are established.

Since transportation cost considerations from the lower level are not yet introduced in iteration zero, the upper-level model initially chooses the cheapest option, which tends to be static charging stations. This preliminary step sets the stage for more detailed optimization in subsequent iterations. Using Gurobi, a linearized version of the problem is solved to find an initial feasible solution. The upper-level optimization focuses on minimizing the total infrastructure cost, including installation and maintenance expenses. The decision variables at this level include the placement of static chargers and the segments of highways to be equipped with ERS.

3. **Lower Level: Routing Decision**

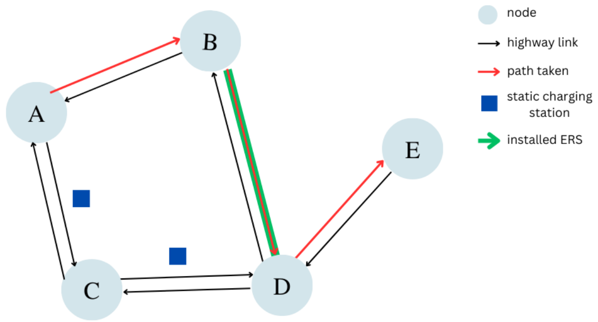


Figure 5.4: Vehicles reroute based on the cheapest transportation cost

Once the charging infrastructure is allocated, the lower level addresses the routing decisions for the freight vehicles. This involves introducing routing constraints such as continuity, vehicle conservation constraints, battery constraints, and charging constraints. The decision variables from the upper level (x_{ij}^{s} and y_{ij}) indicating established chargers are used as inputs. Vehicles then choose their routing based on these established charging stations, aiming to minimize their transportation costs, which include charging costs.

The lower-level optimization ensures that the chosen routes are efficient given the constraints imposed by the available charging infrastructure. This step also considers the battery capacities and energy consumption rates of the vehicles to ensure feasibility. This level outputs the decision variables $\pi_{(i,j)}^{(o,d)}$ and $r_{v,(i,j),s}^{(o,d)}$, which denote the chosen and charging decisions.

4. **Bi-level Optimization Loop**

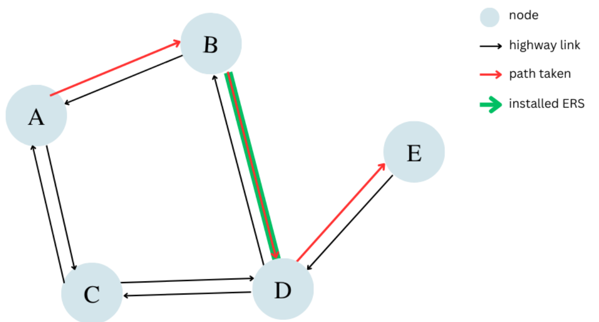


Figure 5.5: Upper level model optimize the charger allocation based on the routing of the vehicles and their charging needs, while minimizing cost

The bi-level optimization loop iteratively refines the solutions obtained from the upper and lower levels. At this stage, the actual link usage by vehicles, charging station usage, and the number of uses are known. The upper level re-examines the type and location of charging stations, balancing cost-effectiveness and charging needs. The more a charger is used, the higher the maintenance cost, directly impacting the upper-level objective function. Hence, the upper level decides again on the decision variables x_{ij}^{s} and y_{ij}. These updated decisions are then fed back into the lower level, which re-optimizes vehicle routing based on the new charger installations. This loop continues until either 99 iterations are reached (*itermax*) or the optimization gap falls below 0.01 (*tolerance*).

5. **Best Solution**

   The final step involves selecting the best solution from the optimization loop. This solution represents the most cost-effective and efficient configuration of static and dynamic charging facilities, balancing the investment and operational costs. The best solution is evaluated based on its lowest objective value, which means lowest investment cost. The results are then validated using case studies to ensure robustness and reliability.

5.2. Genetic Algorithm

The model includes a significant number of binary and continuous decision variables, which poses substantial challenges for commercial solvers, particularly as the number of binary variables increases exponentially with the addition of nodes and links in the network. To address this complexity, a metaheuristic approach based on a Genetic Algorithm (GA) are employed for this purpose.

A GA is a class of evolutionary algorithms that mimic the process of natural selection, making them particularly adept at navigating large and complex search spaces to find near-optimal solutions. The genetic algorithm's iterative process of selection, crossover, and mutation helps in efficiently exploring and exploiting the solution space, accommodating the complex nature of the problem and the high-dimensional data involved.

A GA has become a widely-used optimization technique inspired by the principles of natural selection and genetics. GAs have been effectively applied to a range of challenging optimization problems across various disciplines. For instance, GA have been used to optimize the design of complex engineering systems, such as aerodynamic shapes and structural layouts, as demonstrated by Deb in 2002 [17]. In operations research, GAs have been successfully employed to solve difficult combinatorial problems, including the well-known traveling salesman problem, as illustrated by Potvin (1996) [64]. Additionally, the literature highlights the use of GAs in solving complex bi-level optimization problems, such as those involving encoding schemes, as discussed by Wang (2007) [78]. Given the complexity of the bi-level programming model presented in this study, which involves numerous binary decision variables, the application of GA is a natural and well-suited choice for the solution methodology.

In this research, the GA is designed to find near-optimal values for the decision variables y_{ij} and x_{ij}^{s}, while the remaining decision variables are determined by solving a set of linear programming models. This approach involves decomposing the lower-level problem into a set of subproblems, with the number of subproblems corresponding to the number of origin-destination pairs in the network. This method is chosen over using GA to solve for continuous decision variables due to the vast search space associated with these variables — such as the number of vehicles of each type 1 or 2 traversing each link — which would be computationally prohibitive. Instead, a more efficient mechanism is implemented, where the type of vehicles for each flow is determined using a Bernoulli random variable, with the probability of success equal to the imposed acceptance rate. This approach balances the computational complexity while effectively navigating the search space.

A Genetic Algorithm typically consists of the 5 key components: chromosome encoding, initial population, crossover, mutation, and fitness evaluation. The subsequent sections provide a detailed explanation of the approach used to implement each of these steps.

5.2.1. Chromosome encoding

Chromosome encoding determines how solutions are represented within the Genetic Algorithm. Each chromosome, or individual, corresponds to a potential solution to the optimization problem. In our approach, the decision variables y_{ij} and x^s_{ij} are binary, meaning that they can take on values of either 0 or 1. To represent these variables, a specific encoding scheme is employed, illustrated in Figure 5.6, where each gene within a chromosome is assigned a value of 0 or 1. This binary encoding effectively captures the structure of the decision variables, enabling the GA to explore the solution space efficiently.

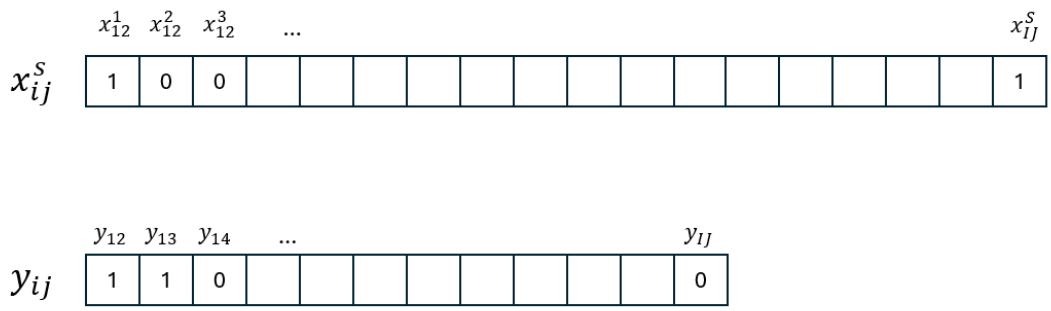


Figure 5.6: Chromosome encoding

5.2.2. Initial Population

The initial population is the first set of candidate solutions that the GA begins with. This population serves as the starting point and evolves over successive generations to explore the solution space. In this approach, the initial population is generated by randomly assigning a value of 0 or 1 to each gene within a chromosome, ensuring a diverse set of potential solutions from the outset. The `population size`, a critical parameter that influences the algorithm's ability to explore and converge on optimal solutions, is set to 50 for this implementation. This choice balances the need for diversity in the population with computational efficiency, providing a robust foundation for the GA's evolutionary process.

5.2.3. Crossover

Crossover is a genetic operator that combines the genetic information of two parent solutions to create new offspring, mimicking the processes of reproduction and recombination found in natural genetics. In this implementation, the `single point crossover` method is employed, as illustrated in Figure 5.7. This method involves selecting a random crossover point within the parent chromosomes and exchanging the genetic material beyond that point to produce the offspring. The use of single-point crossover ensures a balance between preserving existing structures from the parents and introducing new combinations, thereby enhancing the exploration of the solution space.

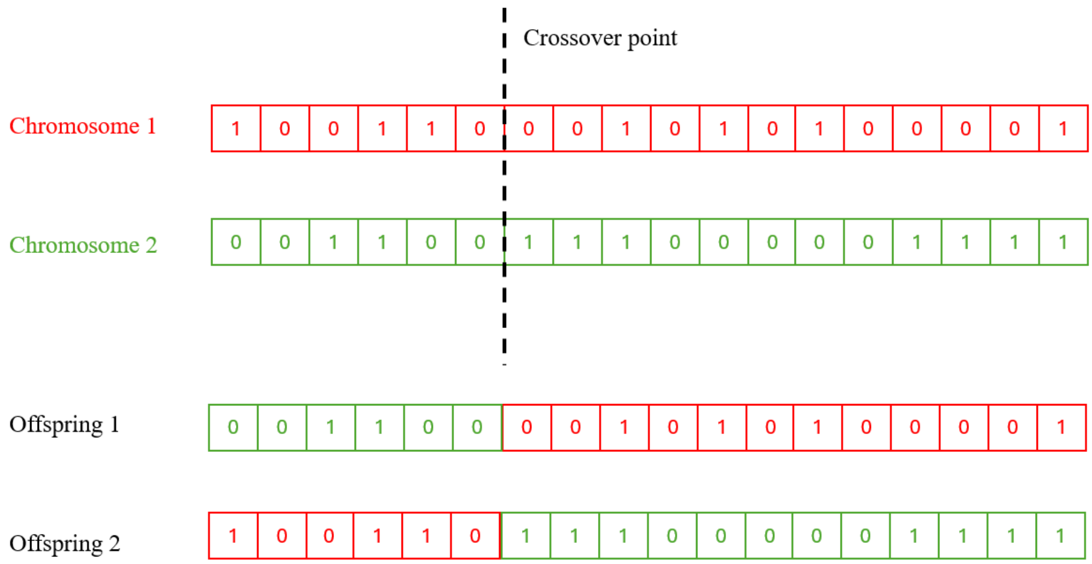


Figure 5.7: Single point crossover mechanism

5.2.4. Mutation

Mutation is a genetic operator that introduces diversity into the population by randomly altering the genes (variables) of an individual. This process plays a crucial role in exploring the solution space and helps prevent the algorithm from becoming trapped in local optima. In this implementation, mutation is governed by the `mutation rate` parameter. During the mutation process, each gene is evaluated, and with a probability defined by the mutation rate, the gene's value is changed, as illustrated in Figure 5.8. This controlled introduction of randomness ensures that the GA maintains a proper level of diversity, thereby enhancing its ability to search for optimal solutions across the entire solution space.

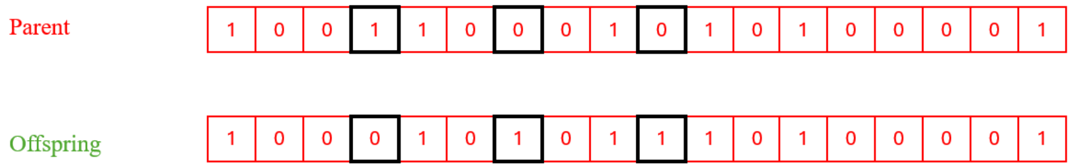


Figure 5.8: Mutation process

5.2.5. Fitness Evaluation

Fitness evaluation is a critical step in determining how well each individual (chromosome) in the population satisfies the objective function. It guides the selection process by identifying which individuals are more likely to produce superior offspring in subsequent generations. In this GA, the quality of each solution is assessed using Objective Functions (3.6) and (3.37). Additionally, a penalty function is applied if the number of vehicles of type 1 falls below the specified acceptance rate. This penalty ensures that solutions aligning with the acceptance criteria are favored, thereby maintaining adherence to the problem's constraints while guiding the algorithm toward optimal solutions.

Final modeling approach

While the initial plan was to utilize both the exact approach and a genetic algorithm for solving the model, the complexity of the problem—particularly the large number of decision variables and the extensive dataset—presented significant computational challenges. Despite efforts to streamline the genetic algorithm, even with a small population size, the algorithm required a prohibitively long computational time and still failed to reach convergence. Given these limitations, it was ultimately decided to proceed exclusively with the exact approach, using the Gurobi optimizer to solve the problem efficiently. However, it is important to note that the genetic algorithm remains a promising alternative method for addressing such complex optimization problems. With further refinement, it could potentially offer a viable solution in future iterations or for related problems, particularly when computational resources or time constraints are less stringent.

6

Results

Before applying the model to large-scale freight trip data, it is first tested on a smaller scale in one highway corridor spanning from Delft to Nuremberg, to assess its performance and interpret the results in a controlled environment. This preliminary testing is crucial for verifying the model's accuracy and reliability before scaling it up to larger datasets. By conducting this verification, potential issues can be identified and addressed early, ensuring the model's robustness when applied to more complex and extensive datasets.

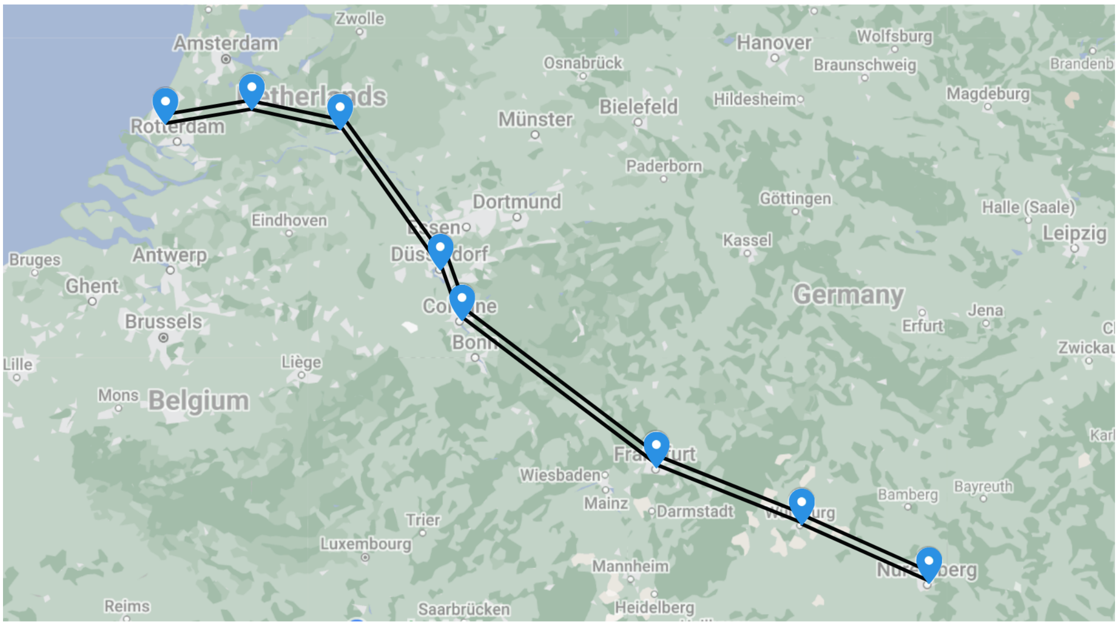


Figure 6.1: Verification test on Map 1: Netherlands-Germany highway corridor

For this verification, the highway network of the corridor will be utilized, as shown in Figure 6.1. The network includes 8 nodes: Nuremberg, Wurzburg, Frankfurt, Cologne, Dusseldorf, Arnhem, Utrecht, and Delft. These regions are interconnected by 7 bidirectional links, resulting in a total of 14 highway lanes with a combined length of 1,574 km.

6.1. Tradeoffs between infrastructure cost and transportation cost

As is well known, one of the major concerns with installing ERS is the high installation cost, despite the significant benefits it offers. Even with the increased infrastructure costs, ERS has proven to be beneficial. To support this assertion, a test was conducted using the model on a test map, referred to as Map 1, shown in Figure 6.2. The test map was selected to allow for a more detailed analysis of the model's behavior and to reduce computational time, making it easier to observe the nuances of the model's performance under specific conditions.

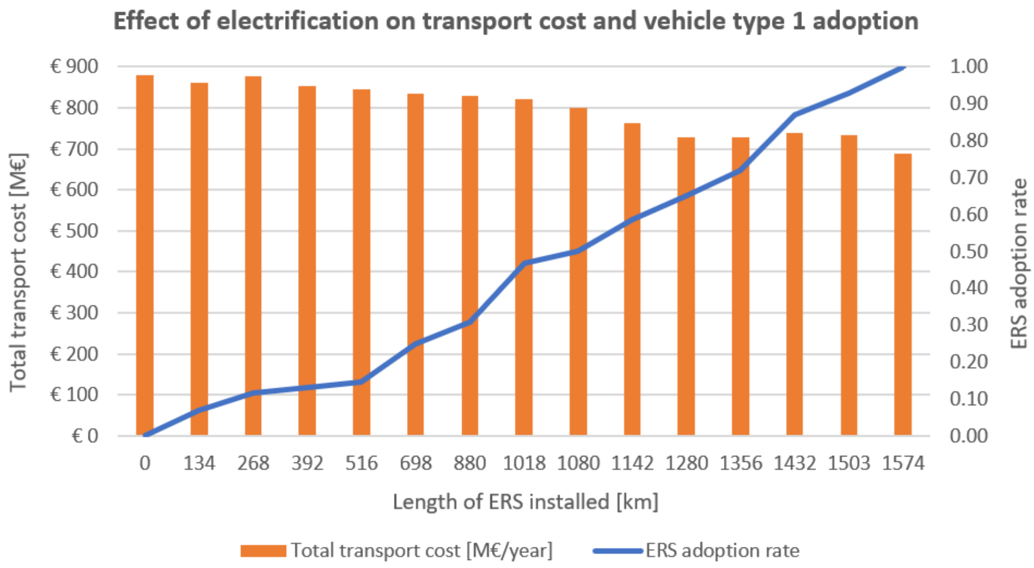


Figure 6.2: Result of the model on test map: analysing effect of electrification on total transport cost and vehicle type 1 adoption

Figure 6.2 offers an analysis of the impact of ERS length on both total transport costs and the adoption rate of vehicle type 1, which is equipped with ERS-compatible technology. As the ERS length increases, a downward trend in total transport costs is observed. Initially, at 0 km of ERS, transport costs are extremely high, reaching €900 million per year. This high cost can be attributed to the reliance on static chargers and the need for larger batteries, which are more expensive and less efficient. As more ERS charger is installed, transport cost savings increase significantly, reaching approximately €190 million per year when all highway segments are fully electrified. This highlights the considerable economic advantages of ERS by reducing the need for large batteries and elimination of downtime due to static charging. The detailed breakdown of transport cost can be seen in Table 6.1.

On the other hand, the ERS adoption rate, exhibits a strong positive correlation with the length of ERS installed. The adoption rate starts zero and rises sharply, reaching 100% when ERS is installed in all segments. This indicates that as more ERS infrastructure becomes available, users are increasingly incentivized to adopt ERS-compatible vehicles, considering the transport costs benefits. This trend demonstrates that the availability of ERS is a strong driver for the adoption of these vehicles. The steep rise in adoption rate, particularly beyond 800 km of installed ERS, suggests a threshold effect, where a critical mass of infrastructure encourages rapid user adoption. This could be due to increased route coverage, making ERS-compatible vehicles more practical.

Furthermore, another critical factor that must be considered in this analysis is the potential externalities not captured by the graph, such as environmental benefits, reductions in carbon emissions, or societal benefits from reduced dependence on fossil fuels. These factors might justify ERS adoption despite the static nature of transport costs.

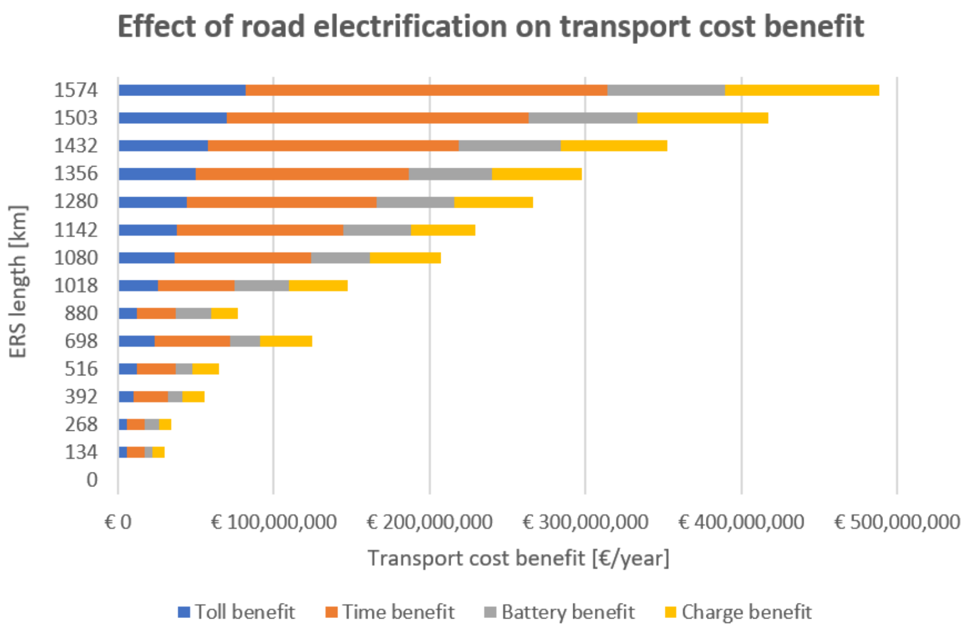


Figure 6.3: Contribution of each benefit component in transport cost saving

Figure 6.3 shows how transport cost savings are distributed across different components—value of time savings, battery cost savings, and charging cost savings—based on varying lengths of ERS. This visualization provides a detailed breakdown of how each component contributes to overall cost efficiency as the ERS network expands.

As the ERS length increases, a significant portion of these savings is attributed to battery cost reductions. However, it has to be noted that the ERS adoption rate is also higher when more ERS is installed. The high cost of travel time extension for using static charging is a significant factor in overall cost savings and is arguably the most influential benefit driving the deployment of ERS. The second major contributor to cost savings is the value of time savings by using continuous charging ERS rather than the static chargers. The reduction in downtime when using ERS directly translates into time savings, which is particularly valuable in the freight industry, where time is often equated with money. On the other hands, charging cost savings, shown in gray, is perceived to be less significant to the overall benefit. These savings are derived from the reduced dependency on static charging stations, which are typically more expensive per kWh compared to dynamic charging via ERS.

ERS length [km]	Number of static chargers	Number of vehicle type 1	Number of vehicle type 2	Toll cost [M€]	Time cost [M€]	Battery cost [M€]	Charging cost [M€]
0	13	0	49958	245	221	118	295
134	13	3319	49958	236	190	113	323
268	14	6191	43767	211	217	109	340
392	13	6304	43654	203	190	108	353
516	13	7211	42747	198	178	107	362
698	13	12689	37269	194	128	99	412
880	13	15433	34525	152	231	95	351
1018	14	23062	26896	168	158	83	412
1080	13	24882	25076	166	118	81	436
1142	13	29014	20944	163	112	74	414
1280	13	32878	17080	141	94	69	423
1356	13	35471	14487	140	79	65	443
1432	10	43603	6355	141	81	52	464
1503	7	46460	3498	140	63	48	483
1574	0	49958	0	140	0	43	506

Table 6.1: Summary of ERS length, static chargers, number of vehicles, and transport cost

Moreover, the adoption of ERS-compatible vehicles, while encouraged by the growth in infrastructure, may still be constrained by external factors such as the availability of charging stations, electricity costs, or user preferences. The "chicken and egg" dilemma discussed earlier remains relevant: transport companies may hesitate to invest in ERS-compatible vehicles until sufficient infrastructure is in place, and infrastructure developers may be reluctant to expand networks without guaranteed user demand. Thus, while the benefits outlined in the graph are promising, their realization is contingent on coordinated action between governments, industry stakeholders, and freight operators to ensure that both ERS infrastructure and vehicle adoption progress in tandem.

In terms of strategic planning, these insights highlight the importance of considering how different cost-saving components contribute to the overall economic viability of ERS infrastructure. The significant impact of battery and time savings suggests that these should be considerations when justifying the investment in ERS.

Table 6.1 shows a consistent number of static chargers, even as ERS length increases. This is likely because the model assumes static chargers have unlimited capacity, allowing them to handle an unrestricted number of vehicles simultaneously. In reality, static chargers are capacity-limited, and if this constraint were applied, we would expect to see more static chargers installed when less ERS is available. This would likely shift the infrastructure balance, requiring additional static chargers to support vehicles in regions with limited ERS coverage, potentially altering the cost-benefit analysis.

Moreover, an analysis should be done is whether there is an optimal ERS length that maximizes these benefits, beyond which the returns on further investment may diminish. This finding is crucial for policymakers and planners, as it emphasizes the need for a balanced approach that focuses on optimizing the placement and length of ERS infrastructure rather than simply extending it indefinitely. By carefully targeting ERS deployment to high-impact areas and considering the saturation point of vehicle adoption, it is possible to achieve significant cost savings and efficiency gains in electric freight transport.

Priority in segment electrification

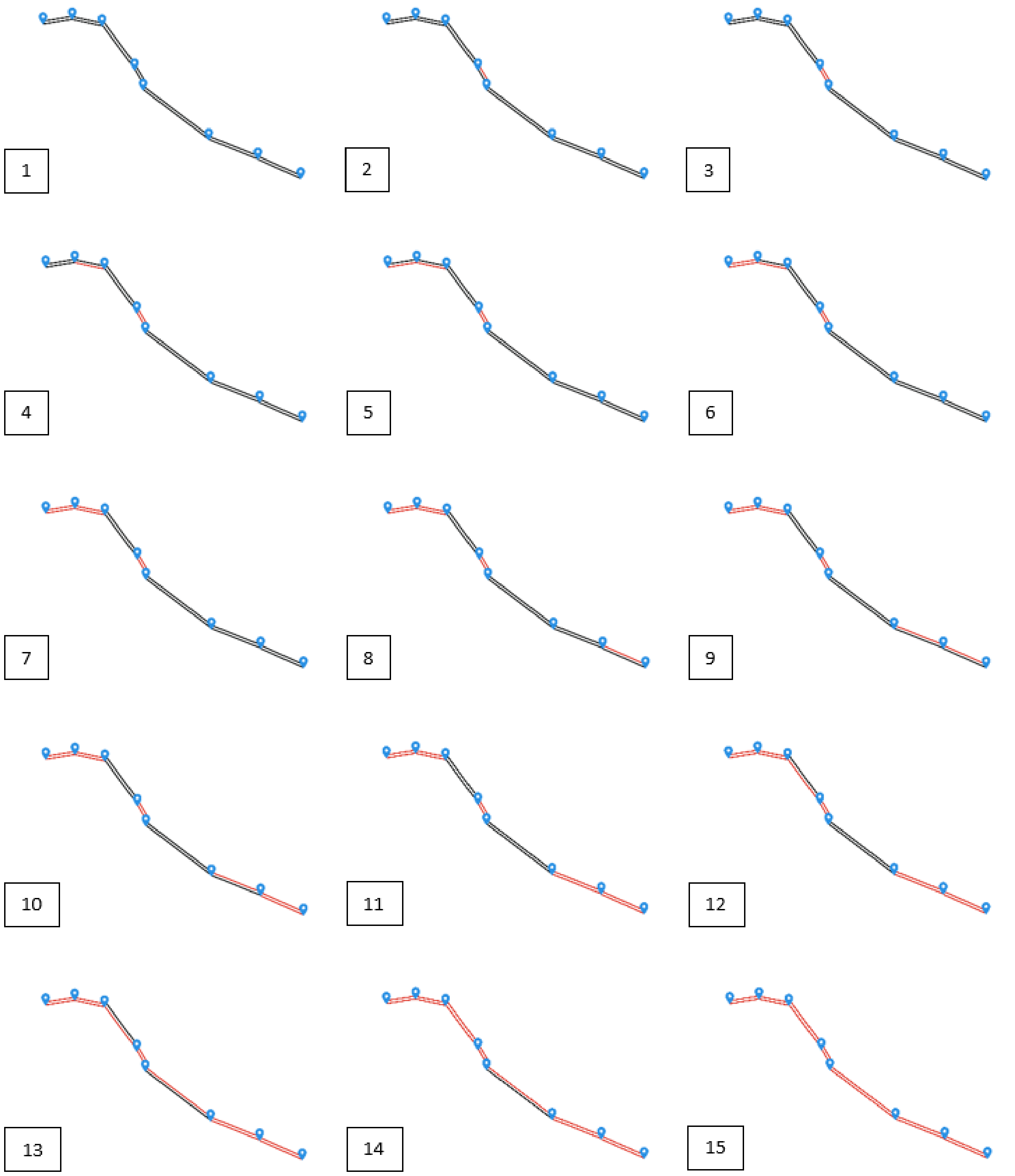


Figure 6.4: Priority in choosing lanes to be electrified. Red lines: electrified lanes, black lines: non-electrified lanes

Table 6.2 outlines the electrification order of various road segments based on their traffic density, measured in vehicles per kilometer, which is visually depicted in Figure 6.4. A critical observation from this analysis is that traffic density can serve as a quick and effective criterion for determining which road segments should be prioritized for electrification, proven by

Electrification order	Electfied segment	Segment traffic density [vehicle/km]
1	Dusseldorf - Cologne	43807
2	Cologne - Dusseldorf	40840
3	Arnhem - Utrecht	17040
4	Utrecht - Delft	16832
5	Delft - Utrecht	16568
6	Utrecht - Arnhem	14699
7	Wurzburg - Nuremberg	9137
8	Frankfurt - Wurzburg	8181
9	Nuremberg - Wurzburg	7702
10	Wurzburg - Frankfurt	7536
11	Dusseldorf - Arnhem	5499
12	Cologne - Frankfurt	3937
13	Arnhem - Dusseldorf	3607
14	Frankfurt - Koln	3332

Table 6.2: Order of electrification and the segment's traffic density

the result of the model. Segments with higher traffic densities, such as the Düsseldorf-Cologne route (43,807 vehicles/km) and Cologne-Düsseldorf (40,840 vehicles/km), are at the top of the electrification order. Higher traffic density implies that more vehicles will use the electrified segment, maximizing the benefits of the ERS and making it more cost-effective relative to the investment required.

However, while traffic density provides a simple and effective method for prioritizing which segments to electrify, it does not reduce the overall complexity of the model. The model still operates iteratively, where, at each step, the upper-level decision-making process determines whether it is beneficial to install ERS on a given segment. This decision is not based solely on traffic density but also on other factors such as vehicle routes, the availability of charging infrastructure, operational costs, and potential savings from ERS implementation. This iterative approach ensures that the benefits of ERS are not simply determined by the busiest routes but are distributed across the network in a way that accounts for long-term efficiency. In other words, while traffic density is one of the key indicators, the model needs to consider a wide range of variables to ensure that the electrification strategy maximizes both economic and operational benefits.

Additionally, determining how many segments should be electrified adds another layer of complexity to the problem. Electrifying every high-traffic segment may not be feasible due to budgetary constraints, and installing ERS on too many segments could lead to diminishing returns if some routes are underutilized. Thus, there is a need for a balance between prioritizing high-traffic routes and ensuring the entire network remains cohesive and efficient. The challenge for policymakers and planners is to find the right balance between investing in high-traffic segments and ensuring that the ERS network is distributed in a way that maximizes overall efficiency and cost-effectiveness.

Chargers deployment under different acceptance rate

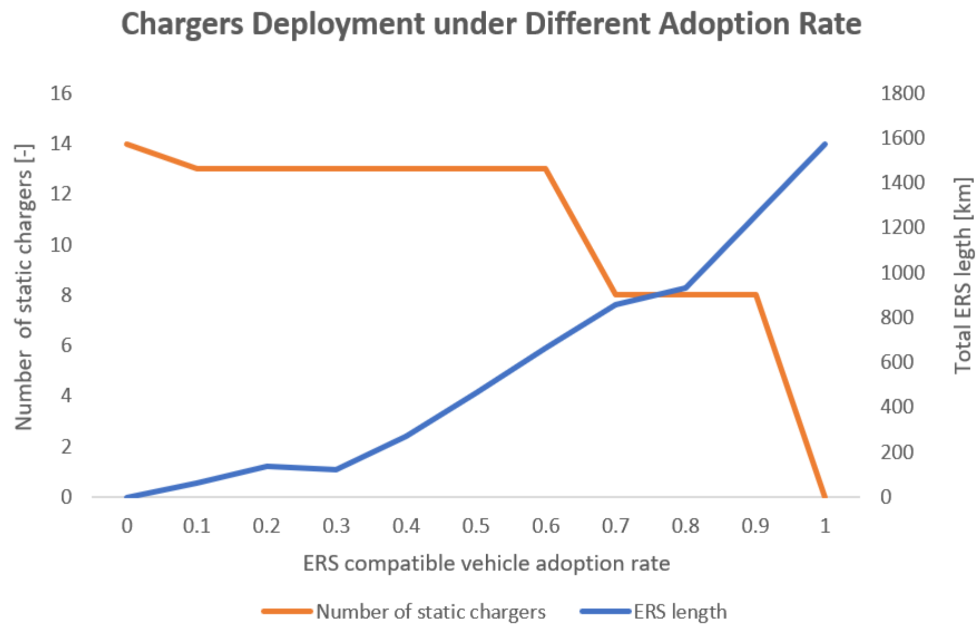


Figure 6.5: Installed ERS and static chargers under different acceptance rate using test map

As elaborated earlier, given that ERS is still a new technology, its adoption may be limited. In this model, ERS adoption is represented by the number of vehicles equipped with pantographs, referred to as vehicle type 1. Hypothetically, the level of adoption significantly influences the decision to implement ERS. The greater the number of users willing to adopt ERS, the stronger the justification for the government to implement it, as this would increase the potential savings in terms of transportation costs.

This analysis tests various ERS acceptance rates to observe their influence on charger deployment decisions. As expected, seen in Figure 6.5, higher adoption rates lead to a shift from static chargers to more ERS coverage. Once adoption exceeds a certain threshold, vehicles increasingly rely on dynamic charging, reducing the need for static chargers. However, between adoption rates of 0.0 and 0.6, static charger deployment remains stable. One possible reason for this outcome, as previously noted, is that the static chargers are not capacity-constrained. If they were, more static chargers could potentially be installed at adoption rates below 0.5.

The increase in ERS length at higher adoption rates indicates that the benefits of ERS eventually outweigh the high initial costs. As adoption grows, the ERS network expands, suggesting that once a critical mass of ERS-compatible vehicles is reached, the system becomes economically viable, with reduced operational costs justifying the investment. Conversely, at lower adoption rates, ERS is not the preferred solution. The insufficient number of ERS-compatible vehicles during the early stages of adoption creates a situation where the benefits derived from dynamic charging do not yet justify the high installation costs. In this phase, the economic rationale for ERS deployment is weaker, as the high capital expenditure is spread across too few users, limiting the return on investment in a form of users' surplus. As a result, static chargers continue to play a dominant role in supporting the charging needs of these early adopters.

This dynamic highlights the importance of reaching a critical threshold in ERS adoption to fully realize its economic and environmental benefits. It also justifies the earlier mentioned phenomenon, the "chicken and egg" dilemma: without sufficient user adoption, ERS investment is hard to justify, but without infrastructure, users are reluctant to switch. Coordinated policies, financial incentives, and a strategic rollout are needed to ensure that ERS infrastructure and vehicle adoption grow in parallel.

6.2. Chargers Deployment in Netherlands highway Network

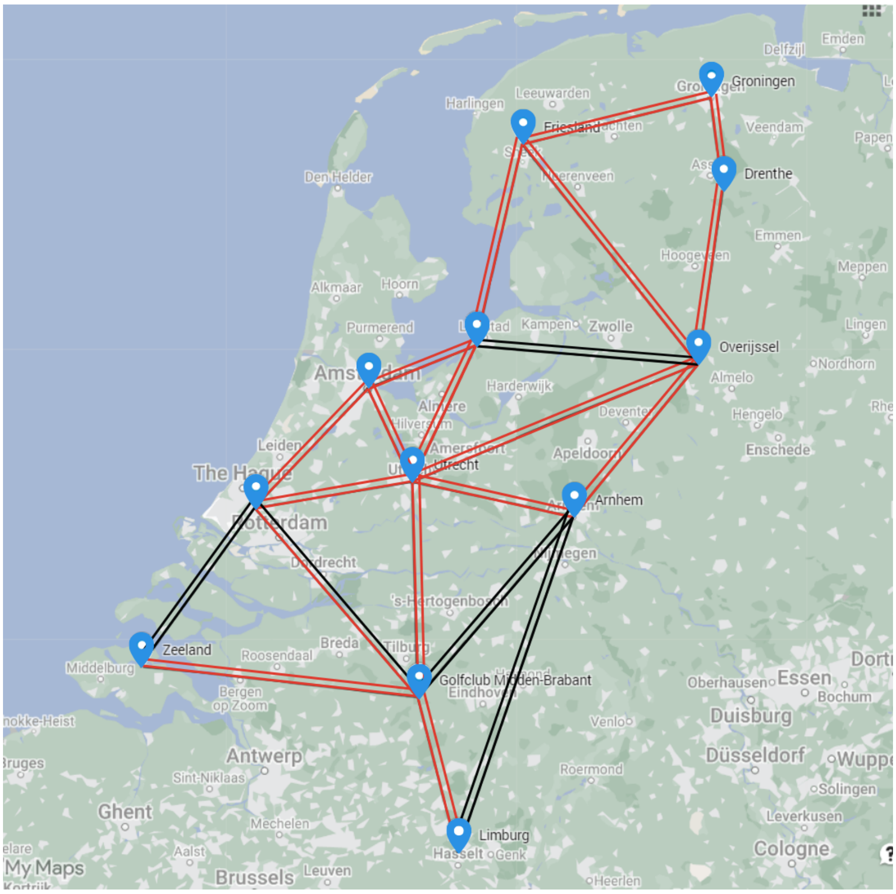


Figure 6.6: Network deployment in Netherlands highway network with 100% ERS adoption rate. Red lines: electrified lanes, black lines: non-electrified lanes

The map in Figure 6.6 illustrates the deployment of ERS and static chargers across the Netherlands' full highway network, assuming a 100% adoption rate of vehicle type 1. The network is visually represented with blue nodes indicating key cities or regions, covering: Groningen, Friesland, Drenthe, Overijssel, Arnhem, Flevoland, Utrecht, Amsterdam, Delft, Zeeland, Brabant, and Limburg. The red lines indicate the optimal selection of electrified highway links.

A notable observation is the absence of static chargers in hte optimal solution, with the model relying solely on ERS for charging, reflecting its efficiency when full adoption is achieved. Based on the model implementation in the given map, it reflects an optimized distribution where ERS is likely prioritized along the most heavily trafficked routes, such as those connecting major cities like Amsterdam, Delft, Utrecht, Flevoland, and the north region of Groningen and Drenthe. These routes are vital for national and regional logistics, indicating a focus on ensuring that the busiest corridors are well-equipped with ERS to support continuous and efficient transport of goods.

However, real-world implementation would need to account for potential disruptions, such as road maintenance or temporary closures, that could affect dynamic charging access and connectivity. While the map offers a robust solution, additional considerations like system redundancy or static chargers on secondary routes may be necessary for full network resilience.

Varying value of travel time

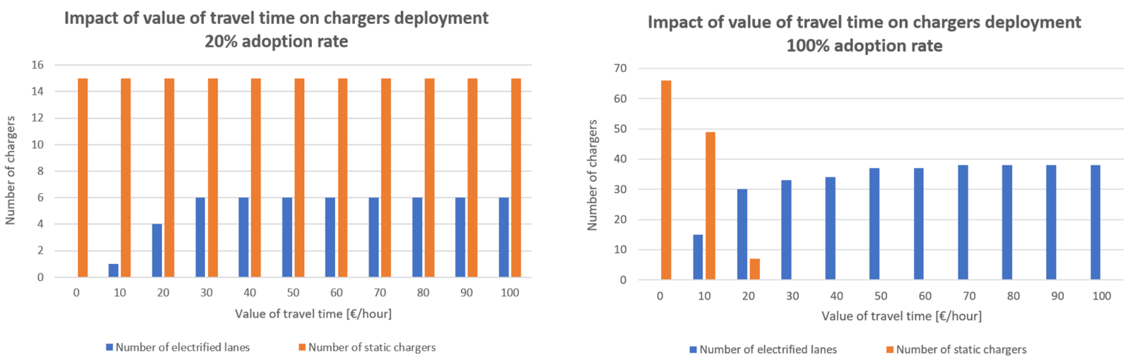


Figure 6.7: Results of chargers deployment under different value of time and acceptance rate

Figure 6.7 illustrating the impact of the value of travel time on the deployment of ERS and static chargers provides insightful data into how infrastructure decisions are influenced by the economic importance of travel time, particularly in scenarios where the adoption rate of vehicle type 1 is 20% and 100%, respectively. Value of travel time influences the decision-making around charger deployment, as optimizing travel time becomes a priority for minimizing costs in a competitive freight environment.

In the 20% adoption rate scenario (left graph), the number of static chargers remains constant at 14 across all values of travel time, whereas the number of electrified lanes increases gradually as the value of travel time rises. This pattern suggests that at a low adoption rate, static chargers play a dominant role in the charging infrastructure, irrespective of the value of travel time. The consistency of static chargers implies that under low adoption conditions, travel time has little effect on their deployment, likely because the system relies heavily on them for charging. Nevertheless, the uncapacitated charger model still applies as a reason why the number of static chargers remain constant. However, when time is valued highly, electrified lanes become a more attractive option for reducing delays.

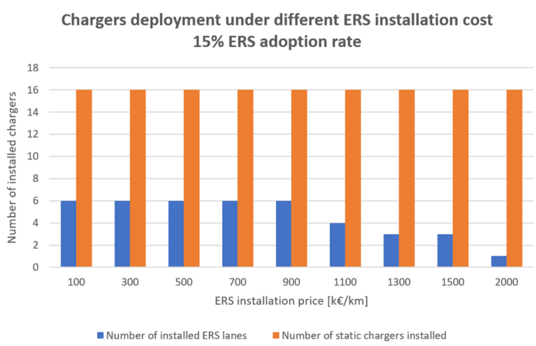
Interestingly, even at high values of travel time, such as from €40 to €100/hour, the number of electrified lanes remains stable on 6 ERS lanes. This suggests that under a 20% adoption scenario, the infrastructure remains skewed toward static chargers, even when minimizing travel time becomes more valuable. It indicates that the system may not yet be optimized for high-efficiency dynamic charging, with static chargers continuing to serve as the backbone of the network. The system may lack the economic justification to invest in widespread ERS lanes when the adoption rate is still low, as the benefits from electrified lanes are limited by the small number of ERS-compatible vehicles.

In contrast, the 100% adoption scenario (right graph) shows a significant shift in charger deployment. At a travel time value of £0/hour, there is heavy reliance on static chargers, with over 66 units installed due to the lower infrastructure cost. However, as the value of travel time increases, the number of static chargers declines rapidly, while the deployment of electrified lanes rises sharply. By the value of travel time reaches £40/hour, electrified lanes dominate the system, and static chargers are reduced to zero. This shift occurs because, with all vehicles being type 1 (equipped with smaller batteries), the need for frequent charging increases. As the value of time rises, the cost of frequent stops for charging outweighs the high initial investment in ERS, making it the preferred option due to its ability to reduce downtime.

Additionally, once the value of time exceeds £50/hour, the number of electrified lanes stabilizes, with 38 ERS lanes deployed across 42 highway segments. This plateau suggests that the charging demand has been fully met, and further expansion of ERS would not yield additional cost savings in transport.

One point that stands out in this analysis is how differently the system behaves under different adoption rates. This highlights the inefficiencies of ERS at low adoption rates, where static infrastructure remains indispensable and the full potential of dynamic charging cannot be realized. The implication is that early stages of ERS deployment will require a hybrid system, heavily reliant on static chargers to meet charging needs until vehicle adoption scales up. This demonstrates that the deployment of ERS is more economically justified in scenarios where reducing travel time is critical. Conversely, in scenarios where the value of time is lower, the model suggests that static chargers, with their lower installation and maintenance costs, are more appropriate despite the additional time required for charging.

Varying ERS cost per km



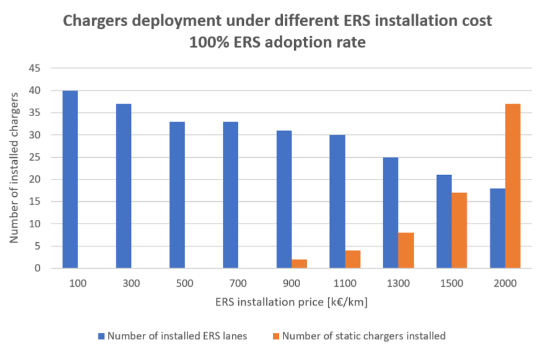


Figure 6.8: Impact of different ERS installation price to the overall chargers deployment

The two graphs in Figure 6.8 illustrate how static chargers and electrified lanes vary with different ERS installation costs under two adoption scenarios: 15% and 100%. In the 15% adoption scenario, static chargers dominate, maintaining around 13-14 units. Electrified lanes, however, decrease as ERS installation costs rise—from 6 lanes at 100,000 €/km to one or two at 2,000,000 €/km. This highlights the sensitivity of ERS to high installation costs, making static chargers the more viable solution at low adoption levels. The current price of catenary system ERS can go from 500,000 to 3,000,000 €/km, and we see in this grpah that with 15% adoption rate in the Netherlands, the number of electrified lanes starts decreasing after 900,000 €/km.

In contrast, under 100% adoption, electrified lanes increase significantly at low ERS installation costs, with over 40 lanes installed when costs are 100,000-300,000€/km. As costs rise, static chargers gradually replace electrified lanes. At 2,000 k€/km, static chargers outnumber electrified lanes, underscoring that even with full adoption, high installation costs make a fully electrified road system less feasible, necessitating reliance on static chargers. ERS are still attractive and no static chargers are needed with ERS cost below 900,000 €/km. However, above 900,000 €/km, electric lanes that does not give enough benefit to cover the cost starting to be replaced by static chargers.

Policymakers and investors must prioritize cost-effective ERS deployment. Even at full adoption, cost constraints suggest a continued need for hybrid infrastructure. This suggests a hybrid approach, where both static and dynamic charging solutions are used strategically based on cost and regional demand. Policymakers must focus on reducing costs and promoting adoption to optimize infrastructure investments and maximize the benefits of ERS. Strategies to reduce installation costs, such as technological innovations, economies of scale, or public-private partnerships, could be essential in making ERS deployment more feasible.

7 Discussion

7.1. Limitations

- **Capacitated Charging Stations:** One limitation is that the model does not account for the capacity of static charging stations or ERS infrastructure. In real-world scenarios, these stations have limited capacity and cannot serve all vehicles simultaneously, leading to potential bottlenecks. The absence of capacity constraints in the model could result in an overestimation of system efficiency, as it assumes that all vehicles can charge without queuing delay.

- **Environmental Benefits Exclusion:** The model does not factor in the environmental benefits of chargers, such as the reduction of CO2 emissions or the integration of renewable energy sources into charging networks. These elements could add a layer of both cost (e.g., investment in renewable energy infrastructure) and benefit (e.g., reductions in carbon taxes, pollution mitigation) that might affect decision-making. Future iterations of the model could include environmental costs and savings to provide a more holistic view of the true economic impact.

- **Resilience of the System:** Another limitation is the lack of attention to network resilience. The results suggest that, in some scenarios, the Netherlands' entire highway network could be electrified with ERS, making static chargers unnecessary. However, this creates a vulnerability—if a segment of the ERS fails (e.g., due to maintenance or an accident), there are no backup static chargers, which could lead to system-wide disruptions. A resilient charging network would require redundancy, ensuring that if one component of the system fails, alternative charging options are available. This real-life consideration is critical for ensuring the system remains functional under stress conditions.

- **Computational Complexity:** The model is highly computationally intensive, particularly when optimizing large networks. The bi-level optimization and genetic algorithm approaches used require substantial computational power, making real-time decision-making difficult in large-scale applications. This computational demand limits the practical use of the model in real-time or dynamic planning environments, where immediate responses to changes in traffic, energy demand, or infrastructure availability may be required.In addition to the optimization approach using Gurobi, a heuristic method such as a genetic algorithm can serve as an alternative or supplementary approach. However, due to the high computational demands of the genetic algorithm, only a low population size could be utilized in this research, leading to unreliable results and a lack of convergence. As a result, the genetic algorithm outcomes were excluded from the final modeling results.

7.2. Result interpretation

The results from the analysis indicate a clear trade-off between infrastructure costs and transportation efficiency, particularly between the use of static chargers and ERS for road freight electrification. The core finding is that as ERS deployment increases, the reliance on static charging decreases, but the two infrastructures complement each other based on the adoption rates and traffic density on different routes.

In one scenario, when ERS adoption is high (i.e., more vehicles are equipped with the necessary technology for in-motion charging), the model shows a significant reduction in the number of static chargers needed. The deployment of ERS on high-traffic routes, such as in the Netherlands, where dense highway networks exist, results in considerable transportation cost savings. This happens because ERS reduces the need for large batteries and eliminates the downtime for static charging, which ultimately lowers both vehicle operating costs and infrastructure costs in the long run. For instance, when ERS is deployed extensively, the model suggests that the entire transport network can function with minimal static chargers, resulting in cost reductions of up to 22-25%.

Furthermore, the model suggests that an optimal configuration of dynamic and static charging infrastructure depends heavily on the rate of ERS adoption by stakeholders, particularly vehicle manufacturers and freight companies. In scenarios with low ERS adoption, the model shows a continued reliance on static charging infrastructure to meet demand. Conversely, with high adoption rates, the expansion of ERS infrastructure becomes more viable, as the demand for in-motion charging justifies the significant upfront costs of ERS.

Additionally, the model is sensitive to the costs associated with ERS installation. The results demonstrate that as ERS installation costs rise (e.g., above €900,000 per kilometer), the economic advantage of using ERS diminishes, favoring static chargers instead. This highlights the importance of cost control and technological innovation to make ERS a more attractive option for wider-scale deployment. The sensitivity of the model to installation costs emphasizes the need for balanced investment strategies This suggests that while ERS has the potential to minimize operational costs long-term, it will be heavily dependent on upfront cost management and technological advancements to make its widespread deployment viable.

The relationship between static chargers and ERS shows a clear complementary dynamic. As ERS infrastructure is expanded, the need for static chargers decreases, particularly in high-traffic areas where in-motion charging through ERS can meet most of the energy demands for heavy-duty electric vehicles. ERS allows vehicles in reducing reliance on large onboard batteries and the infrastructure required for static charging. However, the results also suggest that static chargers continue to play an important role. In regions with lower traffic density or where ERS installation may not be feasible, static chargers are still necessary to ensure full network coverage. Therefore, static chargers serve as a backup in the hybrid infrastructure, supporting routes where ERS deployment is limited or impractical. This interdependence indicates that while ERS reduces the need for static chargers, it does not completely replace them.

Another interesting result highlighted by the model is that infrastructure resilience is not inherently built into the system. While the model suggests that a fully ERS-enabled network could theoretically meet the demand without static chargers in some regions, real-world conditions require considering redundancy and backup options. If an ERS segment fails (due to technical issues or road maintenance), the absence of static chargers could lead to significant disruptions. This is an important insight when considering the reliability of the infrastructure, particularly for critical routes where downtime could severely impact freight operations.

The results of the optimization model also highlight significant economic and geopolitical benefits of ERS adoption. One key advantage is the reduction in the need for large batteries, which are not only costly but also heavily reliant on the supply of rare minerals like lithium. Currently, a large portion of the global lithium supply comes from countries like China, creating a dependency that can lead to vulnerabilities in supply chains. By integrating ERS into the transport infrastructure, the Netherlands can reduce its reliance on lithium, which in turn lessens its dependence on foreign suppliers.

Even with a modest 10% adoption rate of ERS in the Netherlands, the model estimates that the country could save approximately €10.5 million annually on battery costs alone. These savings come from the reduced need for larger battery capacities, as vehicles would be able to charge while driving, minimizing the size of the onboard batteries required. This reduction in battery size not only alleviates supply chain pressures but also promotes more sustainable transportation practices by decreasing the environmental impact associated with battery production.

Moreover, the results of the optimization model offer important insights into the interaction between current government policies and the potential benefits of integrating ERS into the charging infrastructure. At present, the government policy mandates the installation of static charging stations every 60 kilometers on highways. However, this policy was developed without considering the potential of ERS technology. According to the model's results, in a scenario where 30% of the Netherlands' highway network is electrified with ERS, the need for static chargers can be significantly reduced. The results suggest that, instead of placing static chargers every 60 kilometers, the intervals can be extended to every 78 kilometers, reducing approximately 23% of static chargers. It is important to note that this scenario assumes 100% of vehicles are equipped with smaller batteries. In cases of lower ERS adoption rates, the demand for static chargers would decrease even further, leading to additional reductions in static chargers needs.

This extension not only meets the charging needs of vehicles but also substantially reduces the capital investment required for static charger infrastructure. With fewer static chargers needed due to the support of ERS, the government can allocate resources more efficiently, directing funds toward other aspects of the transport electrification initiative and subsidies. Furthermore, the model demonstrates that ERS is highly beneficial for users.

These findings challenge the current static charging policy and suggest that a combined approach, integrating ERS and static chargers, would be more cost-effective and efficient. The results imply that infrastructure planning should consider ERS deployment to optimize both capital investments and operational efficiency, showing that a one-size-fits-all approach to static charger placement may not be necessary in an ERS-supported network.

7.3. Results implication

With the limitations mentioned above, the implications of these results extend beyond the Netherlands, as the model offers a versatile framework adaptable to various regions and contexts. By adjusting parameters like traffic data, adoption rates, or installation costs, this model can be applied to different countries, making it a valuable tool for global infrastructure planning. This flexibility allows policymakers and investors to tailor infrastructure deployment strategies according to local conditions, ensuring that resources are allocated in a way that maximizes coverage and operational savings while minimizing unnecessary expenditure.

In real-world applications, this model could guide infrastructure investments by helping governments and private stakeholders identify optimal configurations of dynamic and static charging facilities. For example, it could recommend prioritizing ERS deployment along major freight corridors while ensuring that static chargers remain available in lower-density regions to provide network resilience. This approach not only supports the broader transition to electric freight vehicles but also ensures that the infrastructure is robust and adaptable to future technological advancements.

Furthermore, the decreased reliance on large batteries aligns with global sustainability goals, including reducing greenhouse gas emissions and encouraging the use of renewable energy sources for charging. The integration of ERS into freight transportation infrastructure allows for a more resilient, cost-effective, and environmentally friendly system, all while minimizing dependency on critical minerals from foreign markets.

Lastly, the model's flexibility and detailed cost analysis make it a crucial tool for achieving long-term sustainability targets, such as those set out in the Paris Agreement. By optimizing the deployment of charging infrastructure, governments can take strategic steps to decarbonize the freight transport sector while simultaneously reducing operational costs for businesses. This, in turn, encourages greater adoption of electric vehicles, creating a positive feedback loop that accelerates the transition to clean energy transport.

8

Conclusion and Future Research

8.1. Conclusion

The objective of this research is to develop an optimization model that determines the optimal configuration of dynamic and static charging facilities for heavy-duty electric trucks, considering varying levels of ERS adoption. The research aims to answer the main research question: *"How does an integrated approach combining ERS and static charging infrastructure optimize cost and coverage for road freight transport?"* The answers to this question explored through several sub-questions which have been explored in this thesis, including:

1. *What are the key trade-offs between ERS and static charging for heavy-duty truck electrification?*

   The study revealed that ERS and static chargers complement one another rather than being mutually exclusive. While static chargers are necessary in areas where traffic density or infrastructure investment cannot justify ERS deployment, ERS becomes economically attractive on high-traffic routes due to the reduction in battery size requirements and the elimination of downtime associated with static charging, as well as cheaper charging and toll costs. Static chargers act as complimentary infrastructure in low-traffic regions or in scenarios where ERS installation is inefficient. The model indicates that as ERS adoption increases, the number of static chargers needed decreases substantially, offering up to 22-25% savings in infrastructure and operational costs.

2. *Which modeling approaches are most suitable for developing a model that optimizes the configuration of dynamic and static charging stations, and how can this model be effectively developed and validated?*

   The chosen bi-level optimization model, solved using the Gurobi optimizer, proved effective in addressing the complexity of the problem. The model successfully captured the trade-offs between dynamic and static charging stations, considering factors like ERS adoption rates, traffic density, and cost constraints. Testing the model on the Netherlands highway network validated its accuracy and applicability. The sensitivity analysis on ERS installation costs highlighted the need for precise investment strategies. Due to the model's complexity, with numerous variables and extensive data, higher computational capacity is required to efficiently run larger datasets or cover broader areas. An alternative approach considered in this research is the use of genetic algorithms, which were initially explored as a potential solution for addressing the model's complexity.

3. *How does different ERS adoption rate impact the ERS network design?*

   Varying adoption rates significantly influenced the design and deployment of ERS infrastructure. When adoption rates were low, the model indicated a heavier reliance on static chargers. In contrast, higher ERS adoption rates made the expansion of ERS networks more cost-effective and reduced the number of static chargers needed. Importantly, the model showed a strong correlation between ERS deployment and the increased adoption of ERS-compatible vehicles, particularly when over 800 kilometers of ERS were installed. However, high installation costs (e.g., exceeding €900,000/km) reduced the economic advantage of ERS, tipping the balance in favor of static charging.

4. *What is the optimal configuration of ERS and static charging stations for heavy-duty electric trucks in the context of a specific case study?*

   In smaller analysis using a long highway segment from Delft to Nuremburg, the model suggested electrification in highly trafficked area, such as Düsseldorf and Cologne, Utrecht and Delft, and Arnhem and Utrecht. The model also suggested that static chargers should be strategically placed in less densely trafficked areas to ensure network resilience and coverage. The model demonstrated that a hybrid approach, where both ERS and static chargers are utilized based on traffic density and adoption rates, maximized cost savings and coverage. Similarly, for the case study focused on the Netherlands, the optimal configuration prioritized ERS deployment along heavily trafficked routes, such as the Randstad and north area, covering almost 80% of the overall highway network. These routes support the majority of freight traffic, making ERS more cost-effective and operationally efficient. The model also suggest that no static chargers are needed in under this condition.

   Additionally, the findings reveal that traffic density, measured as the number of vehicles per kilometer, plays a key role in determining the priority for highway segment electrification. This priority is adjusted iteratively based on vehicle routing within the model. In budget-constrained scenarios, this approach provides a simplified method for identifying which highway segments should be electrified first. However, it is essential to consider other influencing factors to ensure well-informed decision-making and avoid potential oversights.

5. *What considerations and recommendations can be given to different stakeholders in the ERS project based on the case study?*

   Based on the findings, stakeholders and policymakers should focus on reducing ERS installation costs through innovation and public-private partnerships, as this is a critical factor in making ERS more attractive. Additionally, static charging should not be entirely replaced by ERS but instead should serve as a backup in areas where ERS installation is not viable. Importantly, the model results suggest that the current policy of installing static chargers every 60 kilometers could be optimized. In scenarios where 30% of the Netherlands' highway network is electrified with ERS, the distance between static chargers could be extended to 78 kilometers, reducing the number of static chargers needed by 23%. This scenario assumes 100% adoption of ERS-compatible vehicles, which are equipped with smaller batteries, thereby necessitating a greater number of static chargers. However, as the adoption rate of ERS-compatible vehicles decreases, the demand for static chargers is expected to decline further. This reduction in infrastructure requirements would result in significant cost savings for policymakers. This could result in significant capital savings, allowing the government to allocate resources more efficiently and promote a more integrated, cost-effective charging infrastructure. For infrastructure planners, prioritizing high-traffic routes for ERS deployment is crucial for maximizing return on investment. Furthermore, stakeholders should work collaboratively to promote ERS-compatible vehicle adoption, as this accelerates the benefits derived from an integrated charging network.

This research highlights that an integrated approach combining ERS and static charging infrastructures can optimize both costs and coverage in road freight electrification. However, the effectiveness of such a system hinges on the strategic deployment of infrastructure and the adoption of ERS-compatible vehicles. The results of this study provide actionable insights for stakeholders, suggesting that future investments in road electrification should be guided by both traffic density and ERS adoption rates, while also considering cost control in ERS installation.

8.2. Future research recommendation

Future research should explore into the resilience of the combined ERS-static charging network, particularly in the face of unexpected disruptions such as infrastructure failures or extreme weather conditions. Since both static and dynamic charging systems are critical to ensuring continuous freight operations, understanding how these systems cope under critical condition is vital. Investigating how the network responds to outages, malfunctions, or severe weather, as well its connectivity, would provide valuable insights into maintaining system reliability. This research could also explore redundancy measures, such as backup power sources or alternate charging routes, to ensure the network remains functional even when parts of the system fail. A resilient charging infrastructure will be key to maintaining service continuity, minimizing downtime, and ensuring that electric freight transport remains viable during unforeseen disruptions.

Additionally, future work should focus on limited infrastructure capacity and the impact of queuing at static charging stations. In the current study, access to charging facilities was assumed to be seamless, but real-world operations will face capacity limitations. Incorporating queuing theory and analyzing waiting times during peak usage periods would offer a more practical view of how the system performs under high demand. Understanding these dynamics is crucial for optimizing the placement and number of static chargers, as well as ensuring that ERS infrastructure can handle the anticipated traffic volumes. This research could inform policies for reducing congestion at charging points, ensuring faster turnarounds for trucks, and ultimately improving the operational efficiency of the network.

9

Appendix A: Optimal Charging Configuration in the Netherlands

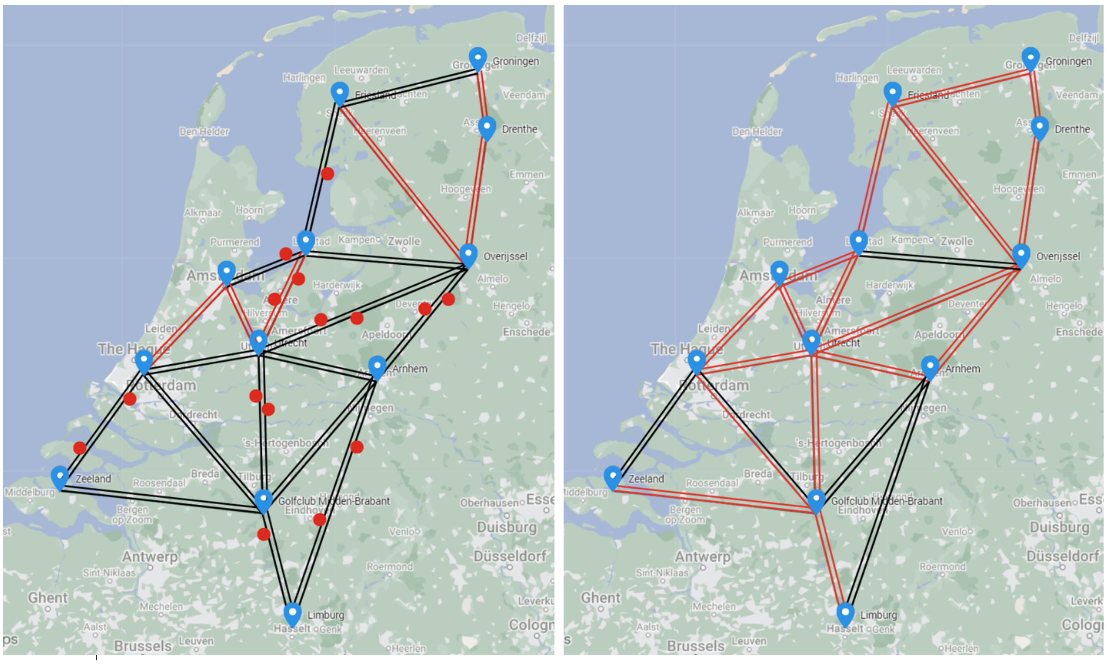


Figure 9.1: Network deployment in Netherlands highway network with 20% (left) and 100% (right) ERS adoption rate. Red lines: electrified lanes, black lines: non-electrified lanes, red dots: installed charging stations

10

Appendix B: Genetic Algorithm Approach

```python
import numpy as np
import matplotlib.pyplot as plt

# Parameters
population_size = 26 # this has to be even number
generations = 10
crossover_rate = 0.8
mutation_rate = 0.1
tournament_size = 3  # Number of individuals in each tournament

charging_stationsMappingForward = {}
charging_stationsMappingBackward = {}
counter = 0
for i in charging_stations.keys():
    charging_stationsMappingForward[i] = counter
    charging_stationsMappingBackward[counter] = i
    counter += 1

dynamic_linkMappingForward = {}
dynamic_linkMappingBackward = {}
counter = 0
for i in dynamic_links.keys():
    dynamic_linkMappingForward[i] = counter
    dynamic_linkMappingBackward[counter] = i
    counter += 1

def heuristic_charging_strategy_with_decision(network, charging_stations, path, battery_capacity, consumption_rate,
penalty_cost, EV_type, lookahead_distance=2):
    battery = battery_capacity
    total_cost = 0

    for i, link in enumerate(path):
        segments = network[link]['segments']
        wireless_link = network[link]['wireless']

        for j, segment in enumerate(segments):
            segment_id = segment['id']
            distance = segment['length']
            static_station = charging_stations[link][segment_id]['static']
            wireless_segment = segment['wireless'] and wireless_link

            # Calculate energy needed to traverse the segment
            energy_needed = distance * consumption_rate

            # Lookahead to see the next few segments and their energy demands
            future_energy_needed = 0
            for k in range(1, lookahead_distance + 1):
                if i + k < len(path):
                    future_link = path[i + k]
                    future_segments = network[future_link]['segments']
                    future_energy_needed += sum(s['length'] * consumption_rate for s in future_segments)

            # Decision making: Compare static and wireless charging if both are available
            if battery < energy_needed or battery < future_energy_needed:
                if EV_type == 1:  # EV type 1 can use both static and wireless
                    static_cost = charging_stations[link][segment_id]['cost'] if static_station else float('inf')
                    wireless_cost = charging_stations[link][segment_id]['cost'] * (min(energy_needed,
battery_capacity - battery)
                                                                                          / energy_needed) if
wireless_segment else float('inf')

                    # Choose the cheaper option
                    if static_cost < wireless_cost:
                        battery = battery_capacity  # Full recharge
                        total_cost += static_cost
                    elif wireless_cost < static_cost:
                        charge_amount = min(energy_needed, battery_capacity - battery)
                        battery += charge_amount
                        total_cost += wireless_cost
                elif static_station and EV_type == 2:  # EV type 2 can only use static
                    charge_cost = charging_stations[link][segment_id]['cost']
                    battery = battery_capacity  # Full recharge
                    total_cost += charge_cost
                elif wireless_segment and EV_type == 1:
                    charge_amount = min(energy_needed, battery_capacity - battery)
                    charge_cost = charging_stations[link][segment_id]['cost'] * (charge_amount / energy_needed)
                    battery += charge_amount
                    total_cost += charge_cost
                else:
                    # No charging available, incur penalty
                    if battery < energy_needed:
                        deficit = energy_needed - battery
                        penalty = deficit * penalty_cost
                        total_cost += penalty
                        battery = 0  # Battery becomes zero
```

```
            # Update battery after traveling the segment
            battery -= energy_needed

    return total_cost



# Objective function
def objective_function(xVector, yVector):
    lowerLevelObj = 0
    upperLevelObj = 0
    IndicatorVal = {}
    charging_stations = {}
    for i in range(len(xVector)):
        charging_stations[charging_stationsMappingBackward[i]] = xVector[i]

    dynamic_linksVal = {}
    for i in range(len(yVector)):
        dynamic_linksVal[dynamic_linkMappingBackward[i]] = yVector[i]
    for (o,d) in requests.keys():
        requestsVal = requests[(o,d)]
        if random.uniform(0, 1) > request_percentage:
            givenVehType = [1]
        else:
            givenVehType = [2]
        flowVal, lvlobjVal =
lowerSubProblem(requestsVal,o,d,link_lengths,charging_stations,dynamic_linksVal,givenVehType)

        for v in vehicle_types:
            for (i, j) in links:
                IndicatorVal[v, i, j, o, d] = flowVal[v, i, j]
        lowerLevelObj += lvlobjVal
        # project back to full solution to be passed to the master problem.
        upperlvlCost = upperLevelSub(IndicatorVal,charging_stations,dynamic_linksVal,givenVehType,requestsVal,o,d)
        upperLevelObj += upperlvlCost
    objectiveOA = 0

    for link in links:
        # Fixed Cost
        objectiveOA +=  ((Cd*link_lengths[link]*yVector[dynamic_linkMappingForward[link]])*(1+ mu_ers*tao_sc)
                         - (Cd*link_lengths[link]*yVector[dynamic_linkMappingForward[link]]*(tao_ers-
tao_sc)/tao_ers))/ann_1
        # Recharging time cost for static charging
        for seg in range(1,num_segments[link]+1):
            objectiveOA += ((Sc *100* xVector[charging_stationsMappingForward[link[0], link[1],
seg]])*(1+mu_sc*tao_sc) ) / ann_1
    # TODO: Add the constraint that number of vehicles shall be at least a certain value
    totalCost = upperLevelObj + lowerLevelObj + objectiveOA
    return totalCost

# Generate initial population
def initialize_population(size_x, size_y, population_size,probSelection):
    population_x = np.random.randint(2, size=(population_size, size_x))
    population_x = np.random.choice([0, 1], size=(population_size, size_x), p=[1-probSelection, probSelection])
    population_y = np.random.randint(2, size=(population_size, size_y))
    return population_x, population_y

# Fitness evaluation
def evaluate_fitness(population_x, population_y):
    fitness = np.array([-objective_function(x, y) for x, y in zip(population_x, population_y)])
    return fitness

# Tournament selection
def tournament_selection(population_x, population_y, fitness, tournament_size):
    selected_x = []
    selected_y = []
    num_individuals = len(population_x)

    for _ in range(num_individuals):
        tournament_indices = np.random.choice(num_individuals, tournament_size, replace=False)
        tournament_fitness = fitness[tournament_indices]
        best_index = tournament_indices[np.argmax(tournament_fitness)]
        selected_x.append(population_x[best_index])
        selected_y.append(population_y[best_index])

    return np.array(selected_x), np.array(selected_y)

# Crossover
def crossover(population_x, population_y, crossover_rate):
    new_population_x = []
    new_population_y = []
    for i in range(0, len(population_x), 2):
        parent1_x, parent2_x = population_x[i], population_x[i+1]
```

```
        parent1_y, parent2_y = population_y[i], population_y[i+1]

        if np.random.rand() < crossover_rate:
            crossover_point_x = np.random.randint(1, len(parent1_x))
            crossover_point_y = np.random.randint(1, len(parent1_y))
            child1_x = np.concatenate((parent1_x[:crossover_point_x], parent2_x[crossover_point_x:]))
            child2_x = np.concatenate((parent2_x[:crossover_point_x], parent1_x[crossover_point_x:]))
            child1_y = np.concatenate((parent1_y[:crossover_point_y], parent2_y[crossover_point_y:]))
            child2_y = np.concatenate((parent2_y[:crossover_point_y], parent1_y[crossover_point_y:]))
        else:
            child1_x, child2_x = parent1_x, parent2_x
            child1_y, child2_y = parent1_y, parent2_y

        new_population_x.extend([child1_x, child2_x])
        new_population_y.extend([child1_y, child2_y])

    return np.array(new_population_x), np.array(new_population_y)

# Mutation
def mutate(population_x, population_y, mutation_rate):
    for i in range(len(population_x)):
        if np.random.rand() < mutation_rate:
            mutation_point_x = np.random.randint(len(population_x[i]))
            population_x[i][mutation_point_x] = 1 - population_x[i][mutation_point_x]
    for i in range(len(population_y)):
        if np.random.rand() < mutation_rate:
            mutation_point_y = np.random.randint(len(population_y[i]))
            population_y[i][mutation_point_y] = 1 - population_y[i][mutation_point_y]

    return population_x, population_y

# Main genetic algorithm loop with recording of objective values
def genetic_algorithm(size_x, size_y, population_size, generations, crossover_rate, mutation_rate, tournament_size,
probSelection):
    population_x, population_y = initialize_population(size_x, size_y, population_size, probSelection)
    best_objective_values = []
    bestSCNames = []
    bestERSNames = []
    bestFound = float('inf')

    for generation in range(generations):
        fitness = evaluate_fitness(population_x, population_y)
        population_x, population_y = tournament_selection(population_x, population_y, fitness, tournament_size)
        population_x, population_y = crossover(population_x, population_y, crossover_rate)
        population_x, population_y = mutate(population_x, population_y, mutation_rate)

        # Record the best objective value of this generation
        best_index = np.argmax(evaluate_fitness(population_x, population_y))
        best_x = population_x[best_index]
        best_y = population_y[best_index]
        best_fitness = objective_function(best_x, best_y)
        best_objective_values.append(best_fitness)
        print(f"Generation number {generation} best value is {best_fitness}, number of CS stations is {sum(best_x)}
and number of ERS is {sum(best_y)}")
        if best_fitness < bestFound:
            bestFound = best_fitness
            bestSCNames = []
            bestERSNames = []
            for indx,value in enumerate(best_x):
                if value >= 0.9:
                    bestSCNames.append(charging_stationsMappingBackward[indx])
            for indx,value in enumerate(best_y):
                if value >= 0.9:
                    bestERSNames.append(dynamic_linkMappingBackward[indx])


    return bestERSNames, bestFound, best_objective_values

# Running the genetic algorithm
best_y, best_fitness, best_objective_values = genetic_algorithm(numCS, numERS, population_size, generations,
crossover_rate, mutation_rate, tournament_size,probSelection)

# Plotting the objective values over generations
plt.plot(best_objective_values)
plt.xlabel('Generation')
plt.ylabel('Objective Function Value')
plt.title('Objective Function Value Over Generations')
plt.grid(True)
plt.show()
```

11

Appendix C: Scientific Paper

Combination of Static and Dynamic Charging Facilities for Road Freight Electrification

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Abstract

The study aims to develop an optimization model that determines the optimal configuration of dynamic Electric Road Systems (ERS) and static charging infrastructure for heavy-duty electric trucks. By considering varying levels of ERS adoption, the model seeks to minimize total infrastructure and operational costs while maximizing demand coverage along key transport routes. The research uses a bi-level optimization model: the upper level addresses government decisions on infrastructure placement to minimize infrastructure costs, while the lower level focuses on user routing to minimize transportation expenses. The model was applied to the Netherlands as a case study, optimizing the placement of ERS and static chargers based on traffic patterns and user behavior. Key findings indicate that ERS and static chargers are complementary, with ERS proving more cost-effective on high-traffic routes, reducing battery size and eliminating charging downtime. In low-traffic areas, static chargers provide essential infrastructure support. The model demonstrated that an integrated charging network could lead to cost savings of up to 25%. The study concludes that a combined ERS-static charging infrastructure is the a cost-efficient approach for electrifying freight transport, offering both economic and environmental benefits .

Keywords: Electric Road Systems (ERS), Freight Electrification, Static Charging, Electric Trucks, Infrastructure Optimization

1. Introduction

The growing environmental impact of freight transport is a pressing concern, with heavy-duty vehicles contributing significantly to global CO_2 emissions. Road freight alone accounts for approximately 8% of energy-related CO_2 emissions, a figure expected to double by 2050 due to increased economic activity, particularly in Asia, Africa, and Latin America (Greene, 2023). Although heavy-duty trucks represent only 5% of the vehicle fleet, they contribute around 28% of the EU's road transport emissions (Unterlohner, 2022). The rapid growth of e-commerce and global trade further exacerbates this environmental challenge, prompting the urgent need for sustainable solutions (OECD, 2023). In response to the Paris Agreement's goal of achieving net-zero emissions by 2050, several alternative fuel solutions, including hydrogen, biofuels, and electric power, have been explored (IEA, 2021). Among these, electric vehicles (EVs) have emerged as the most viable option due to their technological maturity, expanding infrastructure, and direct impact on emissions reduction (McConnell and Leard, 2020; Konstantinou and Gkritza, 2023).

EVs offer significant environmental benefits, such as zero tailpipe emissions and lower long-term operational costs. However, the widespread adoption of electric trucks for freight transport faces critical challenges, particularly in long-haul operations, where the limitations of battery technology hinder practical implementation. Larger batteries are required for long-haul operations to minimize charging stops, but these increase vehicle weight and reduce payload capacity, impacting both operational efficiency and vehicle costs. Additionally, the cost of large batteries escalates, while the current charging infrastructure remains underdeveloped. Long charging times and the downtime associated with static charging stations disrupt delivery schedules and reduce productivity, particularly in comparison to diesel trucks, which can travel much farther without refueling (M and G, 2023; Taheripour et al., 2010). These challenges highlight the need for innovative solutions to optimize the trade-offs between battery size, cost, and range, thereby enhancing the practicality and economic viability of electric trucks.

ERS, a dynamic charging technology, offer a promising solution to the limitations of static charging. ERS enables vehicles to charge while in motion via conductive rails, overhead powerlines, or inductive charging embedded within roadways. By allowing continuous charging, ERS reduces the need for large onboard batteries and eliminates the downtime associated with stationary charging. Studies suggest that ERS can lead to substantial cost savings, with reductions in total ownership costs of up to 30%, primarily due to decreased battery and fuel expenses (Börjesson et al., 2021; Coban et al., 2022; Connolly, 2016). ERS also enhances the environmental sustainability of transport systems, with projections indicating that a full-scale deployment could reduce road transport emissions by up to 40% (Domingues-Olavarría et al., 2018; Olovsson et al., 2021). Technologically, wireless power transfer technology in ERS can achieve energy transfer efficiencies of over 90%, further reducing operational costs (Soares and Wang, 2022).

Despite these benefits, large-scale ERS implementation is still in its early stages. Pilot projects in Sweden, Germany, and France demonstrate the technical feasibility of ERS, but also highlight challenges such as high infrastructure costs and the need for collaboration among stakeholders. For example, Sweden's Smartroad Gotland, the world's first public wireless electric road for heavy-duty vehicles, demonstrated wireless power transfer at speeds of up to 80 km/h, showing its potential for future applications, though further technological improvements are needed (Electreon, 2024; Frost, 2019). The "chicken and egg" dilemma persists, as manufacturers hesitate to invest in ERS-compatible vehicles without clear infrastructure commitments, and investors are reluctant to fund ERS projects without guaranteed market demand. As a result, user acceptance plays a crucial role in ERS viability (Manthey, 2023; Min, 2023a).

To address these challenges, this research aims to develop an optimization model that integrates both ERS and static charging infrastructures for heavy-duty electric trucks. The model seeks to minimize the total cost of infrastructure and operations while maximizing demand coverage along key transport routes. By considering varying levels of ERS adoption, the study aims to provide insights into the optimal deployment strategies for dynamic and static charging networks (Hou et al., 2021; Piarc, 2018). This research contributes to the existing literature by addressing the gap in studies that have primarily focused on static or dynamic charging systems independently (Danese et al., 2021; Campaña and Inga, 2023; Csiszár et al., 2020; Sun et al., 2020).

The primary research question is: How can a configuration of dynamic and static charging stations be developed for heavy-duty electric vehicles that optimizes demand coverage within a limited budget, while accounting for varying acceptance levels of ERS among stakeholders? This research will explore the trade-offs between ERS and static charging, the impact of different ERS adoption rates on network design, and the optimal configuration of charging stations for electrified freight transport.

This study is crucial for informing future policy and investment decisions in electrifying freight transport. By balancing cost, efficiency, and environmental impact, the research aims to guide the strategic deployment of ERS and static charging systems, contributing to decarbonizing road freight transport.

2. Literature Review

The rise of EVs and HDEVs has led to extensive research on developing efficient charging infrastructure. Two key methods, static charging stations and ERS, are under study for their potential to support electrification at scale. A critical area of research is the optimal design and deployment of these infrastructures to balance cost, energy efficiency, and user convenience, with ERS showing promise in reducing range anxiety and battery size for long-haul freight operations.

2.1. ERS overview

Electric Road Systems (ERS) offer continuous, on-the-go charging through different technologies: overhead conductive, ground-based conductive, and inductive (wireless) systems. Overhead conductive systems use pantographs that connect vehicles to overhead power lines, as seen in Sweden's eHighway project. This system has proven effective in reducing carbon emissions for heavy trucks but faces challenges such as high costs and limitations for smaller vehicles Min (2023b); Akerman (2016); Zhang et al. (2014). Ground-based conductive systems, like the eRoadArlanda project, provide power via conductive rails embedded in roads but are vulnerable to weather conditions and pose safety risks for motorcyclists Piarc (2018); Schaap (2021). Inductive systems, while safer and aesthetically pleasing due to their wireless nature, suffer from lower energy transfer efficiency and high installation costs Schaap (2021).

2.2. Network Design for Charging Infrastructure

Network design for charging infrastructure is a critical factor influencing the adoption of ERS and static chargers. Several researchers have developed models to optimize the placement of charging facilities, balancing costs, user convenience, and energy demands. Chen, Liu, and Yin Chen et al. (2017) proposed a charging-facility-choice equilibrium model that compares the deployment of stationary and dynamic charging infrastructure. Their research indicates that dynamic charging lanes can be highly competitive, particularly for commercial vehicles with high time-value, and can attract drivers by minimizing downtime and charging stops. Their results show that dynamic charging lanes, while costly, can be financially sustainable through either public provision or private-sector investment.

Path-constrained network equilibrium models, such as those explored by Qiu et al. (2020), aim to minimize total travel time and optimize the location of electrified roads while considering budget constraints. These models explore the impact of various factors, including battery size and charging efficiency, to ensure that the infrastructure meets the needs of EV users efficiently. Other research, such as that by Pagany et al. (2019), uses Geographic Information System (GIS)-based models to determine optimal locations for static charging stations. This method minimizes walking distances to charging stations while ensuring sufficient energy coverage in high-demand areas, as demonstrated in their case study in southern Germany.

A corridor-based design for ERS, which focuses on long-haul routes, is often considered more efficient for reducing emissions, particularly for heavy goods vehicles. This approach ensures higher utilization rates and justifies the investment in high-power dynamic charging infrastructure Bakker et al. (2024). However, dense infrastructure networks, which include multiple short routes and static chargers, may offer greater flexibility and user adoption in the early stages of electrification Bakker et al. (2024). Studies suggest that a phased approach—starting with dense static charging networks and gradually expanding to ERS corridors—could maximize both early adoption and long-term environmental benefits.

Several mathematical and heuristic methods have been employed to optimize charging station networks. Mixed Integer Linear Programming (MILP) models have been used to solve the location problem, considering factors such as detour mileage and budget constraints Li et al. (2022). MILP-based approaches are particularly useful for large-scale problems, as seen in the research of Kuby and Lim (2005); Lin et al. (2008); Wang and Lin (2009), where the optimization of static charging stations along intercity highways reduced overall travel time and increased system efficiency. Other methods, such as genetic algorithms, particle swarm optimization (PSO), and Non-Dominated Sorting Genetic Algorithm (NSGA-II), have been applied to enhance computational efficiency and handle complex, multi-objective optimization problems Kizhakkan et al. (2019).

3. Methodology

Current research on EV charging infrastructure often focuses either on ERS or static charging solutions, neglecting the potential synergies of combining the two technologies. This oversight creates a research gap in understanding how to optimize the deployment of both static chargers and ERS in a unified network to minimize costs while maximizing coverage and efficiency. The main issue lies in determining the optimal configuration that addresses both government infrastructure investment strategies and user route optimization, considering varied acceptance levels of ERS among stakeholders. Furthermore, existing methodologies often overlook the operational differences between high-traffic and low-traffic areas, where ERS and static charging infrastructure must be deployed differently. This research aims to address this gap by developing a comprehensive model that integrates both technologies to minimize infrastructure costs and operational inefficiencies while providing maximum demand coverage for heavy-duty trucks.

The research employs a combination of bi-level optimization modeling and case study analysis to explore the optimal configuration of static and dynamic charging infrastructure for heavy-duty trucks. The methodology is built on two interdependent levels of optimization. The lower-level optimization focuses on minimizing transportation costs for users. This includes the cost of travel time extended by static charging, toll costs (which are subsidized for ERS usage), electricity costs for both ERS and static chargers, and battery costs (with smaller batteries required for ERS-equipped vehicles). The total transportation cost is minimized under constraints, ensuring that vehicle battery levels remain within limits, vehicles follow flow conservation laws, and charging demand is met at all times.

In the upper-level optimization, the model aims to minimize the total infrastructure cost. This includes the installation and maintenance costs of ERS and static chargers, along with a penalty for any unfulfilled charging demand. The model also accounts for broader societal benefits, such as cost savings from using smaller batteries and reduced toll costs for ERS users. By considering these factors, the government can evaluate the potential long-term benefits of ERS, promoting the adoption of electric vehicles.

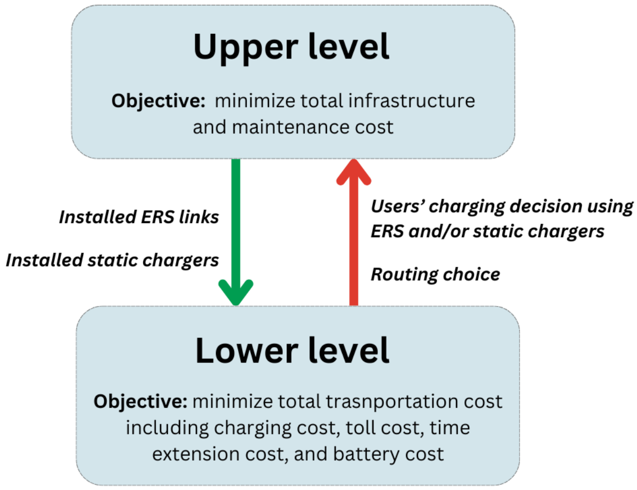

Figure 1: Bilevel optimization scheme

Figure 1 illustrates the iterative process of the bi-level optimization model. At the upper level, the government strategically decides where to install charging infrastructure based on common travel routes, aiming to meet demand while minimizing costs. At the lower level, users adjust their routes to minimize individual travel and charging costs in response to the infrastructure. This feedback loop allows the government to continually refine charger placement based on actual usage, while users adapt their routes to the evolving infrastructure. By incorporating real-world data like traffic patterns and energy consumption, the model optimizes the number of chargers needed to meet EV truck demand while minimizing costs.

The optimization process involves a mathematical model that includes various decision variables for infrastructure placement, charging station capacities, and vehicle routing. Static charging stations are assumed to be placed every 10 kilometers along highway segments, and ERS can be installed in specific, high-traffic routes. The model considers multiple constraints, such as the battery capacity of trucks, energy consumption rates, travel costs, and toll fees for using ERS infrastructure. By simulating different levels of ERS acceptance, the model is capable of identifying trade-offs between investment in ERS and static charging stations, depending on user behavior and traffic density.

The model is applied to a case study based on real-world data from the Netherlands, focusing on the country's major highways. Freight demand data, traffic patterns, and infrastructure costs were collected from Eurostat and national transportation databases to simulate various configurations of ERS and static chargers. The case study validates the model's applicability and provides insights into the real-world implications of infrastructure deployment strategies.

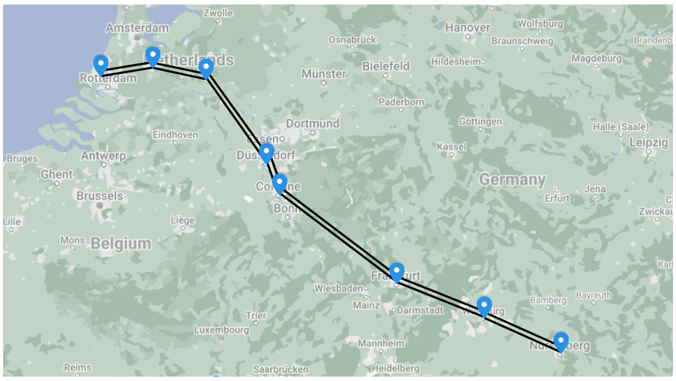

Figure 2: Verification test on Map 1: Netherlands-Germany highway corridor

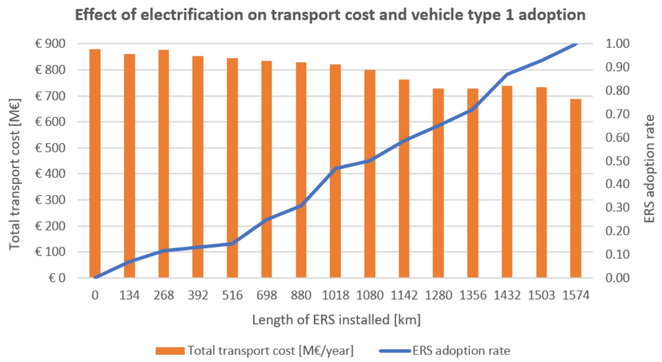

Figure 3: Result of the model on test map: analysing effect of electrification on total transport cost and vehicle type 1 adoption

4. Results

4.1. Data overview

The freight data is derived from European road freight transport data, specifically focused on the Netherlands. It includes traffic flows, an Origin-Destination (OD) matrix, and highway links. The data has been updated for 2030, converting freight volumes to the number of vehicles using an average loading factor of 14 tons per truck. Routes are determined using Dijkstra's algorithm, ensuring optimal paths for the vehicles.

The network data includes nodes (cities) and edges (highway links), detailing direct connections between regions. Distances between regional centers are calculated using Dijkstra's algorithm, providing the shortest path data for the model.

Before applying the model to large-scale freight data, it is first tested on a smaller highway corridor from Delft to Nuremberg to assess its performance in a controlled setting. This step helps verify the model's accuracy and address any issues before scaling up.

As shown in Figure 2, the corridor includes 8 nodes—Nuremberg, Wurzburg, Frankfurt, Cologne, Dusseldorf, Arnhem, Utrecht, and Delft—connected by 7 bidirectional links, covering a total distance of 1,574 km across 14 highway lanes.

4.2. Assumptions and simplifications

- The model focuses on conductive ERS, such as overhead or side pantographs, considered the most developed technology.
- Only battery electric trucks (BETs) are included, with varying adoption rates of pantographs. Personal and alternative fuel vehicles (e.g., diesel, hydrogen) are excluded.
- Highways are fully electrified, with separate sections for regular traffic and ERS charging. Only pantograph-equipped trucks can charge, and partial highway electrification is not considered.
- Subsidized tolls apply to ERS users, while non-ERS vehicles pay standard toll rates.
- Two categories of BETs are modeled: those with pantographs (vehicle type 1) and those without (vehicle type 2).
- All highways are eligible for ERS installation.
- Charging rates and energy consumption are constant, excluding variables like vehicle weight, speed, or road conditions.
- All vehicles are assumed to fully charge at stations, and charging time is based on the kWh needed to reach full capacity.
- Vehicles start each trip with a full battery, and only one-way trips are modeled.
- Electricity costs are constant, with ERS users receiving a government-subsidized rate.
- Varying adoption rates of pantographs are analyzed to assess their impact.
- A fixed discount rate is used for future costs.
- All costs are projected for the year 2030, with a one-year model timespan.

4.3. Tradeoffs between infrastructure cost and transportation cost

A key concern with ERS is its high installation cost, despite its benefits. To assess the model's performance and impact, a test was conducted on a simplified map (Map 1) for easier analysis. Figure 3 shows the relationship between ERS length, transport costs, and adoption of ERS-compatible vehicles.

As the length of ERS increases, total transport costs show a clear downward trend. At 0 km of ERS, transport costs are around €900 million per year due to the reliance on static chargers and the larger, more expensive batteries required for non-ERS vehicles. As ERS coverage expands, transport costs drop significantly, reaching approximately €190 million per year when the entire highway network is electrified. This demonstrates the economic advantages of ERS, including reduced battery size requirements and the elimination of static charging downtime.

The adoption rate of ERS-compatible vehicles follows a similar trend, starting at 0% and climbing rapidly as more ERS is installed, reaching 100% adoption when all highway segments are electrified. The sharp increase, especially after 800 km of ERS installation, suggests a critical threshold where broader ERS coverage makes adopting ERS-equipped vehicles more practical and appealing.

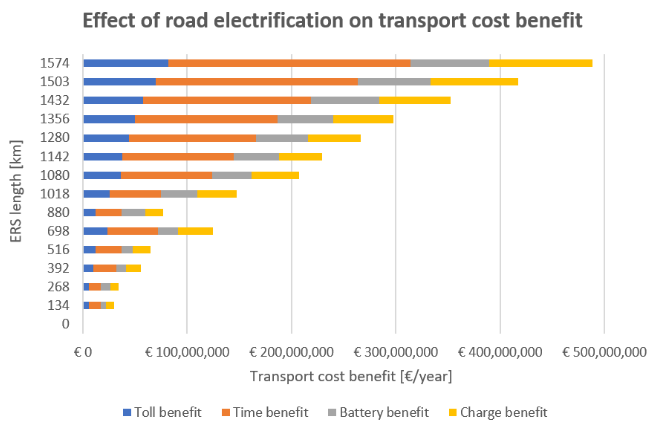

Figure 4: Contribution of each benefit component in transport cost saving

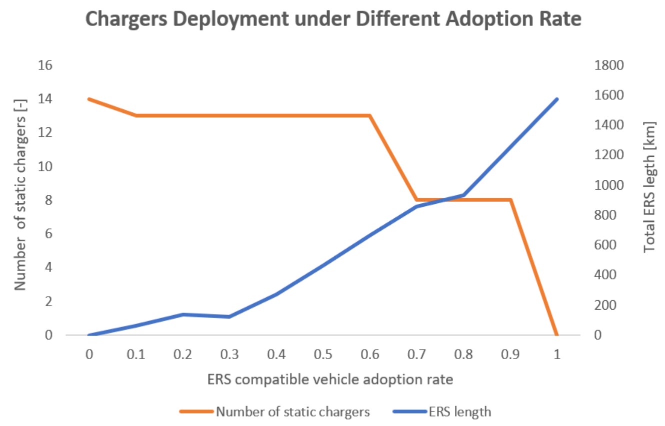

Figure 5: Installed ERS and static chargers under different acceptance rate using test map

Additionally, while the analysis primarily focuses on transport costs, it is important to consider external benefits like reduced carbon emissions and environmental impacts, which further support ERS adoption despite its higher initial infrastructure costs.

Figure 4 breaks down the transport cost savings across three components—value of time, battery, and charging costs—relative to increasing ERS lengths. The majority of savings come from battery cost reductions and time savings, with time savings being the most influential, particularly in the freight industry, where reduced downtime is critical. Charging cost savings, though present, are less significant due to the higher costs of static chargers compared to ERS.

The analysis highlights the "chicken and egg" issue, where ERS adoption depends on sufficient infrastructure, and infrastructure expansion relies on user demand. Coordinated efforts between governments and industry are essential to balance infrastructure development and vehicle adoption.

Table 1 summarizes the results, showing a consistent number of static chargers, as the model assumes no capacity limits. In practice, more chargers would likely be needed with less ERS coverage. Additionally, optimizing ERS length is key, as beyond a certain point, further investment yields diminishing returns. This underscores the importance of strategic ERS deployment in high-impact areas for maximizing cost savings and efficiency in electric freight transport.

4.4. Priority in segment electrification

Table B.5 show the electrification order of road segments based on traffic density, with high-traffic segments such as Düsseldorf-Cologne (43,807 vehicles/km) prioritized. This traffic-based approach is effective in identifying which segments should be electrified first to maximize the benefits of ERS and ensure a cost-effective investment.

However, traffic density alone does not simplify the overall complexity of the model. The model still operates iteratively, with the upper-level decision process evaluating factors beyond traffic, such as vehicle routes, infrastructure availability, operational costs, and potential savings from ERS. This ensures a well-distributed electrification strategy that balances immediate traffic demands with long-term network efficiency.

Moreover, determining the optimal number of segments for electrification adds another challenge. Budgetary constraints make it unfeasible to electrify every high-traffic segment, and over-electrification could lead to diminishing returns if some routes are underutilized. Policymakers must strike a balance between focusing on high-traffic routes and ensuring that the ERS network is cohesively and strategically developed to maximize overall system efficiency and cost-effectiveness.

4.5. Chargers deployment under different acceptance rate

Figure 5 illustrates the impact of varying ERS adoption rates on the deployment of ERS infrastructure and static chargers. ERS adoption, represented by the number of vehicles equipped with pantographs (vehicle type 1), significantly influences the decision to expand ERS coverage. As adoption increases, reliance on dynamic charging rises, reducing the need for static chargers. Between 0.0 and 0.6 adoption rates, static charger deployment remains stable, likely due to the assumption of unlimited charger capacity.

At higher adoption rates, the ERS network expands, indicating that once a critical mass of ERS-compatible vehicles is reached, the economic benefits outweigh the high initial costs. Conversely, at lower adoption rates, ERS is less viable, as the limited number of compatible vehicles cannot justify the significant infrastructure investment. This reinforces the "chicken and egg" dilemma, where both ERS infrastructure and vehicle adoption must grow in tandem to realize economic and environmental benefits. Coordinated policies and incentives are essential to achieve this balance.

5. Insights from Case Study

5.1. Chargers Deployment in Netherlands highway Network

At a 20% ERS adoption rate, the optimal network includes 12 electrified lanes out of the 42 possible routes, as seen in Figure 6. This indicates that electrification is focused on a limited

ERS length [km]	Number of static chargers	Number of vehicle type 1	Number of vehicle type 2	Toll cost [M€]	Time cost [M€]	Battery cost [M€]	Charging cost [M€]
0	13	0	49958	245	221	118	295
134	13	3319	49958	236	190	113	323
268	14	6191	43767	211	217	109	340
392	13	6304	43654	203	190	108	353
516	13	7211	42747	198	178	107	362
698	13	12689	37269	194	128	99	412
880	13	15433	34525	152	231	95	351
1018	14	23062	26896	168	158	83	412
1080	13	24882	25076	166	118	81	436
1142	13	29014	20944	163	112	74	414
1280	13	32878	17080	141	94	69	423
1356	13	35471	14487	140	79	65	443
1432	10	43603	6355	141	81	52	464
1503	7	46460	3498	140	63	48	483
1574	0	49958	0	140	0	43	506

Table 1: Summary of ERS length, static chargers, number of vehicles, and transport cost

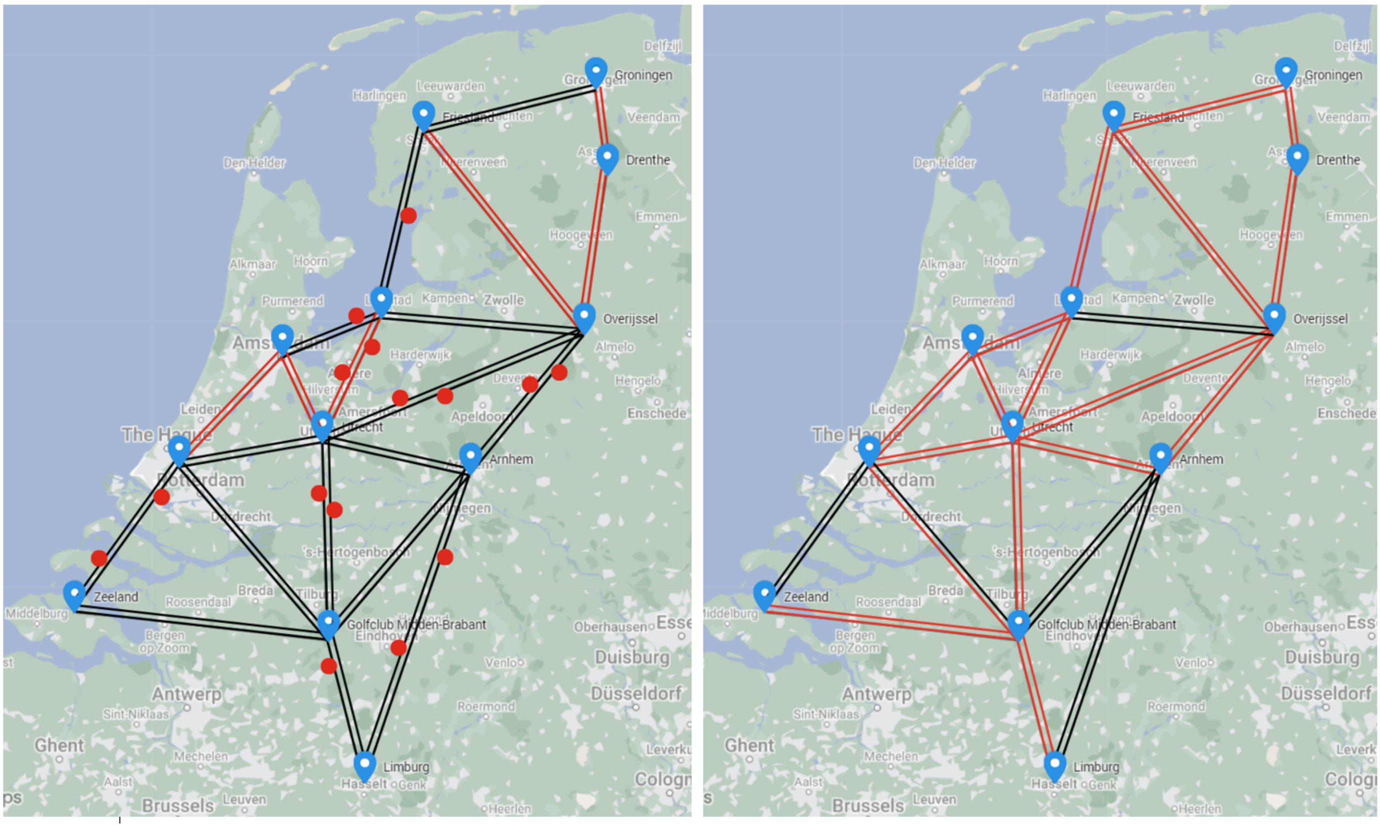

Figure 6: Network deployment in Netherlands highway network with 20% (left) and 100% (right) ERS adoption rate. Red lines: electrified lanes, black lines: non-electrified lanes, red dots: installed charging stations

Electrification order	**Electfied segment**	**Traffic density [vehicle/km]**
1	Dusseldorf - Cologne	43807
2	Cologne - Dusseldorf	40840
3	Arnhem - Utrecht	17040
4	Utrecht - Delft	16832
5	Delft - Utrecht	16568
6	Utrecht - Arnhem	14699
7	Wurzburg - Nuremberg	9137
8	Frankfurt - Wurzburg	8181
9	Nuremberg - Wurzburg	7702
10	Wurzburg - Frankfurt	7536
11	Dusseldorf - Arnhem	5499
12	Cologne - Frankfurt	3937
13	Arnhem - Dusseldorf	3607
14	Frankfurt - Koln	3332

Table 2: Order of electrification and the segment's traffic density

number of high-traffic routes, which are most likely prioritized due to the reduced number of vehicles equipped to utilize ERS. To compensate for the lower adoption of ERS technology, optimal result shows that 15 static charging stations are strategically placed throughout the network. These static chargers are essential in supporting the trucks that do not have access to ERS and still require regular stops for recharging. This setup reflects a hybrid approach, balancing static and dynamic charging methods, with a significant reliance on static charging due to the limited reach of ERS infrastructure.

In contrast, at a 100% adoption rate, the network expands to 33 electrified lanes out of the 42 routes. This increase shows that with full adoption, electrification of the majority of the highway network becomes feasible and cost-effective. The complete reliance on dynamic charging through ERS eliminates the need for static charging stations entirely, as shown by the absence of any static chargers in this scenario. The entire fleet of heavy-duty electric trucks can charge while driving, rendering the static charging infrastructure redundant and leading to a fully electrified road system that supports continuous operation without the need for frequent charging stops.

While the model prioritizes ERS on major routes, real-world implementation must consider potential disruptions, such as road maintenance, which could affect dynamic charging access. Additional measures, like system redundancy or static chargers on secondary routes, may be necessary for network resilience.

5.2. Varying value of travel time

Figure 7 illustrates the impact of travel time value on the deployment of ERS and static chargers, highlighting how economic factors influence infrastructure decisions under 20% and 100% ERS adoption scenarios.

In the 20% adoption scenario, shown left chart in Figure 7, static chargers remain constant at 14 units, regardless of travel time value, while the number of electrified lanes increases gradually. This suggests that, at low adoption rates, the system relies heavily on static chargers, and travel time has little influence on their deployment. Even at high travel time values (€40-€100/hour), static chargers dominate, as the limited number of ERS-compatible vehicles restricts the benefits of electrified lanes.

In contrast, the 100% adoption scenario in the right chart of Figure 7 shows a shift as travel time value rises. Initially, static chargers dominate with over 66 units installed, but as the value of travel time increases, the number of static chargers decreases rapidly, and electrified lanes become the primary solution. By €40/hour, the system relies almost entirely on ERS, reducing static chargers to zero and deploying 38 electrified lanes across 42 segments.

This analysis underscores the inefficiencies of ERS at low adoption rates, where static chargers remain essential. As adoption grows, dynamic charging becomes more viable, especially when reducing travel time is critical. In early stages of ERS deployment, a hybrid system is necessary until vehicle adoption scales up, while lower travel time values favor static chargers due to their lower costs.

5.3. Varying ERS cost per km

In the 15% adoption scenario, static chargers dominate with 13-14 units, while electrified lanes decrease as ERS costs rise—from 6 lanes at €100,000/km to 1-2 lanes at €2,000,000/km. This shows ERS's sensitivity to high installation costs, making static chargers more viable at low adoption rates. The number of electrified lanes begins to drop after €900,000/km.

In contrast, at 100% adoption, over 40 electrified lanes are deployed when ERS costs are below €300,000/km. As costs rise, static chargers increasingly replace ERS, with static chargers dominating at €2,000,000/km. Above €900,000/km, electrified lanes are gradually replaced by static chargers due to diminishing cost-effectiveness.

This analysis suggests a hybrid approach, combining static and dynamic charging, as ERS alone may not be feasible at high installation costs. Policymakers must focus on reducing ERS costs through technological advances, economies of scale, and partnerships to maximize the benefits of ERS and ensure cost-effective deployment.

6. Discussion

6.1. Limitations

- *Capacitated Charging Stations:* The model does not consider the capacity limits of static chargers or ERS infrastructure, assuming all vehicles can charge without delay. In reality, capacity constraints could cause bottlenecks, leading to an overestimation of system efficiency.

- *Exclusion of Environmental Benefits:* Environmental factors, such as CO_2 reduction and the integration of renewable energy, are not included in the model. These considerations could impact both costs (e.g., investment in renewable energy) and benefits (e.g., reduced emissions), providing a more complete economic analysis.

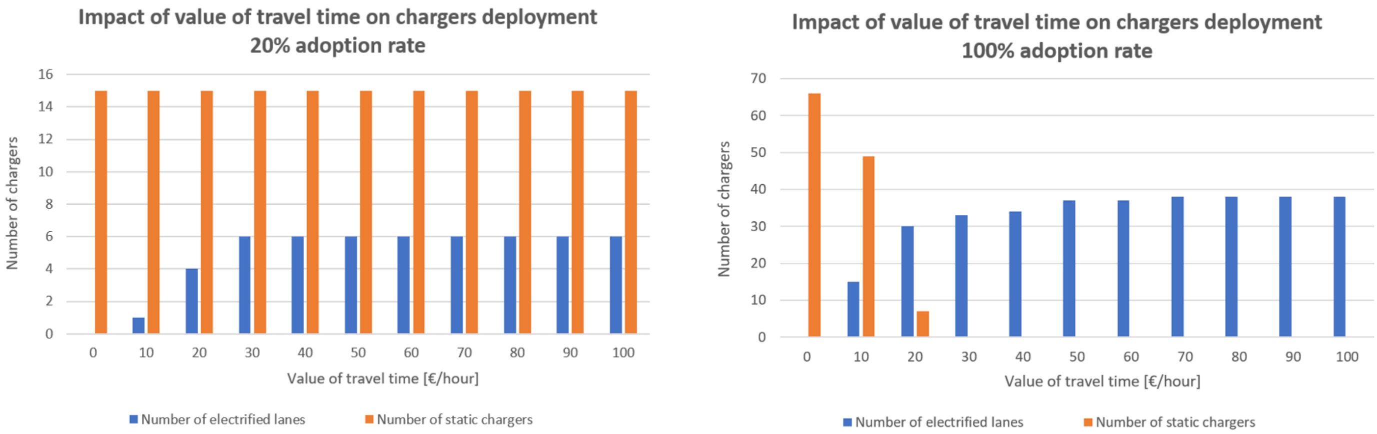

Figure 7: Results of chargers deployment under different value of time and acceptance rate

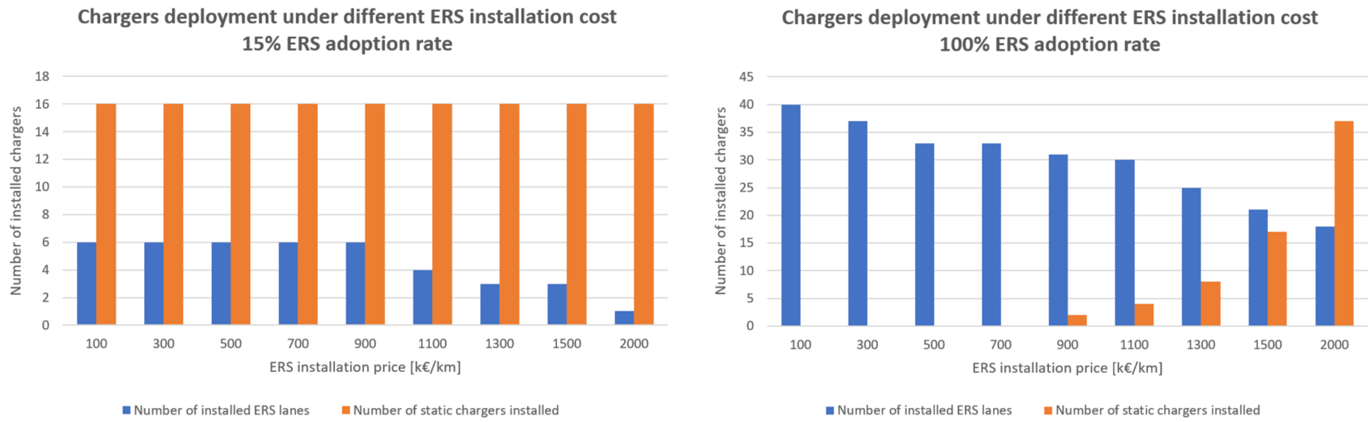

Figure 8: Impact of different ERS installation price to the overall chargers deployment

- *System Resilience:* The model assumes full ERS electrification, eliminating the need for static chargers. However, this creates a vulnerability—if an ERS segment fails, there is no backup infrastructure, potentially causing system-wide disruptions. A resilient charging network would require redundancy, such as backup static chargers.
- *Computational Complexity:* The bi-level optimization approach used in the model is computationally intensive, making it challenging to apply in real-time or large-scale scenarios. Additionally, due to the high computational demands, the genetic algorithm used in earlier tests was excluded from the final results because of unreliable outcomes and lack of convergence.

6.2. *Result interpretation*

The results of the analysis highlight a trade-off between infrastructure costs and transportation efficiency, particularly between static chargers and ERS for road freight electrification. As ERS deployment increases, the reliance on static chargers decreases, with the two infrastructures complementing each other based on adoption rates and traffic density.

In scenarios with high ERS adoption, the need for static chargers significantly declines, especially on high-traffic routes. ERS reduces the need for large batteries and minimizes downtime, resulting in long-term cost savings of up to 22-25%. However, at lower adoption rates, static chargers remain essential to meet demand, as the benefits of ERS are limited by the small number of compatible vehicles.

The model also shows that ERS installation costs are a key factor in determining the optimal infrastructure mix. As costs rise above €900,000 per km, static chargers become more economically viable than ERS. This underscores the importance of cost management and technological advancements to make ERS more feasible for widespread deployment.

The complementary relationship between ERS and static chargers is evident—ERS reduces the need for static chargers in high-traffic areas, but static chargers remain crucial in regions where ERS is not viable. Static chargers serve as a backup, ensuring network resilience, particularly on routes where ERS installation may not be practical.

The model also highlights the need for system redundancy. A fully ERS-enabled network could meet demand without static chargers, but real-world conditions require backup options to prevent disruptions from technical failures or maintenance.

Additionally, ERS offers economic and geopolitical benefits by reducing dependence on large batteries and rare minerals like lithium. Even a 10% ERS adoption rate in the Netherlands could save €10.5 million annually on battery costs, reducing supply chain pressures and promoting sustainability.

The results also suggest that current government policies on static charger placement may need revision. With 30% of the highway network electrified by ERS, the interval for static chargers could be extended from 60 km to 78 km, reducing the number of static chargers by 23%. This could lower infrastructure costs and improve resource allocation, supporting a more efficient transport electrification strategy.

In conclusion, the findings indicate that a combined approach integrating ERS and static chargers is more cost-effective and efficient than a static-only strategy. Policymakers should consider the potential of ERS in infrastructure planning to optimize both investment and operational efficiency.

6.3. Result implication

The implications of these results extend beyond the Netherlands, as the model provides a flexible framework adaptable to various regions. By adjusting parameters like traffic data, adoption rates, or installation costs, it can be applied to different countries, making it a valuable tool for global infrastructure planning. This allows policymakers and investors to tailor strategies for maximizing coverage and operational savings while minimizing unnecessary costs.

In practical applications, the model can guide infrastructure investments by identifying optimal configurations of ERS and static chargers. It suggests prioritizing ERS along major freight routes while maintaining static chargers in lower-density areas to ensure network resilience. This approach supports the transition to electric freight vehicles and prepares infrastructure for future technological advances.

Additionally, the reduced reliance on large batteries supports global sustainability goals by lowering greenhouse gas emissions and encouraging renewable energy integration. The model's cost analysis helps governments strategically plan for decarbonizing freight transport, aligning with long-term goals like those in the Paris Agreement, while reducing operational costs and promoting electric vehicle adoption.

7. Conclusion and Future Research

This research developed an optimization model for configuring dynamic ERS and static charging infrastructure for heavy-duty electric trucks, accounting for varying ERS adoption rates. The integrated approach of combining ERS and static chargers optimizes costs and coverage, with ERS proving cost-effective on high-traffic routes by reducing battery size, charging downtime, and operational costs. Static chargers complement ERS in lower-traffic regions where ERS installation is less feasible. The study showed up to 25% savings in infrastructure and operational costs with increased ERS adoption, and a strong correlation between ERS network expansion and reduced static charger reliance. Traffic density and vehicle routing played crucial roles in determining optimal highway segment electrification, with budget constraints guiding deployment strategies.

Policy recommendations highlight reducing ERS installation costs, promoting ERS-compatible vehicle adoption, and optimizing static charger placement, particularly by extending the distance between them as ERS infrastructure grows.

Future research should focus on exploring the resilience of the combined ERS-static charging network. This includes investigating how the system responds to disruptions such as infrastructure failures or extreme weather conditions, and assessing backup systems and alternate routes to ensure continuous operations. Additionally, the impact of charging station capacity limitations and queuing should be examined. By incorporating queuing theory, future studies can provide insights into system performance during peak demand periods and optimize the placement and number of charging stations. These areas of research are essential for enhancing the reliability and operational efficiency of electric freight transport networks.

Appendix A. Model formulation

The model formulation section details the mathematical and logical structures that define the sets, parameters, variables and decision variables that are going to be modeled using bi-level optimization algorithm. Moreover, the detailed optimization objectives and constraints will be elaborated.

The formulation starts with the sets and indices to represent the problem, which are listed as follows:

- $\mathcal{N}$: a set of nodes in the network representing set of cities. The individual city is represented with $i \in \mathcal{N}$
- $\mathcal{A}$: a set of links connecting pairs of nodes, representing a unidirectional highway road with several links. The link is denoted as $(i, j) \in \mathcal{A}$
- $\mathcal{Q}$: a set of traffic demand from origin $o \in \mathcal{N}$ to destination $d \in \mathcal{N}$, denoted as (o, d)
- $\mathcal{V}$: a set of truck types where $v = 1$ is trucks with receiver coils and $v = 2$ is trucks without the receiver coils. $\mathcal{V} = \{1, 2\}$

- $\mathcal{S}$: a set of potential static charging station locations $s \in \mathcal{S}$ that are set every certain distance called segment length, along the highway link $(i, j) \in \mathcal{A}$. Potential static charging location s is denoted as $s \in \mathcal{S}_{i,j}$

The following part enumerates the parameters integral to the model, each of which holds the input data for the model, shaping the outcomes. The parameters included in the models are:

- dr: Discount rate for future cost *[-]*
- efE: Transfer efficiency when charging using ERS *[-]*
- efS: Transfer efficiency when charging using a static charger *[-]*
- len: Segment length, which is the distance between each potential static charger location in S. The length is constant of 10km. *[m]*
- t: Time spent as vehicle downtime when charging using static charger to recharge vehicle type 2 battery until full capacity *[hour]*
- $tollE$: Toll price a vehicle has to pay after using ERS charger *[€/km]*
- $tollS$: Toll price a vehicle has to pay when using battery or when not charging using ERS *[€/km]*
- vot: Value of travel time which is related to translate the t in monetary value *[€/hour]*
- B_v: The battery capacity of vehicle type $v \in \mathcal{V}$. This set consist of B_1 being the vehicle with receiver coils for pantograph, and B_2 being the vehicle without receiver coils. *[kWh]*
- Cb: Battery price of the vehicle *[€/kWh]*
- Cd: Catenary cost to install ERS on the highway link *[€/km]*
- Ce: Charging cost using ERS *[€/kWh]*
- Csc: Chagring cost when using static charging stations *[€/kWh]*
- Sc: Installation cost of a static charging station *[€/unit]*
- veh_1: Number of vehicle of type 1. This is calculated after each iteration of lower level model. *[-]*
- ywd: Number of trips a vehicle have in a year *[trips/year]*
- α: Percentage of type 1 vehicle, which has pantograph *[-]*
- β: Truck energy consumption rate while driving on a highway *[kWh/km]*
- γ: Penalty to be paid in case in case if there is not enough charging station available, which results in unfulfilled charging demand. In order to reach the destination, the vehicle is forced to reload the battery without an actual charging station available, calculated as a penalty *[-]*
- η_{max}: Maximum battery level that the vehicle effectively can use, represented by a percentage of full battery capacity *[-]*
- η_{min}: Minimum battery level that the vehicle need to have, represented by a percentage of full battery capacity *[-]*
- μ_{ers}: Annual operation and maintenance cost rate of the installed ERS. This value is a percentage of the whole investment of the installed ERS *[-]*
- μ_{ers_use}: Maintenance cost for parts reparation and replacement, which is represented by a cost per km per vehicle using the ERS charger *[€/km.v]*
- μ_{sc}: Maintenance cost for parts reparation and replacement, which is represented by a cost per km per vehicle using the static charger *[€/unit.year]*
- μ_{sc_use}: Maintenance cost for parts reparation and replacement, which is represented by a cost per charger unit per vehicle using the static charger *[€/unit.v]*
- τ_{batt}: Operational life of vehicle battery *[years]*
- τ_{ers}: Operational life of ERS infrastructure *[years]*
- τ_{sc}: Operational life of static charger *[years]*
- ϕ: Charging rate of ERS on the vehicle *[kWh/km]*

The variables used in the optimization model are outlined in the following part. These variables are essential for defining the decision-making framework and for solving the optimization problem effectively. The key variables in the model are:

- $bl^{(o,d)}_{v,(i,j),s}$: Positive continuous variable denoting battery level of each vehicle v that travels from origin o to destination d at location s on link (i, j) *[kWh]*
- $cl^{(o,d)}_{v,(i,j),s}$: Positive continuous variable denoting the power consumed to recharge trucks of type $v \in \mathcal{V}$ traveling on link $(i, j) \in \mathcal{A}$ for demand $(o, d) \in Q$ at the end of segment $s \in S_{ij}$ *[kWh]*
- $Ecl^{(o,d)}_{v,(i,j),s}$: Amount of kWh added to vehicle type v to finish a trip from origin o to destination d while there is no charging station at location s on link (i, j) to fulfil this demand. When there are insufficient charging stations to meet the demand, vehicles are compelled to draw additional energy, measured in kilowatt-hours (kWh), to ensure they can reach their destination, calculated as a penalty.
- $f^{(o,d)}_{v,(i,j)}$: Positive continuous variable denoting the number of trucks of type $v \in \mathcal{V}$ traveling on link $(i, j) \in \mathcal{A}$ for demand $(o, d) \in Q$

Apart from the variables written above, the following part lists the decision variables that represent the choices to determine the optimal solution. The decision variables in the model are:

- x^s_{ij}: Binary variable stating 1 if a static charging station is established at location s in link (i, j), and 0 otherwise $x^s_{ij} \in \{0, 1\}$
- y_{ij}: Binary variable stating 1 if ERS is implemented on the link (i, j) $\quad y_{ij} \in \{0, 1\}$
- $r^{(o,d)}_{v,(i,j),s}$: Binary variable that equals to 1 if trucks type $v \in \mathcal{V}$ traveling on link $(i, j) \in A$ for demand $(o, d) \in Q$ use the static charging to recharge at the end of segment $s \in S_{ij}$, and 0 otherwise $\quad r^{(o,d)}_{v,(i,j),s} \in \{0, 1\}$
- $\pi^{(o,d)}_{(i,j)}$: Binary variable that equals to 1 if vehicles type 1 traveling on link (i, j) for demand (o, d) use ERS for recharging. The charging activity using ERS happens from the start until the end of the link. $\quad \pi^{(o,d)}_{(i,j)} \in \{0, 1\}$
- $w^{(o,d)}_{v,(i,j)}$: Binary variable whether vehicle type v traveling with origin-destination (o, d) choose to travel through the link (i, j) to reach the destination $\quad w^{o,d}_{v,(i,j)} \in \{0, 1\}$

Appendix A.1. Lower-level optimization model

- **Travel time extension cost due to static charging:** When a vehicle uses a static charger, it incurs downtime, calculated by multiplying the number of charging stops, the time to fully charge, and the value of travel time in euros. This value includes operational costs, driver wages, and potential delivery delays.

$$\sum_{(o,d)\in Q}\sum_{v\in\mathcal{V}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} t \cdot vot \cdot r^{(o,d)}_{v,(i,j),s} \cdot Q^{(o,d)} \tag{A.1}$$

- **Toll cost:** Toll costs are incurred on highways, with lower rates for ERS users due to government subsidies. The toll cost is calculated by multiplying the toll rate per kilometer by the highway length and by the proportion of vehicles using ERS ($\pi^{(o,d)}_{(i,j)}$) or not using ERS ($1 - \pi^{(o,d)}_{(i,j)}$).

$$\begin{aligned}\sum_{(o,d)\in Q}\sum_{(i,j)\in\mathcal{A}} \Bigg\{ & tollE \cdot \pi^{(o,d)}_{(i,j)} \cdot d_{ij} \cdot w^{(o,d)}_{v,(i,j)} \cdot Q^{(o,d)} \\ & + \sum_{v\in\mathcal{V}} \left[tollS \cdot \left(1 - \pi^{(o,d)}_{(i,j)}\right) \cdot d_{ij} \cdot w^{(o,d)}_{v,(i,j)} \cdot Q^{(o,d)} \right] \Bigg\}\end{aligned} \tag{A.2}$$

- **Charging cost:** This refers to the charging expense, varying between ERS and static chargers. It's calculated by multiplying the required energy (kWh) by the respective rate for ERS or static charging, depending on the method used.

$$\begin{aligned}\sum_{(o,d)\in Q}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} \Bigg[& Ce \cdot cl^{(o,d)}_{1,(i,j),s} \cdot \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} + \\ & \sum_{v\in\mathcal{V}} \left(Csc \cdot cl^{(o,d)}_{v,(i,j),s} \cdot r^{(o,d)}_{v,(i,j),s} \cdot Q^{(o,d)} \right) \Bigg]\end{aligned} \tag{A.3}$$

- **Battery cost:** Vehicles with ERS technology have smaller, less expensive batteries. The battery cost is calculated by multiplying the price per kWh by the battery capacity for each vehicle type and the number of vehicles, which is determined by dividing the total trips by the number of trips per vehicle per year.

  Since the model spans one year, but batteries, static chargers, and ERS infrastructure have different lifespans, the Equivalent Annual Cost (EAC) is used to account for these differences, comparing the annualized costs of assets with varying lifespans.

$$\sum_{(o,d)\in Q}\sum_{(i,j)\in\mathcal{A}}\sum_{v\in\mathcal{V}} \frac{Cb \cdot B_v \cdot f^{(o,d)}_{v,(o,j)}}{ywd} \cdot ann_{batt} \tag{A.4}$$

$$ann_{batt} = \frac{dr}{1 - (1 - dr)^{-\tau_{batt}}} \tag{A.5}$$

The costs involved in the **total transportation cost** can be combined as lower-level optimization equation, denoted as follows:

$$\begin{aligned}\min_{\mathbf{r},\pi} & \sum_{(o,d)\in Q}\sum_{v\in\mathcal{V}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} \left(t \cdot vot \cdot r^{(o,d)}_{v,(i,j),s} \cdot Q^{(o,d)} \right) \\ & + \sum_{(o,d)\in Q}\sum_{v\in\mathcal{V}}\sum_{(i,j)\in\mathcal{A}} \frac{Cb \cdot B_v \cdot f^{(o,d)}_{v,(i,j)}}{ywd} \cdot ann_{batt} \\ & + \sum_{(o,d)\in Q}\sum_{(i,j)\in\mathcal{A}} \left[tollE \cdot \pi^{(o,d)}_{(i,j)} \cdot d_{i,j} \cdot w^{(o,d)}_{v,(i,j)} \cdot Q^{(o,d)} \right. \\ & + \sum_{v\in\mathcal{V}} tollS \cdot (1 - \pi^{(o,d)}_{(i,j)} \cdot d_{ij} \cdot w^{(o,d)}_{v,(i,j)} \cdot Q^{(o,d)} \\ & + \sum_{(o,d)\in Q}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} \left[Ce \cdot cl^{(o,d)}_{1,(i,j),s} \cdot \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \right. \\ & + \sum_{v\in\mathcal{V}} \left(Csc \cdot cl^{(o,d)}_{v,(i,j),s} \cdot r^{(o,d)}_{v,(i,j),s} \cdot Q^{(o,d)} \right)\end{aligned} \tag{A.6}$$

The lower-level objective function is subject to the following **constraints**:

- **Flow conservation constraints:** These ensure that the number of trucks leaving the origin node equals the total trucks departing from that origin. Similarly, at the destination, the number of trucks entering equals the total trucks arriving. For all other nodes, the trucks entering and leaving must balance.

$$\sum_j \sum_v f^{(o,d)}_{v,(i,j)} - \sum_j \sum_v f^{(o,d)}_{v,(j,i)} = \begin{cases} N_{(o,d)} & \text{if } i = o \\ -N_{(o,d)} & \text{if } i = d \\ 0 & \text{otherwise} \end{cases} \qquad \forall i \in \mathcal{N}, (o, d) \in Q \tag{A.7}$$

- Guarantee that the battery level of any vehicle $v \in V$ does not exceed the maximum level and does not drop below the minimum level of battery, respectively.

$$bl^{(o,d)}_{v,(i,j),s} \le \eta_{min} \cdot B_v \qquad \forall (i, j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o, d) \in Q \tag{A.8}$$

$$bl^{(o,d)}_{v,(i,j),s} \geq \eta_{max} \cdot B_v \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q \tag{A.9}$$

- At the start of the trip, all vehicles begin with their batteries fully charged.

$$bl^{(o,d)}_{v,(o,j),s} \leq B_v \qquad \forall (o,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q, v \in \mathcal{V} \tag{A.10}$$

$$cl^{(o,d)}_{v,(o,j),s} = 0 \qquad \forall (o,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q, v \in \mathcal{V} \tag{A.11}$$

- Battery level constraint: This ensures that the battery level of vehicle type v entering segment s of link *(i,j)* equals the battery level from the previous segment, minus consumption based on distance, plus any recharging that occurs.

$$bl^{(o,d)}_{v,(i,j),s} = bl^{(o,d)}_{v,(i,j),s-1} - \beta \cdot d_{ij} \cdot w^{(o,d)}_{v,(i,j)} + cl^{(o,d)}_{v,(i,j),s} + Ecl^{(o,d)}_{v,(i,j),s}$$
$$\forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q, v \in \mathcal{V} \tag{A.12}$$

- Calculate the recharging quantity for vehicles of type 2, which can only utilize static charging stations.

$$cl^{(o,d)}_{2,(i,j),s} \leq B_2 \cdot r^{(o,d)}_{2,(i,j),s} \cdot x^s_{ij} \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q \tag{A.13}$$

- Calculate the recharging quantity for vehicles of type 1, which have the option to recharge using both static charging stations and the ERS.

$$cl^{(o,d)}_{1,(i,j),s} \leq B_1 \cdot r^{(o,d)}_{1,(i,j),s} \cdot x^s_{ij} + \phi \cdot \pi^{(o,d)}_{(i,j)} \cdot len$$
$$\forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q \tag{A.14}$$

- The vehicle flow cannot exceed the total number of traffic trips, and whenever there is a flow on a link, there must be at least one vehicle operating on that link.

$$w^{(o,d)}_{v,(i,j)} \leq f^{(o,d)}_{v,(i,j)} \leq Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)}$$
$$\forall (i,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q \tag{A.15}$$

- Ensure that the proportion of the fleet consisting of vehicles of type 1 meets or exceeds the specified acceptance rate. Therefore, limiting the number of vehicle type 2.

$$f^{(o,d)}_{2,(o,j)} \leq (1-\alpha) \cdot \sum f^{(o,d)}_{v,(o,j)} \qquad \forall (o,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q \tag{A.16}$$

- Ensure that recharging can only happen at charging stations that are open or ERS that are installed, respectively.

$$\pi^{(o,d)}_{(i,j)} \leq y_{ij} \qquad \forall (i,j) \in \mathcal{A}, (o,d) \in Q \tag{A.17}$$

$$r^{(o,d)}_{v,(i,j),s} \leq x^s_{ij} \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij}, (o,d) \in Q \tag{A.18}$$

- Ensure that the total number of vehicles aligns with the number of trips for all OD pairs.

$$\sum f^{(o,d)}_{v,(o,j)} = Q^{(o,d)} \qquad \forall (o,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q \tag{A.19}$$

- Ensure that all vehicles depart from the origin node and reach the destination node.

$$\sum w^{(o,d)}_{v,(i,d)} = 1 \qquad \forall (i,d) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q \tag{A.20}$$

$$\sum w^{(o,d)}_{v,(o,i)} = 1 \qquad \forall (o,i) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q \tag{A.21}$$

- Domain values of the variables and decision variables

$$r^{(o,d)}_{v,(i,j),s}, \pi^{(o,d)}_{(i,j)}, w^{(o,d)}_{v,(i,j)} \in \{0,1\}$$
$$\forall (i,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q, s \in \mathcal{S}_{ij} \tag{A.22}$$

$$bl^{(o,d)}_{v,(i,j),s}, cl^{(o,d)}_{v,(i,j),s}, Ecl^{(o,d)}_{v,(i,j),s}, f^{(o,d)}_{v,(i,j)} \geq 0$$
$$\forall (i,j) \in \mathcal{A}, v \in \mathcal{V}, (o,d) \in Q, s \in \mathcal{S}_{ij} \tag{A.23}$$

Appendix A.2. Upper-level optimization model

In the upper-level model, infrastructure investments are evaluated based on both financial costs and societal benefits, such as user surplus from reduced charging times, battery costs, and tolls. These cost savings contribute to broader societal gains, aligning with the government's goals of promoting sustainability and economic growth.

The objective function aims to minimize the total cost of installing and maintaining ERS and static charging stations across highway links, incorporating both direct financial costs and societal benefits.

- **ERS installation cost:** This is calculated by multiplying the installation cost per kilometer by the highway length and the binary variable y_{ij}, which indicates if a segment is electrified. The cost is amortized using an annuity factor to account for future expenses and the discount rate.

$$\sum_{(i,j)\in\mathcal{A}} Cd \cdot d_{ij} \cdot y_{ij} \cdot ann_{ers} \tag{A.24}$$

$$ann_{ers} = \frac{dr}{1-(1-dr)^{-\tau_{ers}}} \tag{A.25}$$

- **ERS fixed maintenance cost:** This annual cost, covering operations and regular inspections, is a percentage of the total installation cost and is independent of usage frequency.

$$\sum_{(i,j)\in\mathcal{A}} Cd \cdot d_{ij} \cdot y_{ij} \cdot \mu_{ers} \tag{A.26}$$

- **ERS variable maintenance cost:** This cost depends on usage frequency, with higher use leading to more wear and tear. It's calculated by multiplying the maintenance rate per kilometer by usage frequency and the length of the electrified highway.

$$\sum_{(o,d)\in Q} \sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot \mu_{ers\_use} \cdot d_{ij} \cdot Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)} \tag{A.27}$$

- **Static charging station installation cost:** Calculated by multiplying the number of stations by the installation cost per station, adjusted by an annuity factor to account for the discount rate and lifespan for the annualized cost.

$$\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} Sc \cdot x^{s}_{(i,j)} \cdot ann_{sc} \tag{A.28}$$

$$ann_{sc} = \frac{dr}{1-(1-dr)^{-\tau_{sc}}} \tag{A.29}$$

- **Static charger fixed maintenance cost:** This annual cost, covering maintenance and inspections, is a percentage of the total installation cost of the static chargers.

$$\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} Sc \cdot x^{s}_{(i,j)} \cdot \mu_{sc} \tag{A.30}$$

- **Static charger variable maintenance cost:** This cost is based on usage frequency, calculated by multiplying the cost per use by the number of annual uses.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{v\in\mathcal{V}} r^{(o,d)}_{v,(i,j),s} \cdot \mu_{sc\_use} \cdot Q^{(o,d)} \tag{A.31}$$

- Penalty cost: A high penalty cost of 10^{12} is included to ensure all charging demand is met and to prevent a shortage of stations. The decision variable $Ecl^{(o,d)}_{v,(i,j),s}$ is introduced to avoid infeasible solutions, heavily penalized in the objective function to discourage its use. In the optimal solution, Ecl must remain zero to confirm all demand is met.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{v\in\mathcal{V}} \gamma \cdot Ecl^{(o,d)}_{v,(i,j),s} \tag{A.32}$$

- **Charging time saving with ERS:** Installing ERS reduces vehicle downtime compared to static charging, encouraging electric vehicle adoption and supporting government decarbonization goals. The cost saving is calculated by multiplying the number of ERS uses by the time saved compared to static charging. This saving is included as a negative term in the objective function, representing a benefit.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)} \cdot vot \cdot t \cdot \frac{B_1}{B_2} \tag{A.33}$$

- **Battery saving cost:** Smaller batteries in ERS-compatible vehicles lower purchase costs and vehicle weight, improving operational efficiency and making them more attractive to companies. For the government, promoting smaller batteries supports sustainability goals by reducing the environmental impact, hazardous materials, and waste. These savings are factored into the objective function as a benefit, amortized using an annuity factor.

$$\frac{veh_1 \cdot (B_2 - B_1) \cdot Cb}{ann_{batt}} \tag{A.34}$$

- **Charging cost saving:** ERS charging is cheaper than static chargers due to government incentives and more efficient grid use. The savings are calculated by multiplying the difference in price per kWh between static and ERS charging by the total kWh required for all vehicles.

$$cl^{(o,d)}_{v,(i,j),s} \cdot \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot (Csc - Ce) \tag{A.35}$$

- **Toll cost saving:** ERS tolls are lower than regular highway tolls due to subsidies. Savings are calculated by multiplying the toll rate difference by the distance traveled on ERS-equipped highways, accounting for whether the highway is part of the user's route.

$$\sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot (tollS - tollE) \cdot d_{ij} \cdot w^{(o,d)}_{1,(i,j)} \cdot Q^{(o,d)} \tag{A.36}$$

Combining the components stated above, the upper-level objective function minimizing the **total infrastructure cost** can be written as:

$$\begin{aligned}
\min_{\mathbf{x},\mathbf{y}} & \sum_{(i,j)\in\mathcal{A}} Cd \cdot d_{ij} \cdot y_{ij} \cdot (ann_{ers} + \mu_{ers}) \\
& + \sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot \mu_{ers_use} \cdot d_{ij} \cdot Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)} \\
& + \sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}} Sc \cdot x^{s}_{(i,j)} \cdot (ann_{sc} + \mu_{sc}) \\
& + \sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{v\in\mathcal{V}} r^{(o,d)}_{v,(i,j),s} \cdot \mu_{sc_use} \cdot Q^{(o,d)} \\
& + \sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}}\sum_{s\in\mathcal{S}}\sum_{v\in\mathcal{V}} \gamma \cdot Ecl^{(o,d)}_{v,(i,j),s} \\
& - \sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot w^{(o,d)}_{v,(i,j)} \cdot vot \cdot t \cdot \frac{B_1}{B_2} \\
& - \frac{veh_1 \cdot (B_2 - B_1) \cdot Cb}{ann_{batt}} \\
& - \sum_{(o,d)\in\mathcal{Q}}\sum_{(i,j)\in\mathcal{A}} \pi^{(o,d)}_{(i,j)} \cdot (tollS - tollE) \cdot d_{ij} \cdot w^{(o,d)}_{1,(i,j)} \cdot Q^{(o,d)} \\
& - cl^{(o,d)}_{v,(i,j),s} \cdot \pi^{(o,d)}_{(i,j)} \cdot Q^{(o,d)} \cdot (Csc - Ce)
\end{aligned} \tag{A.37}$$

The objective function is subject to the following constraints:

- Domain values of the decision variables

$$x^{s}_{ij}, y_{ij} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, s \in \mathcal{S}_{ij} \tag{A.38}$$

Appendix B. Value of parameters used in the model

Parameter	Symbol	Value	Unit
Installation cost	Cd	500000	€/km
Electricity charging cost	Ce	0.36	€/kWh
Toll rate	toll_e	0.1	€/km
Fixed maintenance cost	μ_{ers}	2	%
Variable maintenance cost	$\mu_{\text{ers\_use}}$	0.07	€/v.km
Charging efficiency	ef_e	0.95	
Discount rate	dr	1.6%	
Charging rate	ϕ	3	kWh/km
Infrastructure lifetime	τ_{ers}	30	years

Table B.3: Order of electrification and the segment's traffic density

Parameter	Symbol	Value	Unit
Installation cost	Sc	200000	€/km
Electricity charging cost	Csc	0.73	€/kWh
Toll rate	toll_s	0.15	€/km
Fixed maintenance cost	μ_{sc}	10	%
Variable maintenance cost	$\mu_{\text{sc\_use}}$	0.5	€/v
Charging efficiency	ef_s	0.90	
Charging time	t	1	hour
Infrastructure lifetime	τ_{sc}	6	years

Table B.4: Order of electrification and the segment's traffic density

Parameter	Symbol	Value	Unit
Battery cost	Cb	80	€/kWh
Value of travel time	vot	38	€/hour
Battery capacities	*battery_capacities*	{80, 220}	kWh
Minimum battery level	*min_battery*	10	%
Maximum battery level	*max_battery*	90	%
Energy consumption rate	β	1.6	kWh/km
Battery lifespan	*life_time*	8	years
Number of operations	*ywd*	250	trips/year

Table B.5: Order of electrification and the segment's traffic density

References

Akerman, P., 2016. ehighway: Electrified heavy duty road transport.

Bakker, J., Alvarez, J.L., Buijs, P., 2024. A network design perspective on the adoption potential of electric road systems in early development stages. Applied Energy 361, Article 122887. doi:10.1016/j.apenergy.2024.122887.

Börjesson, M., Johansson, M., Kågeson, P., 2021. The economics of electric roads. Transportation Research Part C: Emerging Technologies 125, 102990. doi:https://doi.org/10.1016/j.trc.2021.102990.

Campaña, M., Inga, E., 2023. Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition. Energy Reports 9, 5246–5268. doi:https://doi.org/10.1016/j.egyr.2023.04.355.

Chen, Z., Liu, W., Yin, Y., 2017. Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors. Transportation Research Part C: Emerging Technologies 77, 185–206. doi:https://doi.org/10.1016/j.trc.2017.01.021.

Coban, H.H., Rehman, A., Mohamed, A., 2022. Analyzing the societal cost of electric roads compared to batteries and oil for all forms of road transport. Energies 15, 1925. doi:10.3390/en15051925.

Connolly, D., 2016. eRoads: A comparison between oil, battery electric vehicles, and electric roads for Danish road transport in terms of energy, emissions, and costs. Aalborg Universitet.

Csiszár, C., Csonka, B., Földes, D., Wirth, E., Lovas, T., 2020. Location optimisation method for fast-charging stations along national roads. Journal of Transport Geography 88, 102833. doi:https://doi.org/10.1016/j.jtrangeo.2020.102833.

Danese, A., Garau, M., Sumper, A., Torsæter, B.N., 2021. Electrical infrastructure design methodology of dynamic and static charging for heavy and light duty electric vehicles. Energies 14, 3362. doi:10.3390/en14123362.

Domingues-Olavarría, G., Márquez-Fernández, F., Fyhr, P., Reinap, A., Alaküla, M., 2018. Electric roads: Analyzing the societal cost of electrifying all danish road transport. World Electric Vehicle Journal 9, 9. doi:10.3390/wevj9010009.

Electreon, 2024. Findings from the world's first public wireless electric road for heavy-duty commercial vehicles.

Frost, A., 2019. Sweden to build world's first dynamic "electric road" system.

Greene, S., 2023. Freight transportation.

Hou, H., Tang, J., Zhao, B., Zhang, L., Wang, Y., Xie, C., 2021. Optimal planning of electric vehicle charging station considering mutual benefit of users and power grid. World Electric Vehicle Journal 12, 244. doi:10.3390/wevj12040244.

IEA, 2021. Net zero by 2050. Licence: CC BY 4.0.

Kizhakkan, A., Rathore, A., Awasthi, A., 2019. Review of electric vehicle charging station location planning, pp. 1–5. doi:10.1109/ITEC-India48457.2019.ITECINDIA2019-226.

Konstantinou, T., Gkritza, K., 2023. Examining the barriers to electric truck adoption as a system: A grey-dematel approach. Transportation Research Interdisciplinary Perspectives 17, 100746. doi:https://doi.org/10.1016/j.trip.2022.100746.

Kuby, M., Lim, S., 2005. The flow-refueling location problem for alternative-fuel vehicles. Socio-Economic Planning Sciences 39, 125–145. doi:https://doi.org/10.1016/j.seps.2004.03.001.

Li, J., Xie, C., Bao, Z., 2022. Optimal en-route charging station locations for electric vehicles: A new modeling perspective and a comparative evaluation of network-based and metanetwork-based approaches. Transportation Research Part C: Emerging Technologies 142, 103781. doi:https://doi.org/10.1016/j.trc.2022.103781.

Lin, Z., Ogden, J., Fan, Y., Chen, C.W., 2008. The fuel-travel-back approach to hydrogen station siting. International Journal of Hydrogen Energy 33, 3096–3101. doi:https://doi.org/10.1016/j.ijhydene.2008.01.040. 2nd World Congress of Young Scientists on Hydrogen Energy Systems.

M, A., G, P.K., 2023. Hydrogen towards sustainable transition: A review of production, economic, environmental impact and scaling factors. Results in Engineering 20, 101456. doi:https://doi.org/10.1016/j.rineng.2023.101456.

Manthey, N., 2023. Sweden pioneers permanent electrified road to charge evs on the move.

McConnell, V., Leard, B., 2020. Progress and potential for electric vehicles to reduce carbon emissions.

Min, R., 2023a. Sweden is building the world's first permanent electrified road for evs to charge while driving.

Min, R., 2023b. Sweden plans to build the world's first permanent e-road by 2025.

OECD, 2023. Highlights on road freight transport. Accessed: 2024-06-26.

Olovsson, J., Taljegard, M., von Bonin, M., Gerhardt, N., Johnsson, F., 2021. Impacts of electric road systems on the german and swedish electricity systems—an energy system model comparison. Frontiers in Energy Research 9, 631200. doi:10.3389/fenrg.2021.631200.

Pagany, R., Marquardt, A., Zink, R., 2019. Electric charging demand location model—a user- and destination-based locating approach for electric vehicle charging stations. Sustainability 11. doi:10.3390/su11082301.

Piarc, 2018. Detail of a publication: Virtual library of piarc: Electric road systems: A solution for the future?

Qiu, Y., Du, Y., Yu, S., Jiang, S., 2020. Location design of electrification road in transportation networks for on-way charging. Journal of Advanced Transportation 2020, 1–13. doi:10.1155/2020/7096767.

Schaap, S., 2021. Review of Electric Road Systems: Both a Conventional and Innovative Technology. Bachelor degree in vehicle engineering. KTH

Royal Institute of Technology, School of Engineering Sciences. Stockholm, Sweden. URL: `file:///path/to/FULLTEXT01.pdf`. sA115X, Bachelor Degree in Vehicle Engineering.
Soares, L., Wang, H., 2022. A study on renewed perspectives of electrified road for wireless power transfer of electric vehicles. Renewable and Sustainable Energy Reviews 158, 112110. doi:https://doi.org/10.1016/j.rser.2022.112110.
Sun, X., Chen, Z., Yin, Y., 2020. Integrated planning of static and dynamic charging infrastructure for electric vehicles. Transportation Research Part D: Transport and Environment 83, 102331. doi:https://doi.org/10.1016/j.trd.2020.102331.
Taheripour, F., Hertel, T.W., Tyner, W.E., Beckman, J.F., Birur, D.K., 2010. Biofuels and their by-products: Global economic and environmental implications. Biomass and Bioenergy 34, 278–289. doi:https://doi.org/10.1016/j.biombioe.2009.10.017.
Unterlohner, F., 2022. Truck co2: Europe's chance to lead. Transport Environment .
Wang, Y.W., Lin, C.C., 2009. Locating road-vehicle refueling stations. Transportation Research Part E: Logistics and Transportation Review 45, 821–829. doi:https://doi.org/10.1016/j.tre.2009.03.002.
Zhang, D., Li, W., Xiong, X., 2014. Overhead line preventive maintenance strategy based on condition monitoring and system reliability assessment. Power Systems, IEEE Transactions on 29, 1839–1846. doi:10.1109/TPWRS.2013.2295379.

Bibliography

[1] Vision on the charging infrastructure for electric transport looking ahead to 2035. Technical report, Government of the Netherlands, 2020. URL https://www.government.nl/documents/reports/2020/10/07/vision-on-the-charging-infrastructure-for-electric-transport.

[2] Comparison of hydrogen and battery electric trucks: Methodology and underlying assumptions, June 2020. URL file:///mnt/data/2020_06_TE_comparison_hydrogen_battery_electric_trucks_methodology.pdf.

[3] Patrik Akerman. ehighway: Electrified heavy duty road transport, Nov 2016.

[4] Matts Andersson, Matthias Gather, Matthias Hartwig, Erik Johansson, Michael Lehmann, and Michael Rodi. Regulating electric road systems in europe: How can a deployment of ers be facilitated?, 2022. URL https://electric-road-systems.eu/. Discussion paper from the CollERS2 project.

[5] Jasper Bakker, Jose Lopez Alvarez, and Paul Buijs. A network design perspective on the adoption potential of electric road systems in early development stages. *Applied Energy*, 361:Article 122887, 2024. doi: 10.1016/j.apenergy.2024.122887.

[6] Matthew Beedham. New eu legislation for ev charging is 'the most significant yet', 2023. URL https://www.tomtom.com/newsroom/explainers-and-insights/new-eu-legislation-for-ev-charging/. Accessed: 2024-10-18.

[7] Abheek Bhadury. Life expectancy of dc fast charger: Effect of load profile on thermal degradation of semiconductors. Master's thesis, TU Delft, August 2023. URL http://resolver.tudelft.nl/uuid:edd49b7c-c112-4b11-a596-041fc36d0ee6. Accessed: 2024-07-15.

[8] Tim Bongard. A system dynamics model for the adoption process of electric vehicles from a consumer perspective. Master's thesis, Eindhoven University of Technology, Department of Technology Management, 2011.

[9] Frida Borin and Linnea Tjernlund. Exploring barriers towards adoption within electric road systems: A case study of the user perspective. Master's thesis, KTH Royal Institute of Technology, School of Industrial Engineering and Management, 2020.

[10] Maria Börjesson, Magnus Johansson, and Per Kågeson. The economics of electric roads. *Transportation Research Part C: Emerging Technologies*, 125:102990, 2021. ISSN 0968-090X. doi: https://doi.org/10.1016/j.trc.2021.102990. URL https://www.sciencedirect.com/science/article/pii/S0968090X21000255.

[11] Miguel Campaña and Esteban Inga. Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition. *Energy Reports*, 9:5246–5268, 2023. ISSN 2352-4847. doi: https://doi.org/10.1016/j.egyr.2023.04.355. URL https://www.sciencedirect.com/science/article/pii/S2352484723007205.

[12] Zhibin Chen, Wei Liu, and Yafeng Yin. Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors. *Transportation Research Part C: Emerging Technologies*, 77:185–206, 2017. ISSN 0968-090X. doi: https://doi.org/10.1016/j.trc.2017.01.021. URL https://www.sciencedirect.com/science/article/pii/S0968090X17300347.

[13] Hasan Huseyin Coban, Aysha Rehman, and Abdullah Mohamed. Analyzing the societal cost of electric roads compared to batteries and oil for all forms of road transport. *Energies*, 15(5):1925, Mar 2022. doi: 10.3390/en15051925.

[14] David Connolly. *eRoads: A comparison between oil, battery electric vehicles, and electric roads for Danish road transport in terms of energy, emissions, and costs.* Aalborg Universitet, July 2016.

[15] Csaba Csiszár, Bálint Csonka, Dávid Földes, Ervin Wirth, and Tamás Lovas. Location optimisation method for fast-charging stations along national roads. *Journal of Transport Geography*, 88:102833, 2020. ISSN 0966-6923. doi: https://doi.org/10.1016/j.jtrangeo.2020.102833. URL https://www.sciencedirect.com/science/article/pii/S0966692319303801.

[16] Alberto Danese, Michele Garau, Andreas Sumper, and Bendik Nybakk Torsæter. Electrical infrastructure design methodology of dynamic and static charging for heavy and light duty electric vehicles. *Energies*, 14(12):3362, Jun 2021. doi: 10.3390/en14123362.

[17] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197, 2002.

[18] Decisio. Cost-effectiveness of ers in the netherlands, March 2022. URL https://decisio.nl/wp-content/uploads/Cost-effectiveness-ERS-in-the-Netherlands-Decisio-March-2022.pdf.

[19] Eelco den Boer, Sanne Aarnink, Florian Kleiner, and Johannes Pagenkopf. Zero emissions trucks: An overview of state-of-the-art technologies and their potential, July 2013. URL http://www.cedelft.eu. Commissioned by The International Council for Clean Transportation (ICCT).

[20] Parth Deshpande, Christopher de Saxe, Daniel Ainalis, John Miles, and David Cebon. A breakeven cost analysis framework for electric road systems. *Transportation Research Part D: Transport and Environment*, 122:103870, 2023. ISSN 1361-9209. doi: https://doi.org/10.1016/j.trd.2023.103870. URL https://www.sciencedirect.com/science/article/pii/S1361920923002675.

[21] Parth Deshpande, Christopher de Saxe, Daniel Ainalis, John Miles, and David Cebon. Analysis of fast charging arrangements for electric heavy goods vehicles, 10 2023.

[22] Designwerk. How long does it take to charge an e-truck?, 2024. URL https://www.designwerk.com/en/post/faq-items/how-long-does-it-take-to-charge-an-e-truck/. Accessed: 2024-07-15.

[23] Gabriel Domingues-Olavarría, Francisco Márquez-Fernández, Pontus Fyhr, Avo Reinap, and Mats Alaküla. Electric roads: Analyzing the societal cost of electrifying all danish road transport. *World Electric Vehicle Journal*, 9(1):9, Jun 2018. doi: 10.3390/wevj9010009.

[24] Electreon. Charge as you drive - france, Jun 2024. URL https://electreon.com/projects/france.

[25] Electreon. Findings from the world's first public wireless electric road for heavy-duty commercial vehicles, Jan 2024. URL https://electreon.com/articles/worlds-first-public-wireless-electric-road.

[26] Henrik Engdahl. How a good charging strategy can extend an electric truck's range, 2021. URL https://www.volvotrucks.com/en-en/news-stories/insights/articles/2021/nov/How-a-good-charging-strategy-can-extend-an-electric-trucks-range.html. Accessed: 2024-07-15.

[27] Eurostat. Road freight transport statistics - statistics explained, 2023. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Road_freight_transport_statistics&oldid=575068. Accessed: 2024-06-26.

[28] Adam Frost. Sweden to build world's first dynamic "electric road" system, Apr 2019. URL https://www.traffictechnologytoday.com/news/traffic-management/sweden-to-build-worlds-first-dynamic-electric-road-system.html.

[29] Keren SSlleson Gerberg. Findings from the world's first public wireless electric road for heavy-duty commercial vehicles, Jan 2024. URL https://electreon.com/articles/worlds-first-public-wireless-electric-road.

[30] Government of the Netherlands. Plans for introduction of hgv toll, 2024. URL https://www.government.nl/topics/freight-transportation/plans-for-introduction-of-hgv-toll. Accessed: 2024-07-15.

[31] Suzanne Greene. Freight transportation, Feb 2023. URL https://climate.mit.edu/explainers/freight-transportation.

[32] Emma Hopkins, Dimitris Potoglou, Scott Orford, and Liana Cipcigan. Can the equitable roll out of electric vehicle charging infrastructure be achieved? *Renewable and Sustainable Energy Reviews*, 182:113398, 2023. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2023.113398. URL https://www.sciencedirect.com/science/article/pii/S1364032123002551.

[33] Hui Hou, Junyi Tang, Bo Zhao, Leiqi Zhang, Yifan Wang, and Changjun Xie. Optimal planning of electric vehicle charging station considering mutual benefit of users and power grid. *World Electric Vehicle Journal*, 12(4):244, Nov 2021. doi: 10.3390/wevj12040244.

[34] IEA. Net zero by 2050, 2021. URL `https://www.iea.org/reports/net-zero-by-2050`. Licence: CC BY 4.0.

[35] Reports Iea. Trends in electric heavy-duty vehicles – global ev outlook 2023 – analysis, 2023. URL `https://www.iea.org/reports/global-ev-outlook-2023/trends-in-electric-heavy-duty-vehicles`.

[36] Reports Iea. Trends in charging infrastructure – global ev outlook 2023 – analysis, 2023. URL `https://www.iea.org/reports/global-ev-outlook-2023/trends-in-charging-infrastructure#abstract`.

[37] InsideEVs. Ev charger efficiency losses, 2023. URL `https://insideevs.com/features/711659/ev-charger-efficiency-losses/`. Accessed: 2024-07-15.

[38] International Energy Agency. Average electric vehicle battery price in the net zero scenario, 2023 and 2030, 2024. URL `https://www.iea.org/data-and-statistics/charts/average-electric-vehicle-battery-price-in-the-net-zero-scenario-2023-and-2030`. Licence: CC BY 4.0.

[39] Akhil Kizhakkan, Akshay Rathore, and Anjali Awasthi. Review of electric vehicle charging station location planning. pages 1–5, 12 2019. doi: 10.1109/ITEC-India48457.2019.ITECINDIA2019-226.

[40] Theodora Konstantinou and Konstantina Gkritza. Examining the barriers to electric truck adoption as a system: A grey-dematel approach. *Transportation Research Interdisciplinary Perspectives*, 17:100746, 2023. ISSN 2590-1982. doi: https://doi.org/10.1016/j.trip.2022.100746. URL `https://www.sciencedirect.com/science/article/pii/S2590198222002068`.

[41] Theodora Konstantinou, Christos Gkartzonikas, and Konstantina Gkritza. Public acceptance of electric roadways: The case of los angeles, california. *International Journal of Sustainable Transportation*, 17:1–25, 10 2021. doi: 10.1080/15568318.2021.1983675.

[42] Michael Kuby and Seow Lim. The flow-refueling location problem for alternative-fuel vehicles. *Socio-Economic Planning Sciences*, 39(2):125–145, 2005. ISSN 0038-0121. doi: https://doi.org/10.1016/j.seps.2004.03.001. URL `https://www.sciencedirect.com/science/article/pii/S0038012104000175`.

[43] Jiapei Li, Chi Xie, and Zhaoyao Bao. Optimal en-route charging station locations for electric vehicles: A new modeling perspective and a comparative evaluation of network-based and metanetwork-based approaches. *Transportation Research Part C: Emerging Technologies*, 142:103781, 2022. ISSN 0968-090X. doi: https://doi.org/10.

1016/j.trc.2022.103781. URL https://www.sciencedirect.com/science/article/pii/S0968090X22002108.

[44] Ximeng Liao, Mahnam Saeednia, Maria Nogal, and Lori Tavasszy. Scaling up dynamic charging infrastructure: Significant battery cost savings. *Transportation Research Part D*, 129:104128, 2024. doi: 10.1016/j.trd.2024.104128. URL https://www.elsevier.com/locate/trd. Available online 1 March 2024.

[45] Zhenhong Lin, Joan Ogden, Yueyue Fan, and Chien-Wei Chen. The fuel-travel-back approach to hydrogen station siting. *International Journal of Hydrogen Energy*, 33(12):3096–3101, 2008. ISSN 0360-3199. doi: https://doi.org/10.1016/j.ijhydene.2008.01.040. URL https://www.sciencedirect.com/science/article/pii/S0360319908001171. 2nd World Congress of Young Scientists on Hydrogen Energy Systems.

[46] Xiao Lu, Ping Wang, Dusit Niyato, Dong In Kim, and Zhu Han. Wireless charging technologies: Fundamentals, standards, and network applications. *IEEE Communications Surveys amp; Tutorials*, 18(2):1413–1452, 2016. doi: 10.1109/comst.2015.2499783.

[47] Nicholas Lutsey and Michael Nicholas. Update on electric vehicle costs in the united states through 2030, 04 2019.

[48] Eva Lövstål, Henrik Sällberg, and Anders Wrenne. Determinants of electric road system adoption by road freight companies. *International Journal of Innovation and Technology Management*, 20, 04 2023. doi: 10.1142/S0219877023500323.

[49] Aravindan M and Praveen Kumar G. Hydrogen towards sustainable transition: A review of production, economic, environmental impact and scaling factors. *Results in Engineering*, 20:101456, 2023. ISSN 2590-1230. doi: https://doi.org/10.1016/j.rineng.2023.101456. URL https://www.sciencedirect.com/science/article/pii/S2590123023005832.

[50] Miranda Maitino. Ev charging station infrastructure costs and breakdown, 2022. URL https://www.sparkcharge.io/blogs/leadthecharge/ev-charging-station-infrastructure-costs. Accessed: 2024-07-15.

[51] Nora Manthey. Sweden pioneers permanent electrified road to charge evs on the move, May 2023. URL https://www.electrive.com/2023/05/09/sweden-pioneers-permanent-electrified-road-to-charge-evs-on-the-move/.

[52] Virginia McConnell and Benjamin Leard. Progress and potential for electric vehicles to reduce carbon emissions, Dec 2020. URL https://www.rff.org/publications/reports/potential-role-and-impact-evs-us-decarbonization-strategies/.

[53] Roselyne Min. Sweden is building the world’s first permanent electrified road for evs to charge while driving, May 2023. URL https://www.euronews.com/next/2023/05/09/sweden-is-building-the-worlds-first-permanent-electrified-road-for-evs-to-charge-whil

[54] Roselyne Min. Sweden plans to build the world's first permanent e-road by 2025, May 2023. URL `https://www.euronews.com/next/2023/05/09/sweden-is-building-the-worlds-first-permanent-electrified-road-for-evs-to-charge-whil`

[55] Jody Emlyn Muelaner. *Electric Road Systems for dynamic charging*, Mar 2022. doi: 10.4271/epr2022007.

[56] NL Times. Electric car charging costs vary drastically across dutch cities, 2024. URL `https://nltimes.nl/2024/03/11/electric-car-charging-costs-vary-drastically-across-dutch-cities`. Accessed: 2024-07-15.

[57] Lina Nordin, Terence McGarvey, and Ehsan Gahfoori. Electric road systems: Impact on road construction, maintenance and operations. *VTI Rapport*, 2020.

[58] OECD. Highlights on road freight transport, 2023. URL `https://www.oecd-ilibrary.org/sites/0c13b23d-en/index.html?itemId=/content/component/0c13b23d-en`. Accessed: 2024-06-26.

[59] Johanna Olovsson, Maria Taljegard, Michael von Bonin, Norman Gerhardt, and Filip Johnsson. Impacts of electric road systems on the german and swedish electricity systems—an energy system model comparison. *Frontiers in Energy Research*, 9:631200, 07 2021. doi: 10.3389/fenrg.2021.631200.

[60] Raphaela Pagany, Anna Marquardt, and Roland Zink. Electric charging demand location model—a user- and destination-based locating approach for electric vehicle charging stations. *Sustainability*, 11(8), 2019. ISSN 2071-1050. doi: 10.3390/su11082301. URL `https://www.mdpi.com/2071-1050/11/8/2301`.

[61] Jan Pettersson. National roadmap for electric road systems. *Swedish Transport Administration*, Nov 2017.

[62] Piarc. Detail of a publication: Virtual library of piarc: Electric road systems: A solution for the future?, 2018. URL `https://www.piarc.org/en/order-library/29690-en-Electric%20road%20systems:%20a%20solution%20for%20the%20future`.

[63] Patrick Plötz, Matts Andersson, Aline Scherrer, and Erik Johansson. The possible future of electric road systems in europe—time to decide and act. *Environmental Research: Infrastructure and Sustainability*, 4(013001), 2024. doi: 10.1088/2634-4505/ad3576. URL `https://iopscience.iop.org/article/10.1088/2634-4505/ad3576`. Open Access, published by IOP Publishing.

[64] Jean-Yves Potvin. Genetic algorithms for the traveling salesman problem. *Annals of Operations Research*, 63:337–370, 1996.

[65] Yue Qiu, Yuchuan Du, Shanchuan Yu, and Shengchuan Jiang. Location design of electrification road in transportation networks for on-way charging. *Journal of Advanced Transportation*, 2020:1–13, Jul 2020. doi: 10.1155/2020/7096767.

[66] Abel Rosales-Tristancho, Ana F. Carazo, Raúl Brey, and Henrik Lindhjem. Meta-analysis of consumers' trade-offs between range and charging infrastructure for electric vehicles. *Transportation Research Part D: Transport and Environment*, 134:104342, Sep 2024. doi: 10.1016/j.trd.2024.104342.

[67] Sam Schaap. Review of electric road systems: Both a conventional and innovative technology. Bachelor degree in vehicle engineering, KTH Royal Institute of Technology, School of Engineering Sciences, Stockholm, Sweden, Spring 2021. URL `file:///path/to/FULLTEXT01.pdf`. SA115X, Bachelor Degree in Vehicle Engineering.

[68] Laura Soares and Hao Wang. A study on renewed perspectives of electrified road for wireless power transfer of electric vehicles. *Renewable and Sustainable Energy Reviews*, 158:112110, 2022. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2022.112110. URL `https://www.sciencedirect.com/science/article/pii/S1364032122000399`.

[69] Daniel Speth, Verena Sauter, Patrick Plötz, and Tim Signer. Synthetic european road freight transport flow data. *Data in Brief*, 40:107786, 2022. doi: 10.1016/j.dib.2021.107786. URL `https://doi.org/10.1016/j.dib.2021.107786`.

[70] Xiaotong Sun, Zhibin Chen, and Yafeng Yin. Integrated planning of static and dynamic charging infrastructure for electric vehicles. *Transportation Research Part D: Transport and Environment*, 83:102331, 2020. ISSN 1361-9209. doi: https://doi.org/10.1016/j.trd.2020.102331. URL `https://www.sciencedirect.com/science/article/pii/S1361920919304146`.

[71] Henrik Sällberg and Emil Numminen. Critical risk factors of electric road uptake on motorways: A swedish delphi study. *Transportation Planning and Technology*, 47(3):303–322, 2024. doi: 10.1080/03081060.2023.2294339.

[72] Farzad Taheripour, Thomas W. Hertel, Wallace E. Tyner, Jayson F. Beckman, and Dileep K. Birur. Biofuels and their by-products: Global economic and environmental implications. *Biomass and Bioenergy*, 34(3):278–289, 2010. ISSN 0961-9534. doi: https://doi.org/10.1016/j.biombioe.2009.10.017. URL `https://www.sciencedirect.com/science/article/pii/S0961953409002207`.

[73] Maria Taljegard, Lovisa Thorson, Mikael Odenberger, and Filip Johnsson. Large-scale implementation of electric road systems: Associated costs and the impact on co2 emissions. *International Journal of Sustainable Transportation*, pages 1–14, 2019. doi: 10.1080/15568318.2019.1595227. URL `https://www.tandfonline.com/doi/full/10.1080/15568318.2019.1595227`.

[74] Web Team. Us to build its first-ever "electric road" that wirelessly charges evs as they drive, Feb 2022. URL `https://www.electrichybridvehicletechnology.com/news/charging-technology/us-to-build-its-first-ever-electric-road-that-wirelessly-charges-evs-as-they-drive.html`.

[75] Kiki Tolentino. How much does it cost to charge an electric car in the netherlands in 2024?, 2024. URL `https://www.tapelectric.app/blog/cost-to-charge-an-electric-car-netherlands/`. Accessed: 2024-07-15.

[76] Fedor Unterlohner. Truck co2: Europe's chance to lead. *Trasnport Environment*, Sep 2022.

[77] Volvo Trucks. The lifecycle of electric vehicle batteries, 2023. URL `https://www.volvotrucks.com/en-en/news-stories/insights/articles/2023/feb/the-lifecycle-of-electric-vehicle-batteries.html`. Accessed: 2024-07-15.

[78] Guang-min Wang, Xian-jia Wang, Zhong-ping Wan, and Shi-hui Jia. An adaptive genetic algorithm for solving bilevel linear programming problem. *Applied Mathematics and Mechanics*, 28(12):1605–1612, 2007.

[79] Ying-Wei Wang. An optimal location choice model for recreation-oriented scooter recharge stations. *Transportation Research Part D: Transport and Environment*, 12(3): 231–237, 2007. ISSN 1361-9209. doi: https://doi.org/10.1016/j.trd.2007.02.002. URL `https://www.sciencedirect.com/science/article/pii/S1361920907000223`.

[80] Ying-Wei Wang. Locating battery exchange stations to serve tourism transport: A note. *Transportation Research Part D: Transport and Environment*, 13(3):193–197, 2008. ISSN 1361-9209. doi: https://doi.org/10.1016/j.trd.2008.01.003. URL `https://www.sciencedirect.com/science/article/pii/S1361920908000059`.

[81] Ying-Wei Wang and Chuah-Chih Lin. Locating road-vehicle refueling stations. *Transportation Research Part E: Logistics and Transportation Review*, 45(5):821–829, 2009. ISSN 1366-5545. doi: https://doi.org/10.1016/j.tre.2009.03.002. URL `https://www.sciencedirect.com/science/article/pii/S1366554509000313`.

[82] Dabo Zhang, Wenyuan Li, and Xiaofu Xiong. Overhead line preventive maintenance strategy based on condition monitoring and system reliability assessment. *Power Systems, IEEE Transactions on*, 29:1839–1846, 07 2014. doi: 10.1109/TPWRS.2013.2295379.