MSc thesis in Transport & Planning

Driving Toward Sustainability: Large-Scale Electric Road Systems for Road Freight - an optimization model for ERS Network Planning

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DAF Trucks

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Abstract

As societies worldwide grapple with the urgent need to mitigate carbon emissions, one domain where substantial strides can be made is heavy-duty road freight transport. Electrification has emerged as a practical and technologically mature solution to address this challenge. However, the widespread adoption of electrification in this sector is met with formidable obstacles. These obstacles encompass the inadequacy of charging infrastructure, restrictions in driving range on a single charge, the demand for robust and high-capacity onboard batteries, and the looming specter of potential battery shortages.

Within the European context, discussions revolve around sustainable solutions that can pave the way for a cleaner and greener future. Among the contenders in this realm, the electric road system (ERS) has risen to prominence. ERS introduces a groundbreaking concept where trucks can recharge their batteries while in motion on highways, promising an array of ecological and economic benefits. However, the journey toward the implementation of ERS infrastructure is not without its intricacies. It necessitates the installation of specialized charging infrastructure, which can take the form of overhead catenaries accessed by a pantograph or embedded road equipment. Moreover, there is a substantial financial commitment required to equip entire truck fleets with the necessary batteries, adding to the complexity of the endeavor.

The central challenge in this landscape revolves around the meticulous design of an optimal ERS network that adeptly balances infrastructure costs with battery expenses. This research aims to address this multifaceted challenge by posing a fundamental question:

How to determine the optimal ERS network, given the trade-off between infrastructure and battery costs?

To tackle this question head-on, this paper introduces a sophisticated multi-objective optimization model. This model is a computational framework that concurrently minimizes the costs associated with infrastructure investment,

encompassing the installation and maintenance of ERS components, and the total transport expenses. These total transport costs encompass a range of factors, including the procurement of batteries, energy consumption, and toll charges. This comprehensive approach takes into account the diverse perspectives and interests of both investors and logistics companies, providing a holistic view of the intricate challenges associated with ERS adoption.

One pivotal advantage of ERS becomes evident in its capacity to extend the lifespan of batteries by reducing wear and tear during typical driving conditions. The model thoughtfully incorporates this aspect, factoring in battery purchase costs that hinge on projected lifespans. These projected lifespans, in turn, are influenced by the chosen route's electrification rate (ERS implementation).

To validate the model's effectiveness and practicality, it is subjected to a rigorous real-world case study. This case study delves into the intricacies of road freight transport in Germany, the Netherlands, Belgium, and Luxembourg. Additionally, this research introduces an enhanced Genetic algorithm, complemented by an Elitism strategy. These enhancements are designed to optimize solutions effectively within the confines of this practical context.

The findings derived from this rigorous analysis reveal a diverse Pareto set. This set showcases the delicate equilibrium between infrastructure investment and total annual transport costs. Notably, when budget constraints are absent, investing in ERS consistently proves advantageous. The total reductions in transport costs demonstrably surpass the initial ERS investment. For instance, the comprehensive electrification of 27,114 kilometers of highway results in a remarkable 30% reduction in total transport costs.

However, in scenarios where budget considerations take center stage, the concept of a break-even design emerges as an enticing proposition. This concept deftly navigates the dynamics between infrastructure expenditure and total transport costs, with a particular focus on battery expenses. Two distinct break-even designs are thoughtfully proposed:

Comprehensive Break-Even Design (Considering Toll, Energy, and Battery Costs): By electrifying 19,595 kilometers of highway annually with an investment of 0.7 billion euros, substantial savings of 2.6 billion euros in total transport costs per year are achieved. This strategy is accompanied by an impressive 84% reduction in annual battery demand.

Focused Break-Even Design (Centered on Battery Costs Only): Electrifying 15,375 kilometers of highway annually with an investment of 0.5 billion euros results in significant savings of 1.6 billion euros in annual battery procurement costs. Furthermore, this approach reduces annual battery demand by 78%.

Moreover, this study underscores the potential for substantial reductions in battery purchase costs and the requisite battery capacity. These reductions are directly attributable to the implementation of the electric road system (ERS). These valuable insights are poised to play a pivotal role in informing the decisions of EU policymakers. They provide critical guidance as these policymakers contemplate the construction of ERS infrastructure, particularly in light of the financial constraints often encountered in real-world budgetary considerations.

Acknowledgements

This master's thesis represents the culmination of my studies in Transport and Planning at TU Delft, marking the final step towards obtaining my degree. This research delves into the planning of the Electric Road System network in Europe, a journey filled with challenges. However, my persistence, confidence, and a love for tackling challenges made this research an enjoyable endeavor, knowing it contributes to making the world a little better.

I owe the successful completion of this thesis to the invaluable support and guidance of my supervisors: Prof. Lori Tavasszy, Dr. Mahnam Saeednia, Dr. Maria Nogal Macho, and Mr. Jack Martens. Their insightful advice and comments during our official meetings were instrumental.

I want to extend a special and heartfelt thanks to my daily supervisor, Dr. Mahnam Saeednia. Your unwavering support and encouragement during challenging moments, along with your consistent communication to track research progress and problem-solving, were truly appreciated. Your initiative in arranging Q&A meetings with researchers from other countries when we faced complex issues provided invaluable insights.

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Acronyms

- BETs: battery electric trucks
- HDVs: heavy-duty vehicles
- HDTs: heavy-duty trucks
- HDBETs: heavy-duty battery electric trucks
- HGVs: heavy-good vehicles
- OEMs: original equipment manufacturers
- GA: genetic algorithm

1. Introduction

1.1. Background

1.1.1. High demand to decarbonize HGTs transport sector

As the 21st century unfolds, the global economy surges forward, ushering in a period of rapid expansion. However, this advancement is accompanied by a disquieting surge in greenhouse gas (GHG) emissions, casting a shadow over the horizon. GHGs have emerged as a pivotal challenge confronting humanity, necessitating prompt and adept responses. The International Energy Agency (IEA) recently underscored this crisis in their report, revealing a disconcerting elevation in global emissions emanating from energy combustion and industrial processes. Notably, in 2021, these emissions reached a new zenith at 36.3 Gt CO2—an alarming 6% surge from the 34 Gt in 2020 (Figure 1.1). Despite a modest dip in 2020 precipitated by the Covid-19 pandemic, the global economic engine rapidly rebounded, underscoring the persistent upward trajectory. Within this panorama, the transport sector emerges as a formidable contributor to GHG emissions—accounting for a significant 22% of total emissions in Europe, with road transport alone contributing 21.1%. Delving deeper into this tapestry, passenger cars shoulder 12.8% of the European Union's (EU) emissions, while Heavy-Duty Vehicles (HDVs) bear the responsibility for 5.6% (Figure 1.2). Astonishingly, despite constituting a mere 2% of the total vehicle fleet in the EU, HDVs contributed a staggering 28% of the transport emissions in 2020.

Beyond the existing challenge of significant emissions stemming from Heavy-Duty Vehicles (HDVs) in Europe, the post-pandemic economic resurgence and flourishing international and intra-EU trade have fuelled an almost 2% upswing in new heavy truck registrations, culminating in a noteworthy 6,230,100 units in 2022 [5]. Furthermore, the European Commission envisages a staggering 44% growth in truck activities between 2020 and 2040 [19]. Intriguingly, research projections cast an even graver light, estimating that HDT emissions could swell by a startling 100% when compared to 2015 levels [36].

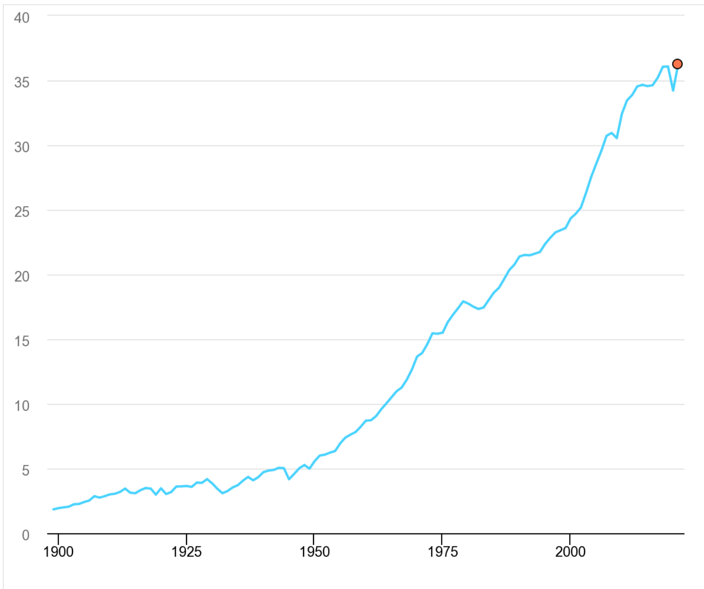


Figure 1.1.: CO_2 emissions from energy combustion and industrial processes, 1900-2021[35]

Amidst this backdrop, the European Commission has etched an ambitious goal—zero net greenhouse gas (GHG) emissions by 2050. This aspiration dovetails with a steadfast commitment to curtailing GHGs by at least 55% by 2030 in contrast to the 1990 emission levels [24].

However, juxtaposing these statistics with the EU's overarching vision of carbon neutrality reveals a glaring discord. The escalating present and anticipated surge in transport emissions diverge markedly from the EU's long-term aim. Consequently, the transport sector emerges as a pivotal arena for environmental protection. A transition from fossil fuels to clean energy, particularly electricity, stands not just as a requisite but an imperative. This landscape highlights a stark disparity. While the realm of passenger cars, vans, buses, and light trucks embarks steadfastly on the path to zero emissions, Heavy-Duty Trucks (HDTs) lag conspicuously behind. In 2021, electric trucks merely constitute a paltry 0.47% of the HDT landscape [4]. Without purposive policies to galvanize the adoption of electric HDTs, the emissions gains anticipated from the electrification of conventional vehicles could be eroded by the emissions churned out by diesel-powered HDTs [72]. Against this backdrop, a compelling urgency arises—a swift and resolute shift from diesel-powered HDTs to zero-emission alternatives. Deliberation is not a luxury; a swift and imperative transformation is an inescapable necessity.

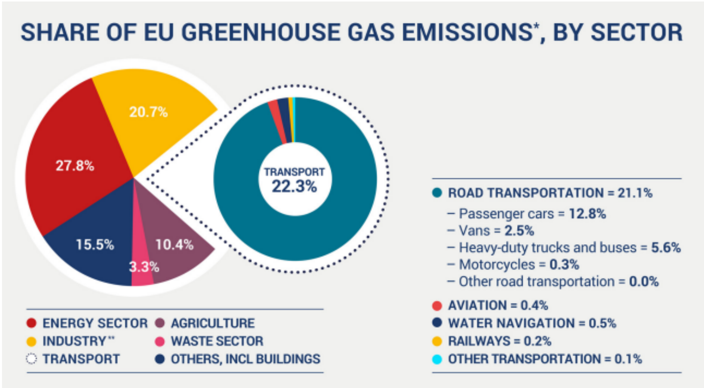


Figure 1.2.: Share of EU's GHG emission, by sector[3]

1.1.2. Why ERS and challenges

The process of decarbonizing the HDTs fleet is challenging since they are conceptually different from the passenger cars. They are normally used for long-haul logistics or construction delivery use, which means compared with other vehicles, its requirement in driving range and weight(payload) is high. The sustainable solutions that scientists have developed now cannot meet such demand, making it difficult for the transition from fossil fuels to zero-emission energy. The first solution that is discussed most is the battery-electric truck(BET). Even though the current electric powertrain can supply enough power to propel the heavy-goods trucks, the capacity of battery does not meet the requirement of long distance they want to cover since the improvement in battery weight/size would lead to the net payload loss of HGTs[78]. Another challenge for BETs is, to depoy the BETs, that a huge number of charging infrastructures are essential as long-haul HGTs that usually have a multi-day intercity travel need to get enough power along the routes. However, currently the charging stations for trucks across Europe are lacking, which undoubtedly slows down the electrification of trucks. Moreover, a more serious problem could appear in the near future is the potential battery shortage, as with the vigorous promotion of BETs in the market, EU's battery demand will surge. But EU does not have a coherent strategy to attract battery manufacturers, making European EV OEMs struggle to secure a stable battery supply and show a high reliance on the battery supply from China. China produced more than 70 percent of world's total lithium-ion batteries every year while only 1% of them is supplied by European manufacturers[37].

The second option is the hydrogen-powered fuel cell electric vehicles(FCETs).

This vehicle technology has comparable travel range and refueling mode as diesel trucks and shares the same powertrain components as BETS but with smaller onboard battery pack. However, only if the hydrogen fuel is produced from renewable electricity rather than the steam methane reforming from natural gas[78], it can be seen as the green energy, which is hardly feasible and expensive currently. Moreover, the conversion losses of hydrogen fuel when converting it to electricity for trucks is still not small with efficiency of 54% in 2020[78, 54]. And the lack of refueling infrastructures as well as the high hydrogen-powered vehicle production cost hinders the deployment of FCETs[78].

Finally, the last two alternatives are the e-fuels and biofuels which are not considered as ideal solutions to decarbonize the HGTs. For food biofuels, the deforeatation could be caused, making even more emissions than they save, while for advanced biofuel whose production is based on the limited avalability of wastes and residues, scaling the use of it in trucking seems to be impossible[77]. The research shows that more CO2 is emitted by the e-fuel(a blend of fossil and synthetic petrol)-powered cars than battery electric cars during their whole lifecycle[79], which means it helps little in realizing the fully sustainable transport. Therefore, the last two alternatives only can be regarded as the transitional product at the mid-term stage of process of zero-emission HGTs.

The achievement of zero-emission HGTs seems to be impossible via one single technology and the fact that only in the way of the mixture of technologies can we realize it starts to be recognised by many policymakers and researchers[73]. The ERS(Electric road system) can provide continuous power to the electric vehicles for propulsion and charging battery via lines and could be a cost-effective solution to electrify the long-haul trucks, which could also be a complement for the BETs(technically, the ERS can also be used by hybrid/efuel/hydrogen trucks when they are running on the E-highway and other power is only necessary for off-E-highway) against the challenge of large size of onboard battery. The electric road system(ERS) consists of three different technological bases which are wireless/inductive charging, catenary and rail. Firstly, based on the maturity of technology development, the wireless charging electric road using magnetic fields to transfer energy[29] is the least feasible solution since its transmission efficiency is too low to suffice the demand of HGTs and the high production cost of onboard wireless charging modules in some cases accounting for 1/4 of the total cost of EVs is not acceptable for the market[23, 13]. For rail-based ERS, it uses the conductive rails installed on the road surface to transfer the energy via a power receiver under the vehicle. Due to its high complexity in operation and installation, few research and projects have considered it even though it can support all types of vehicles. The last one is the catenary ERS(ERS-OC) that is operated by using overhead contact line and it has been considered as one of the most applicable solutions for the decarbonization of long-haul trucks because the similar mature technologies have been applied in tram/light rail for many years. When truck is running on the E-highway with the catenary installed on the right side of road, the pantograph on the roof of vehicle will extend automatically to connect with the catenary, which means the BETs receive power directly from the grid to charge battery and propel[29]. There is a possibility of reducing the discharging and charging cycles of battery causing a potential imporvement in battery lifespan. And some research found directly tapping electricity from catenary leads to higher energy efficiency than charging station and battery-swapping station[68]. Countries such as Sweden, Germany, UK and USA have conducted or are planning to conduct some demonstration projects (only on some short-distance highway corridors) regarding the ERS freight transport. In 2016, the world's first ehighway was launched in Swenden under the cooperation of Siemens and Scania, and the 2-year pilot trail showed that the system can reduce local air pollution and 50% of energy consumption[66]. Moreover, In 2017 California, USA, Siemens and Volve tested their ERS system near the ports of Los Angeles and Long Beach to see its potential of reducing emissions[65]. The Germany government is also interested in investing in ERS-OC as one of their main solutions (the other two are battery-electric and hydrogen) to decarbonize HGTs with some demonstration projects running in the state of Hesse[64, 14, 78]. According to [44], 100 km or shorter length accounts for 95% of tractor/trailers' trips off the German motorway network, which means a battery with range of 200 km could cover the electrification gaps like bridges and tunnels and the distance between the motorway and the final destination of unloading[78], making optimization of battery size for specific travel range possible without losing much net payload[31]. **Therefore, ERS-OC has been regarded as the most applicable solution to accelerate the process of untake of zero-emission HGTs in Europe**. The ERS-OC projects that has been conducted are listed in table1.1 showing that the ERS-OC seems to be the most acceptable one.

For now, the BETs is the most feasible solution among others which have been commercialized in the market. However, their advantages could be offset by the range limitation(limited battery capacity) leading to range anxiety, potential payload loss and battery shortage problem in the future. These are the main factors that would slow down the uptake of zero-emission trucks(Etrucks) as mentioned above, and they could be complemented by

Project	Location	Solutions	Start of project	End of project
E16 Electric road	E16 in Region Gävleborg, Sweden	Overhead lines	2016	2020
eRoadArlanda	Arlanda Airport, Sweden	Rails	2018	2019
SCAQMD	Los Angeles County, USA	Overhead lines	2017	2017
ELISA	A 5, Germany	Overhead lines	2019	2022
FESH	A 1, Germany	Overhead lines	2019	2022
eWayBW	B 462, Germany	Overhead lines	2020	2023

Table 1.1.: Conducted ERS projects[29]

ERS-OC. The key challenge of the large deployment of ERS-OC emerges: how to balance the optimal trade-off between vehicle costs including battery and infrastructure cost so that the optimized ERS transport system can be obtained, as with the extension of ERS network, a smaller battery size is required and battery lifespan improves, which shows a potential to help us solve above issues of BETs. But tt should be noted that the cost of battery and electrifying the highway each kilometer with catenary is very high, so for a realistic assessment of ERS-OC system, it is of great importance to make decisions wisely on which a highway segment needs to be electrified and what the optimal battery size satisfying each truck tour is. Since the charging infrastructure for HDTs is capital intensive and will be used by many different companies, it should be considered from the nationwide perspective of view, we use total costs of nation/internationwide infrastructure as the key performance indicator(objective) including operation, maintenance, purchase and investment cost.

1.2. Overview of ERS and its subsystem

The formal system design of ERS proposed by Siemens mobility is introduced in this section, but it should be noted that the international standard-/regulations regarding the ERS-OC has not been determined. As illustrated in figure 1.3, the general electric road system consists of 5 different subsystems.

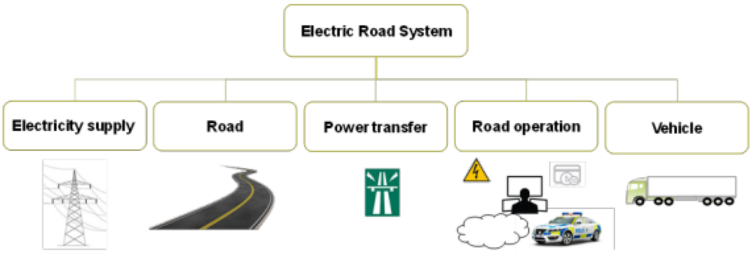
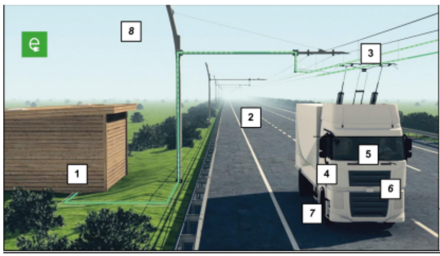


Figure 1.3.: Overall system layout, derived from[29, 64]

Road system: consists of pavement, auxiliary and barriers components, substations and catenaries. **Electricity supply:** is responsible for the energy transmission, distribution and management from source over long distance. **Power transfer:** consists of onroad and in-vehicle equipments used for electricity transfer such as pantograph. **Road operator:** controls the energy management and real-time trucks/users information as well as records the payment for the energy consumption **Vehicle:** includes the vehicles with essential components such as pantograph, battery, electric motor and so on.

And a overview of ERS-OC (overhead contact line) is provided as following figure1.4 to show how the ERS project works.



#	interface
1	substation to overhead contact line (i. e. power supply to transfer)
2	contact line to road (power transfer to driveway)
3	contact line to pantograph (power transfer to vehicle pick-up)
4	pantograph to electric drive (vehicle pick-up to hybrid base vehicle)
5	pantograph to driver/ truck cabin (vehicle pick-up to operation)
6	*vehicle to hybrid drive*
7	*vehicle to road*
8	*vehicle to OCC*

Figure 1.4.: Example of ERS-OC, derived from[29, 64]

2. Literature review–related work

This chapter presents an overview of current reaseach and reviews relevant work.

2.1. State of knowledge regarding socioeconomic benefits of ERS

The economic and environmental impacts induced by the implementation of large-scale ERS across the road network has been explored by some previous research and institutes. Research[20] investigated the implementation of electric roads in Denmark by comparing it with oil and BEVs. The results showed that the ERS is more expensive than oil and cheaper than BETs under current Danish energy system, but they will be the cheapest solution in the future. Based on the real UK logistics journeys(44 routes on UK road network), it has been modelled by simulating different ranges of ERS against static charging that for fully electrifying the long-haul trucks in UK, that ERS-OC is a more suitable technology from the economic perspective of view, and results showed that the ERS reduces battery size by 41%, 62% and 75% for different ranges of ERS network while the investment can be paid off in 15 years by users' electricity charges[59]. The qualitative analysis on the basis of USA indicated that the dynamic inductive charging is more advantageous in vehicle range extension, reduction of battery capacity and vehicle weight[74]. By conducting the technoeconomic analysis with UK as a case, they[7] found the overhead catenaries and compatible HGVs are more energy-efficient and cost-effective to achieve UK's goal of zero-emission long-haul trucks compared with hydrogen. In France, the implementation of ERS has also been explored with the conclusion that the savings from the reduction of battery demand is far over the cost for the construction of ERS along the French road network[55]. Recent study from RISE[58] explored the complex interaction effects among different transport solutions which are diesel, BETs, dynamic charging via ERS and static charging infrastructures for trucks when they are implemented simultaneously in the future, and it was found that the expansion of electric road system in Sweden would reduce the utility rate of other charging options but significantly decreases the overall consumption of vehicle batteries and the most cost-saving solution for future freight transport system is to develop a 4000 km ERS on the Swedish road network. Ref[12] simulated the three stages of implementation of Catenaries (ERS) on road segment level in Flanders, Belgium, which leads to the reduction of 69% in CO2 emissions and completing the national CO2 reduction goal by comparing it with other transport solutions such as hydrogen, hybrid and etc. A microscopic agent-based simulations has been applied by[51] to capture the driving pattern of each electric vehicle to assess the impacts of different charging infrastructures(ERS and static charging) under different scenarios with various fixed static charging locations, battery pack, and ERS network size. They found ERS can produce more added value to society compared with static charging. Moreover, ref[48] showed that the huge environmental and economic impacts could be induced by implementing ERS serving all kinds of vehicles in USA: compared to ICE Trucks, the summed costs reduced by 63.2% for HGTs while green house gas emissions would be decreased by 30.6%. Finally, research[61] from Sweden using the real-world movement data and spatial analysis of Sweden to assess the benefits of ERS for BEVs found that the ERS combined with homecharging could result in the maximum reduction in battery range by 62–71% which in return made the battery savings fully cover the cost of ERS.

However, it should be noted that the studies above regarding the modelling of ERS to explore the caused impacts were conducted based on the general assumptions of driving patterns, and the size, locations of ERS are almost assumed to be fixed and known. Few of them have tried to explore the optimal ERS network planning for truck transport.

2.2. Network planning approaches

Network design or in other words, the charging infrastructure network planning is one of the most challenging problem in transportation and logistics research now since current transition from conventional power to electric power is being urgently promoted, a huge number of charging infrastructures are needed.

2.2.1. Charging infrastructure planning approach

In the previous research, there are three approaches in general mostly used to deal with the charging infrastructure planning problem within the transportation network which are node-based, path-based and tour-based approaches. The categories are identified based on the spatial units of network.

Node-based approach

The node-based approach is a classical and most popularly used way to deal with the EV charging station placement problem. The objective of this kind of problem is to find the optimal locations of facilities such as charging stations with given candidate locations so that the given demand can be met at these stations. Firstly, a typical node-based approach is the set covering location model(SCLM) which aims at finding the minimum number of facilities and their locations to meet all the demand[76]. The assumption is that all the demand can be served by a facility under a certain distance. [21]proposed a bi-level SCLM with weighted multicriteria methods to maximize the charged energy by EVs in urban area and found that the charging stations should be placed close to high-density areas. Additionally, a muti-objective(minimize cost and maximize population coverage) model based on the SCLM was developed by [82].

Another node-based approach is the maximum covering location model(MCLM). It also assumes the demand could be met under a critical distance as SCLM dose while the only difference between MCLM and SCLM is that the MCLM is allowed to skip some demand nodes[17]. [22]developed a multi-objective MCLM considering cost, power grid and etc, to solve the charging infrastructure planning problem in Guwahati, India. Moreover, a case study of Lisbon, Portugal has been conducted along with the MCLM to determine the best location of charging station as well as the size of the station[25]. And its objective is to maximize the number of EVs charged.

The last node-based method is p-median model first introduced by[30] to find the optimal placement of police station on highway, which is one of the most commonly used methods to handle facility location problem. The objective of P-median method is to optimally place p facilities and allocate demand nodes i to facility j to minimize the total travel distance between demand nodes and facility. [27] adopted the p-median location model to design the electric charging station network in Turkey by incorporating the company preference and capacity concerns. Furthermore, [84]used the capacitated p-median model to select the optimal location of charging station by taking queueing theory into account.

Path-based approach

Rather than place the facility at nodes to serve demand(nodal-based vehicle flows), path-based model aims at maximizing the passing vehicle flows by placing one or more facilities on the paths(pairs of path with origin and destination), which is called the flow-capturing location model(FCLM). The flow capturing location model is first introduced by [34] to design optimal location of emergency facilities. [52] applied the FCLM to find the optimal location-allocation of fast chargers in the United states. A stochastic flow-capturing model was developed by [83] to optimize the location of public fast charging stations with estimated EVs charging demand of uncertain location in Central-Ohio, USA.

The FCLM was extened to flow-refueling location model(FRLM) by [46] to capture the alternative-fuel vehicle movements considering limited driving range, which means the vehicles have to stop one or more times at station to get enough fuel. Then they found that for FRLM, only allocating the stations at the nodes may not be sufficient to capture the entire vehicle flows so a new version of FRLM that could place stations on arcs was proposed[45]. Based on FRLM, in 2009 research[80] proposed a capacitated flow-refueling location model(CFRLM) with limited capacity at refueling stations; ref[43] updated a new FRLM considering the deviation of shortest paths that are determined by drivers to get enough fuel; a FCLM taking stochastic user equilibrium into account to model the drivers' route-choice behaviours was developed by[57] to allocate charging facilities for maximizing the served traffic flow in the network.

Tour-based approach

Tour-based or activity-based approach is the most realistic method to represent or capture the charging/driving patterns of EVs since it is conducted on the basis of data collections of real situations including behaviours like stop, rest and random trips. It always considers a detailed sequence of trips which can better represent the charging needs of EVs. By using parking demand to estimate charging demand represented by vehicle-hour, [41]developed a model to optimize the siting and sizing of charging stations for Stockholm, Sweden under the objective of minimum total costs. Ref[15] considered the dwell time between trips and state of charge during movement for hybrid vehicles and then adopted a approach to allocate charging stations so that the total traveled distance in combustion mode can be minimized. A cost-oriented model was developed by[81] to determine the optimal location and size of charging stations for electric robotaxi fleet. They used Monte Carlo simulation to derive the charging demand in a distribution network.

However, as noted, the tour-based approach which is always data-driven requires a significant and detailed amount of data including travel, route, trip, stop and driving behaviours of drivers to ensure the reality of the model. This data sometimes is hard to collect.

2.2.2. Recent planning approach about dynamic charging/electric road system/charging while driving

The above research mainly focused on the static charging facility location problem, and most existing work focusing on the dynamic charging/electrified road is also formulated under the modelling concepts of flow-capturing location model(FCLM) and the flow-refueling location model(FRLM). But the difference is that the dynamic charging/electric road allows the charging to be on the links while driving and also requires the consideration of limited driving range(battery capacity). In[57] , they proposed a probabilistic model with user equilibrium concept to consider the drivers' route choice at a given set of locations to allocate the dynamic charging facility optimally. Their work is regarded as the benchmark for dynamic charging infrastructure modelling for EVs. [39] investigated the optimal location of dynamic wireless charging tracks and battery capacity for online electric buses in the closed network in KAIST campus, korea. Then they[40] extended their model from the energy logistics perspective to a open environment to see the optimal locations and battery capacity. [49]addressed the DC locations and battery size problems for electric buses, and their study considers both deterministic model and stochastic optimization model involving the uncertainty of travel time and energy demand. A model was proposed by[33] to optimize the location of wireless charging lanes while considering its impact on capacity and users' route choice behaviors. Research[16] investigated the optimal location of wireless charging deployed at stops and battery capacity by taking into account the life cycle of battery for ebuses in a muti-route network. Moreover, ref[10] have developed a optimization model to determine the battery size and allocation of dynamic charging as well as a sub-model regarding the ebuses scheduling in a muti-route newtwork. A case study at Binghamton University was conducted with the application of proposed optimization model, which simultaneously chooses the best location of dynamic charging and battery size for ebuses[10]. Ref[53] designed a model from the perspective of decision makers to place the dynamic charging in the urban network optimally to meet all EVs energy demand at the minimum cost. Recent study[18] presented a multi-objective network design model to determine the optimum electrified roads with the technology of ERS-OC, and their objectives include minimum investment cost, maximum captured truck flows and minimum environmental cost. [32]created a optimization model that considers the dynamic and static charging placement problem on the links for EVs at the same time with objective of obtaining the greatest battery lifetime.

2.2.3. EV transportation network planning

When it comes to the charging infrastructure planning problems on freight transportation with electric vehicles, the amount of literature is limited. A benchmark research on this topic for long-haul transport is published by[11], and they proposed a framework for the optimal deployment of EVs fast-charging stations for short and long distance travel, which is the first contribution that combines the node-based and path-based model to meet the energy demand of both long-haul and suburban travel simultaneously. [69]recently developed a long-haul fast-charging station methodology for Europe to estimate the potential long-haul BETs charging demand at each station with fixed distance between the placement of charging station by taking into account the queuing theory. [62]used a trip-chain-based GIS model to derive the possible charging points for the operation of long-haul BETs in European freight network, and they did it based on the assumed driving patterns of long-haul trucks such as the stop and rest locations. Finally, research[60] provided a detailed optimization approach to modelling the optimal electrified highways that could ensure the sufficient energy supply for BETs under the objective of minimum cost on a German highway.

2.2.4. Summary

The literature review regarding the charging infrastructure network planning approach has been done in section 2, and the main approaches used in previous research are summarized in the following table 2.1.

In addition to the theories in table2.1, the application and development of them in dynamic charging infrastructure planning are summarized in the table2.2. Almost all of them are formulated on the basis of FRLM or tour-based model. And in this paper, our charging infrastructure planning approach is also formulated on the basis of FRLM combined with tour-based approach which is a kind of microscopic model aiming at locating the infrastructure(catenaries) at the detailed positions for a given demand and fixed shortest routes while making sure the given trucks flows have enough energy to finish their delivery.

Approach:	Node-based		
Method	Problem	Objective	Reference
SCLM	location of emergency service facilities	minimum number of facilities	[76]
SCLM	location of charging stations	maximum charged energy by Evs	[21]
SCLM	location of charging stations	minimum cost and maximum captured flows	[82]
MCLM	basis of maximal covering location problem		[17]
MCLM	location of charging stations	minimum cost and maximum captured flows	[22]
MCLM	location and size of charging station	maximum number of Evs charged	[25]
p-median	basis of p-median model	minimum total travel distance	[30]
p-median	location of charging stations and its capacity	minimum total costs for a given demand	[27]
p-median	location of charging stations , limited capacity	minimum infrastructure cost for a given demand	[84]
Approach:	Path-based		
FCLM	basis of flow-capturing location model	maximum captured flows	[34]
FCLM	location of fast chargers in USA	maximize number of EVs charged	[52]
FCLM	location of fast-charging stations	maximize number of EVs charged	[83]
FRLM	basis of flow-refueling location model	maximum number of Evs charged	[46, 45]
FRLM	location and size of charging station	maximum number of Evs charged	[80]
FRLM	location of wireless charging facilities	maximum captured EVs flows	[57]
Approach:	Tour-based		
	location and size of charging station	minimum infrastructure cost for a given demand	[41]
	location and size of charging station	maximum utilization rate	[15]
	location and size of charging station for Etaxi	minimum comprehensive costs	[81]

Table 2.1.: Summaries of literature review about charging infrastructure planning approach

Dynamic charging/electric road system/charging while driving				
Reference	Problem	objective	type of location variable	Solution approach
[57]	location of wireless charging	maximum number of Evs charged	binary	exact
[39, 40]	location of wireless tracks and size of battery	minimum total cost	binary	exact
[49]	location of dynamic charging	minimum total cost	binary	exact
[33]	location of wireless charging lanes	maximum number of Evs charged	binary	exact
[16]	location of wireless charging	minimum total cost	binary	heuristic
[10]	location of wireless charging , battery size, ebus schedulling	minimum total cost	binary	exact
[53]	location of dynamic charging	minimum total cost	binary	exact
[18]	location of electrified highway section	minimum investment cost and maximum captured flows	binary	exact
[32]	location of static and dynamic charging	minimum total cost and battery lifespan	binary	
[60]	location of electrified highway section	minimum total cost	continuous+ binary	exact

Table 2.2.: Summaries of literature review about dynamic charging infrastructure planning approach

3. Problem description

This chapter specifies and summarises the problems we found, which are structured as: the identified challenges in EU under current situation; the problems formulated by companies; problems derived from literature and gaps in the literature.

3.1. Current challenges in European road freight transport

As presented in chapter 1, the introduction section, the HDTs, only accounting for 2% of all vehicles, are responsible for 22% of total CO2 emissions from transport sector. Moreover, while the number of HDTs is expected to expand rapidly in the near future, the energy transition in HDTs from fossil fuel to clean energy is far behind, which is not compatible with the Europe green deal—becoming carbon neutral in 2050. Despite the fact that there is high demand to reduce emissions in heavy-duty road freight, the discussion and attention on this specific sector are still lacking. For now, the battery-electric truck is thought to be one of the most applicable solutions and has been marketed in Europe, but scaling up it still has some problems:

1. Range limitation of battery leads to range anxiety
2. Potential payload loss
3. Lack of charging infrastructures, especially for BETs
4. Vigorous promotion of BETs in the market brings about the potential battery shortage. (European battery supply highly relies on the import from China)

These issues can be suplemented by ERS.

3.2. Problems formulated by company: DAF Trucks

The prominent truck maker DAF, a major player in European truck manufacturing, has been at the heart of this research project. Their current focus is on exploring technology solutions that can tackle sustainability challenges, all while sketching out the roadmap for their upcoming generation of eco-friendly trucks. This effort aligns well with the European Union's goals, which encourage truck manufacturers to gradually shift away from traditional vehicles and ramp up investment in sustainable alternatives. DAF is pursuing two main avenues in this pursuit: hydrogen-powered trucks and battery-electric trucks. However, the latter faces challenges due to issues with batteries and a lack of charging infrastructure. These factors have led DAF to approach this solution more cautiously. DAF's journey is complicated by a lack of in-house battery technology and difficulties in securing local battery supplies in the European Union. As a result, they heavily rely on battery imports from China.

In response to these challenges, both the European Union and DAF are looking into Electric Road Systems (ERS) with dynamic charging. Their goal is to lessen dependence on external sources for batteries and, consequently, reduce the need for large onboard batteries in freight trucks. This reduction is important as batteries can be expensive. For DAF, understanding the feasibility of ERS is vital. This involves assessing its technical and economic viability. The aim is to determine if ERS is an attractive option for customers, which is crucial for maintaining DAF's market presence in the future truck industry. This is particularly important as they vie with competitors like Volvo and Scania.

3.3. Scientific problems in the literature

The gaps identified in the literature review and based on the author's knowledge:

1. the amount of research regarding charging infrastructure planning for heavy-duty trucks, especially on dynamic charging/electric highway is limited.

2. limited research has focused on the potential of ERS implementation in battery downsize
3. Little attention has been paid to the optimal ERS/dynamic charging planning for HDTs in the international(European) highway network level as we only find some country-level research in Europe
4. the battery saving analysis is lacking in ERS freight transport modelling
5. Little research focuses on the battery lifespan extension caused by implementing ERS, and a fixed lifespan was applied in previous research

.

3.4. Research questions and methodology

The vast potential of Electric Road Systems (ERS) in effecting decarbonization and abating the range-related anxieties afflicting heavy-duty trucks has ignited a discourse on their substantial deployment across Europe. However, both the public and private sectors exhibit trepidation when it comes to investing in the intricate infrastructure of dynamic charging, typified by ERS-OC. This hesitance stems from a glaring scarcity in charging facilities, which in turn stifles the broader embrace of Zero Emission Trucks (ZETs), consequently impeding the proliferation of Battery Electric Trucks (BETs) within the market's ambit. In navigating this intricately interwoven conundrum, the imperative emerges to optimize investment costs across the variegated perspectives of diverse stakeholders. The crux lies in fashioning a blueprint or a strategic model that orchestrates the precise and optimal positioning of ERS charging infrastructure.This endeavor takes a distinctive tangent by contemplating charging stations along the course of routes, rather than anchoring them at stationary nodes. The mechanism eschews capacity constraints and is channelled through links predicated upon travel pathways. Our approach to charging infrastructure orchestration draws inspiration from the Flow-Refueling Location Model (FRLM), a microscopic framework tailored to pinpoint the precise locations for infrastructure, specifically catenaries. This delicate choreography ensures that the stipulated truck flows possess the requisite energy to consummate their delivery trajectories.

But the true nucleus of our endeavor lies in illuminating the trade-offs that reside between the investment outlay in ERS and its ongoing operational costs.

Central to this quest is gauging the annual yield in terms of battery augmentation and the resultant reduction in energy expenditures—a clarion call aimed at enlightening policymakers and stakeholders alike. As we intertwine the web of problems and quandaries unveiled in the antecedent chapter, certain facets stand prominently. The exorbitant costs affiliated with batteries and the electrification of highways per kilometer, particularly with the integration of overhead contact lines, presage a discerning approach to ERS planning and the judicious selection of battery dimensions. Thus, the fulcrum of our endeavor is poised to glean nuanced insights into the intricate cost trade-offs that reverberate within the European context. It is, therefore, the pivotal pursuit of this thesis to introduce a multi-objective optimization paradigm, sculpted to blueprint the optimal network for an Electric Road Freight System (ERFS) bedecked with overhead contact lines. The vantage point for this inquiry is the bustling expanse of Western Europe—encompassing the Netherlands, Germany, Belgium, and Luxembourg—an area that epitomizes the throes of freight transportation. A corollary to this model's advent is its adaptability, with suitable modifications, to encompass a spectrum of dynamic charging technologies.

Within this intricate panorama, the following incisive research query takes form, facilitating the operationalization of our overarching research objective:

How to determine the optimal ERS network, given the trade-off between infrastructure and battery costs?

And the sub-questions are developed as follow:

1. What are the determinants of these costs including infrastructure and battery cost?
2. What other factors should be incorporated into model in addition to battery and infrastructure cost?
3. How to model the trade-off so that an optimum can be determined?
4. How to solve the model(What is the suitable solution approach)?
5. What is the result when applied to a case study of Western European area? What is a good network for these four countries?
6. What recommendations and considerations can be made for different stakeholders in ERS project based on our case study?

3.4.1. Research scope

The reality of system is represented by a model. However, not all the details are considered in the model, that is why we need simplification. Moreover, we, as model designer, should understand the way of simplifying and the assumptions behind based on the purposes of model. A clear research scope is essential to show the results within a certain boundaries. The research scope is formulated as follow:

1. **Scale**
   The study aims at determining a ERS-OC charging network for heavy-duty trucks on the basis of national and international highway in B-NL-G-L. The freight transport trip chain would start from origin city, potential paths and end at the destination city. The modelling year will be in 2030, and the assumed electrification share of trucks in 2030 will be used.
2. **Objective**
   The proposed model will minimize the infrastructure investment cost and battery cost. Every indicator used in the model will be transferred to cost. The model is a nonlinear mathematical programming.
3. **Modality and technology**
   My research only focuses on ERS, therefore only BETs(HDTs) in these four countries will be considered.
4. **Network specification**
   The network and node as well as the electrified road sections in the model are assumed to be uncapacitated.
5. **Data**
   All the data used in the model are fixed such as distance, freight demand and cost.
6. **Perspective**
   We conduct the research model from the two conflicting perspectives of view(two stakeholders are considered), which are ERS investors/operators responsible for ERS investment and logistics companies responsible for battery purchase. However, ERS is a completely new innovation, if implementing it highly depends on the policymakers' idea.

3.4.2. Research methodology

There are four methods adopted in the study: literature review, interview, mathematical model and programming and validation through a case study with scenario and sensitivity analysis.

The research methods utilized for solving the research questions are listed in table 3.1

The following figure3.1 illustrated the general steps for the research. Firstly, with the identified current problems, key factors and the methods selected from literature, the multi-objective optimization mode is proposed. Moreover, on the basis of model formulation, data availability, the appropriate solution approach will be studied and chosen to optimize the infrasturcture and battery costs simultaneously. Secondly, the scenario and sensitivity analysis will be performed to assess the network design on which the conclusion and recommendations will be delivered based.

Subquestion	Method	Detail
1	Literature review and interviews	The relevant deteminants are obtained from literature review regarding ERS modelling and interview with experts from DAF
2	Literature review	The relevant other key factors are obtained from literature review regarding freight transportation network design
3	Literature review and interview	The literature review was performed to compare the different optimization approaches existing in the literature and interview is conducted to collect information from DAF so that a suitable optimization model will be chosen and adjusted to our context
4	Literature review, mathematical programming and simulation	Selection of proper solution approach ; Run the model in the software to achieve the goal by using the mathematical modelling
5, 6	Case study with scenarios and sensitivity analysis	Findings are derived from the results analysis

Table 3.1.: Research methods

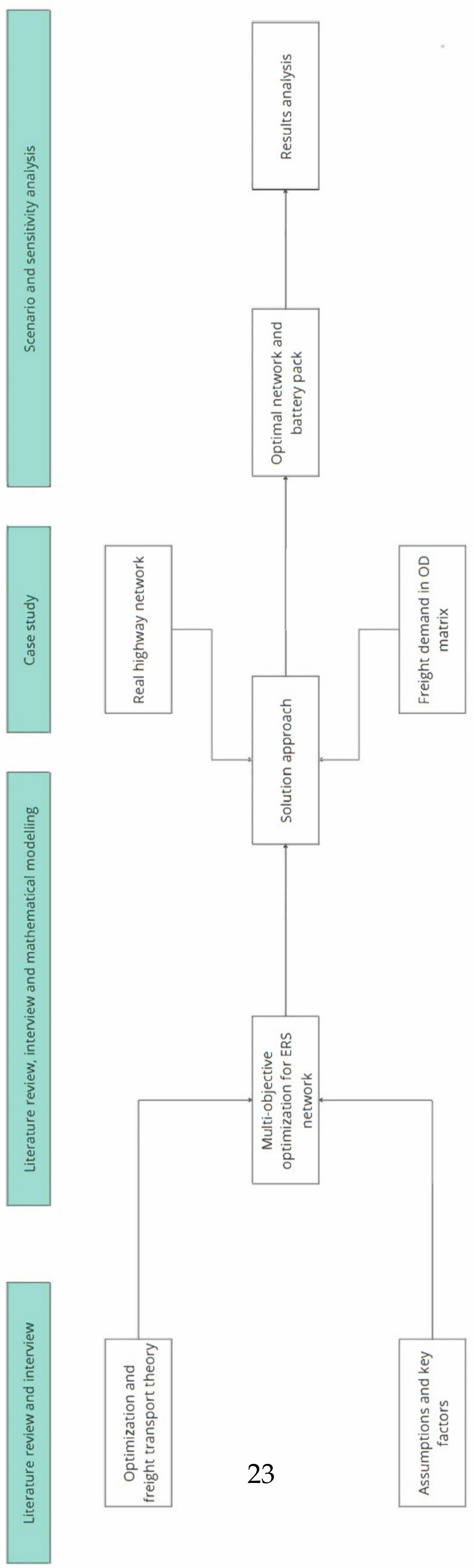


Figure 3.1.: Research framework

4. Model specification

This chapter introduces the reason why mathematical optimization model was chosen, a intuitive details of our problems, and explanations of assumptions and simplifications. Then, a formal model formulation is provided.

4.1. Why Mathematical optimization?

The utilization of mathematical optimization holds considerable promise in facilitating the discovery of optimal or nearly optimal solutions for intricately defined issues. Achieved by establishing variables, constraints, and objectives within specific research parameters, optimization presents a systematic framework for tackling identified challenges. Within the realm of charging infrastructure planning, the literature has witnessed a proliferation of diverse optimization methodologies. Informed by this array of possibilities, the selection for addressing our challenge gravitates towards a multi-objective optimization approach, which aptly aligns with the intricate nature of conflicting goals. Armed with comprehensive information and clearly delineated problems, the challenge metamorphoses into a mathematical model, poised for optimization. The paramount goal here is to craft a model that mirrors real-world dynamics, imbuing it with pragmatic and applicable traits. The results of optimization, whether attaining true optimality or coming proximate, empower the decision-making process.

In the context at hand, the path-based charging infrastructure optimization approach, guided by insights from the literature, emerges as a fitting strategy. This method deftly navigates the delicate equilibrium between infrastructure and battery costs in Electric Road System (ERS) network design. Through the formulation of two distinct objective functions—one entailing infrastructure costs and the other accounting for battery expenses—a concurrent reduction in both dimensions is achieved. The interplay of mathematical optimization and context-specific methodology stands as a potent fusion, engendering solutions characterized by astuteness and applicability. This synergy aids in the advancement of ERS network design while effectively balancing multifaceted financial considerations.

4.2. Problem characterization

The optimization model sets its sights on the intricate task of delineating the electrification of specific highway segments and requisite battery pack sizes within the ambit of a defined highway network and corresponding OD freight demand. This is achieved through the minimization of two divergent costs. As delineated in the research scope, our focus is on private logistics companies as proprietors of all Heavy-Duty Trucks (HDTs), while investment companies assume the role of ERS investors. Within this framework, a discernible and inherent cost trade-off comes to the fore. This trade-off encapsulates a clear contradiction: the potential for larger battery packs in trucks, incurring higher costs borne by the logistics companies, subsequently curtails the extent of electrification required along highways. This, in turn, translates to diminished investment costs for ERS operator companies. Conversely, a reduction in battery sizes lessens the logistics companies' financial commitment while necessitating more extensive highway electrification, thus augmenting the expenditure of ERS operator companies. This intricately woven nexus of opposing costs underpins the core of this investigation.

4.2.1. Example of the transport process to be optimized

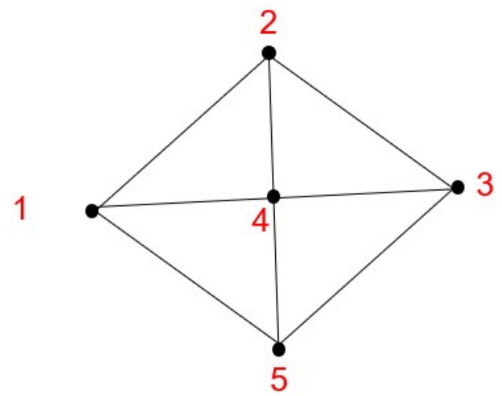


Figure 4.1.: Example

As depicted in Figure 4.1, the example highway network takes form, where nodes (1, 2, 3, 4, 5) correspond to the demand nodes and the interconnecting lines symbolize the highway segments. In the base scenario, Etruck A embarks on a journey from node 1 to node 4, culminating in its arrival at node 3. This feat is achieved with a substantial onboard battery boasting a capacity of 200 kWh, all while traversing a network devoid of any electrified links. However, an intriguing transformation unfurls upon the electrification of link (4, 3); this modification renders a 100 kWh battery sufficient for Etruck A to seamlessly navigate from node 1 to node 3. Evidently, investments are imperative for both battery procurement and ERS establishment, as visually demonstrated in Figure 4.2. The crux of the matter rests in orchestrating an equilibrium between these dual requirements. The question then arises: How can this equilibrium be effectively calibrated?

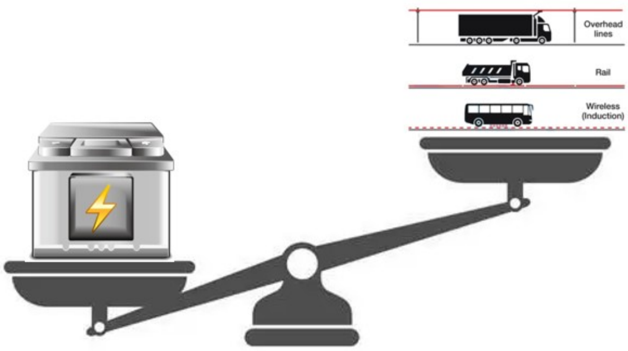


Figure 4.2.: Trade-off problems: battery or ERS

4.2.2. Assumptions and simplifications

One drawback of optimization model is that it cannot replicate the real problem with a 100% similarity, so some assumptions and simplifications should be specified to make the model to be realistic and applicable as much as possible. The assumptions and simplifications of our model are listed below:

- The above problem explanations only consider the battery-electric trucks with pantograph. While driving along the electrified highway, the BETs will be powered by ERS only, if the charging rate is higher than the consumption rate. On non-electrified sections, the truck will use energy from battery.

- All the highway network links can be electrified regardless of any forbidden regions such as tunnels or bridges.
- We assume a predefined constant charging rate for ERS per unit of time. The energy consumption per unit of time is associated with battery weight assigned, meaning that each trip with different assigned battery capacity(which is one of the decision variable) could have different energy consumption rate. However, in reality, the energy consumption rate will be influenced by many factors such as speed and other devices, and speed can vary along the day and under different traffic conditions. So a approximately average speed will be adopted there.
- The number of batteries needed for each trip is estimated based on the freight demand of each OD trip and truck average trips per year, as the truckflows in the network does not equal to the actual number of trucks. More details can be found in next section.
- The constant electricity cost per unit of kwh will be used. However, it should be noted that the market price of electricity is varying along the day depending on whether it is peak hour.
- Since one of the advantage of ERS is to help reduce the battery capacity fade, our assumption is that the battery degradation is related to its utilization rate(charging/discharging cycles)
- The percentage of HDTs that will use ERS is deterministic. But the fact is that it is hard to predict the number of trucks or trips that will actually utilize the ERS when the ERS has been launched finally. The assumption is that a fixed percentage of HDTs will use it, and when the ERS exists on the path they choose, the BETs will always use it.
- The future cost will be discounted with a fixed discount rate.
- all the cost will take place in the year at once in 2030 and be spread out over their lifespan.
- The battery size that the optimization model selects are distinct for every OD trip specifically.

4.3. Model formulation

In this section, the model formulation and definition of its parameters and variables are explained.

The sets of our model are summarised as follow:

- $I = (1, ...i, ..., S)$: set of demand nodes in the network
- $T = (1, 2, ..., t)$: set of the index of OD pair(i, j) or trip t which represents all the freight demand in the network
- O: origin node matrix, and element O_t represents the origin node of trip(OD pair) $t \in T$
- $L = (l_{1,2}, ..., l_{i,1}, ..., l_{i,j})$: set of existing highway links in the network, and $l_{i,j}$ represents the directed link connecting pairs of nodes, $i, j \in I | i \neq j$
- D in km: distance matrix with element $d_{l_{i,j}}$ representing the distance of directed highway link from node i to j, where $l_{i,j} \in L$
- M in vehicles: freight demand matrix with element m_t representing the truck flows of trip(OD pair) $t \in T$ moving from demand node to destination
- A_t: ordered set of highway links of the selected path in trip $t \in T$

The parameters, the inputs and deterministic data for the optimization model, are listed below:

- C_d: Catenary cost(€/km), cost of building ERS per kilometer
- C_b: Battery price(€/kwh)
- C_e: Electricity price(€/kwh)
- $toll_1$: toll for HGVs when using battery only on the highway(€/km)
- $toll_2$: toll for HGVs when using ERS on the highway(€/km)
- P_{ERS}: ERS charging power(kw)
- v: Etruck speed(km/h)
- ρ: air density (kg/m^3)
- C_a: aerodynamic drag coefficient
- C_{rr}: rolling resistance coefficient

- g: gravity
- AF: frontal area of Etruck(m^2)
- a_1: weight of truck+trailer+payload excluding battery weight(kg)
- z: battery energy density(wh/kg)
- SOC_{max}: maximum allowed state of charge of battery
- SOC_{min}: minimum allowed state of charge of battery
- ywd: operation trips per truck per year
- ef: ERS energy transfer efficiency
- $cycf_{min}$: minimum cycle fade rate per year
- $cycf_{max}$: maximum cycle fade rate per year
- $calf$: calendar fade rate per year
- end: battery replacing threshold(in percentage)
- τ: operational life of infrastructure(years)
- r: discount rate per year
- μ: operation and maintenance cost rate per year

The decision variables, which are the main outputs and key elements of the optimization model and determined based on the problem, are specified:

- $x_{l_{i,j}}$={0,1}: binary variable; If directed highway link $l_{i,j} \in L$ is electrified, $x_{l_{i,j}} = 1$, otherwise $x_{l_{i,j}} = 0$
- BAT_t: integer variable; the battery size selected for trip $t \in T$ (kwh)

In addition, other variables, calculated by the mathematical model based on the decision variables, are shown below:

- $annI$: annuity factor of infrastructure investment
- $annb_t$: annuity factor of battery cost of trip $t \in T$
- a_2^t: battery weight of Etrucks of trip $t \in T$ (kg)
- P_t^{truck}: energy consumption rate of Etrucks of trip $t \in T$(kw)
- $e_{l_{i,j}t}^{ERS}$: energy supply from ERS when Etruck of trip(OD pair) $t \in T$ running on electrified link $l_{i,j} \in L$(kwh)

- $e_{l_{i,j}t}$: energy consumption when Etruck of trip $t \in T$ passing through highway link $l_{i,j} \in A_t$(kwh)
- $lifespan_t$: battery lifespan of Etruck of trip $t \in T$
- $nerate_t$: non-electrification rate of route of trip $t \in T$
- $cycf_t$: cycle fade rate per year of Etruck battery of trip $t \in T$
- $SOC_{l_{i,j}t}$: state of charge of Etruck at node j on link $l_{i,j}$ of its route of trip $t \in T$, $l_{i,j} \in A_t$(in percentage)
- TOC_t^{ERS}: total toll cost when Etruck of trip(OD pair) $t \in T$ running on electrified links (€)
- TOC_t^{BAT}: total toll cost when Etruck of trip(OD pair) $t \in T$ using battery only on links (non-electrified links)(€)
- e_t: total energy consumption of trip $t \in T$

In the network, a collection of demand nodes is defined as I, symbolizing the cities where freight demand(in vehicles) m_t appears and needs to move to each other in order to transport goods, necessitating the movement of Etrucks along directed highway links in the network, labelled as $l_{i,j}$ connecting the demand cities. Therefore, the highway network can be visualized as a graph *G=(I, L)* where L represents the established directed link sets connecting demand nodes and I signifies the set of demand nodes(cities). It should be noted that not all OD pairs have a existing highway link in between which depends on the real highway structure. And since the highway normally has two directions, the links in the graph G are all set to be directed to account for this. For a specific trip (OD pair) denoted by t, the Etrucks carrying goods start its journey from the origin node, denoted by $i = O_t$. The Etrucks are assumed to depart with the maximum allowable State of Charge (SOC_{max}) and an assigned battery pack(BAT_t) which serves as one of the decision variables. They then traverse a sequence of highway links defined as $l_{i,j}$, visiting demand nodes(cities) along the way, before finally reaching its intended destination. On link $l_{i,j}$ of route of trip t, a constant energy consumption rate P_t^{truck} associated with the battery weight(a_2^t) is applied to calculate the corresponding energy consumption, denoted as $e_{l_{i,j}t}$. Furthermore, if the value of another decision variable represented by $x_{l_{i,j}}$ equals to 1, it means that the directed link $l_{i,j}$ has been chosen to be electrified, and the Etruck can constantly receive energy from ERS when running on link $l_{i,j}$ with the fixed charging rate of P_{ERS}. This way enables the calculation of both energy supply from ERS and consumption $e_{l_{i,j}}^{ERS}/e_{l_{i,j}t}$ on each link $l_{i,j}$ and the charging state

$SOC_{l_{i,j}t}$ of Etrucks of trip t t at node j after passing through link $l_{i,j} \in A_t$. In addition, as the SOC of Etruck battery cannot fall below SOC_{min}, which is the minimum allowable state of charge of battery, the route of trip(OD pair) t must be equipped with adequate length of electrified links or assigned with a bigger battery to ensure a sufficient energy supply. Consequently, various combinations of electrified links within the network and the battery pack assigned to each trip (OD pair) lead to distinct combinations of cost related to operational and battery cost.

Additionally, since the energy provided by ERS can be directly bypassed to engine, it is not necessary to always use the energy from battery, the total equivalent cycles of battery for trip(OD pair) t, upon reaching its destination, can be significantly reduced, resulting in the reduction in battery capacity degradation. Based on this, a linear lifespan estimation model related to the electrification rate of route is proposed. Likewise, the logistics companies are obligated to pay the road charge to the authority for using highway whose value depends on the distance of link $l_{i,j}$ that the Etruck travel, denoted as $d_{l_{i,j}}$, and in this case the toll for electrified link and normal highway is different. Since the batteries and infrastructures are a kind of asset with high values and will be operated and owned for many years, discounting these costs over their lifespan is essential and considered by applying equivalent annual cost.

4.3.1. Multi-Objective&Constrains

Multi-objective function

As identified problem in previous section, a clear conflicting problem was concluded: investing in ERS or investing in battery, which is also supported by two different stakeholders: ERS investors/operators and logistics companies respectively. The set of solutions is bounded by the constrains, and our goal is to find the best(near-best) solutions for the problem.

Firstly, two objective functions are introduced and explained:

1.Minimize the total amortized infrastructure investment cost for constructing ERS (electrifying highway) along the highway, from the ERS investors' perspective of view:

The first objective function for minimizing amortized annual total ERS investment cost is presented in equation (5.1), which is the summation of total length of electrified links multiplied by investment cost per km plus the annual operation and maintenance cost :

$$Minf_1 = IC = \sum_{l_{i,j} \in L} x_{l_{i,j}} * d_{l_{i,j}} * C_d * (\frac{1}{annI} + \mu) \tag{4.1}$$

2.Minimize total transport cost for the operation of all trips, from the logistics company's perspective of view:

The total transport cost consists of total battery costs and transport costs per year ; this is the main cost that the logistics companies need to pay, and the planning of infrastructures do will influence the way the companies arrange their fleets. It is composed of two main components: BC and TC as defined below:

* BC: amortized total battery cost per year pertains to the cumulative purchase expenditure incurred for all batteries essential to sustain the freight transport system throughout its operational life span. This incorporates the comprehensive battery procurement costs, given our specific scenario where maintenance expenses are encompassed within the battery price. Notably, our approach assumes that batteries retain no residual value upon culmination of their operational life. To compute this cost, we undertake a meticulous calculation, involving the summation of the anticipated battery count for each distinct trip (origin-destination pair). This count is subsequently multiplied by the unit battery cost (C_b) and the chosen battery pack (BAT_t). This product is then divided by the corresponding discounted battery annuity ($annb_t$) to ascertain the amortized total battery cost per year
* TC: the generalized transport costs consisting of toll cost and energy cost that the logistics companies have to pay on the highway

The second objective function aiming at minimizing the total transport cost per year for trip(OD pair) t is introduced below:

$$\begin{aligned} Minf_2 &= BC + TC \\ &= \sum_{t \in T} (\frac{m_t}{ywd} * \frac{BAT_t * C_b}{annb_t} + \\ & m_t * (e_t * C_e + TOC_t^{ERS} + TOC_t^{BAT})) \end{aligned} \tag{4.2}$$

where ymd is the average operation trips per truck per year.

Constraints: for the ERS investment planning problem, the following constrains are proposed.

- annuity factor of Infrastructure($annI$) and battery of each trip t $\in T$ ($annb_t$): The EAC(equivalent annual cost) is applied to reflect the annual cost for owing, operating, maintaining a asset over its entire lifespan, which enables us to compare the amortized annual cost of infrastructure and battery cost that have unequal lifespans[42].

$$annI = \frac{(1-(1+r)^{-\tau})}{r}, \forall t \in T \tag{4.3}$$

$$annb_t = \frac{(1-(1+r)^{-lifespan_t})}{r}, \forall t \in T \tag{4.4}$$

- energy supply from ERS($e^{ERS}_{l_{i,j}}$) on link $l_{i,j} \in L$ if $l_{i,j}$ is electrified:

$$e^{ERS}_{l_{i,j}} = P_{ERS} * ef * d_{l_{i,j}} * x_{l_{i,j}}/v, \forall l_{i,j} \in L \tag{4.5}$$

- Battery weight of trip(OD pair) t(a_2^t). The optimization model will optimally select a battery pack for each trip(BAT_t), and the battery weight assigned for the Etruck of trip t is considered to be associated with battery size(weight), which is calculated by using size(BAT_t) to be divided by battery energy density z:

$$a_2^t = \frac{BAT_t}{z}, \forall t \in T \tag{4.6}$$

- Energy consumption rate of Etruck of trip(OD pair) t(P_t^{Etruck}) in watt. Bigger battery indeed leads to higher total weight of Etruck, which means more energy is required to move the truck. Based on research[26] and company interview, a common energy demand model for HDT is adopted, which is a function of acceleration, rotational inertia, aerodynamic loss, rolling resistance loss, and road gradient. However, in our case, the Etruck is assumed to drive with constant speed v and no road gradient is considered. (where the unit of speed is m/s):

$$P_t^{Etruck} = \frac{\rho * C_a * AF * V^3}{2} + (a_1 + a_2^t) * g * C_{rr} * v, \forall t \in T \tag{4.7}$$

- energy consumption($e_{l_{i,j}t}$) on each link $l_{i,j} \in A_t$ of route of trip $t \in T$

$$e_{l_{i,j}t} = \frac{d_{l_{i,j}}}{v} * \frac{P_t^{Etruck}}{1000}, \forall l_{i,j} \in A_t, t \in T \tag{4.8}$$

- The lifespan of an Etruck battery for a given trip t, denoted as $lifespan_t$, signifies the duration the battery can endure under average driving conditions. This lifespan estimation encompasses two primary facets: cycle aging and calendar aging, driven by the interaction between charging/discharging cycles and time.

  Under average driving conditions, a maximum allowable degradation rate per year (DE_{max}) for EV batteries, as established in prior research, is considered. The battery is deemed ripe for replacement when its capacity dips below a predefined threshold (1 minus End), denoting the maximum permissible degradation rate. Building on these concepts, our model assumes that the battery's capacity fades, reaching the End threshold, which indicates the need for replacement.

  Furthermore, the battery degradation process entails two primary drivers: cycle age, linked to charging/discharging cycles, and calendar age, linked to time. A parameter $calf$ accounts for the average calendar aging ratio per year. Given these assumptions, the maximum cycle aging rate per year ($cycf_{max}$) is derived through the equation:

  $$cycf_{max} = DE_{max} - calf$$

  The intricate nature of battery degradation, influenced by factors like discharge depth, temperature, and charging cycles, makes precise prediction challenging. To offer a simplified strategic perspective, we introduce a linear cycle aging rate per year estimation model (4.3). This model correlates the battery's cycle aging rate per year ($cycf_t$) with the non-electrification rate of the chosen truck route ($nerate_t$). We incorporate a fixed minimum cycle aging rate ($cycf_{min}$) for fully electrified routes (0% $nerate_t$) to account for battery degradation stemming from Etrucks using battery power to access highways from logistics hubs and potential charging actions at these hubs.

  For a more comprehensive understanding, the following figure 4.3is made:

  The relationship between non-electrification rate and cycle aging rate per year:

  $$cycf_t = (cycf_{max} - cycf_{min}) * nerate_t + cycf_{min}, t \in T \tag{4.9}$$

  where $cycf_t$ is cycle aging rate per year of battery of trip t, $cycf_{max}$ is the max cycle aging rate per year, $cycf_{min}$ is the min cycle aging rate

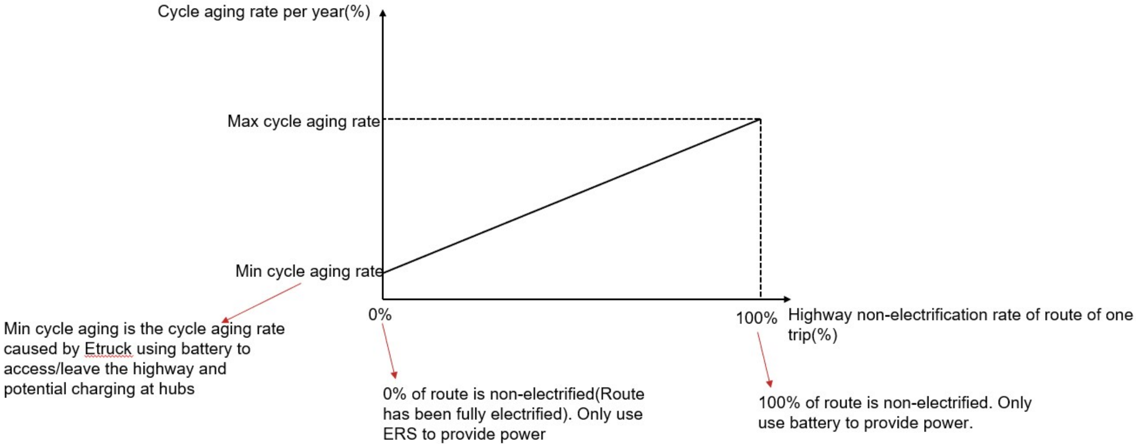


Figure 4.3.: Relationship between non-electrification rate and cycle aging rate per year

per year and $nerate_t$ is the Highway non-electrification rate of route of trip t

In addition, $nerate_t$ represents the Highway non-electrification rate of route of trip t, which is calculated by 1 subtracting the electrification rate of selected route of trip t. And the total electrified distance of selected route of trip t divided by its total route distance is the electrification rate:

$$nerate_t = 1 - \frac{\sum_{l_{i,j} \in A_t} x_{l_{i,j}} * d_{l_{i,j}}}{\sum_{l_{i,j} \in A_t} d_{l_{i,j}}}, \forall t \in T \tag{4.10}$$

In this way, the estimated lifespan of battery of trip t($lifespan_t$) can be obtained:

$$lifespan_t = \frac{End}{cycf_t + calf}, \forall t \in T \tag{4.11}$$

- Energy conservation equation; it tracks the state of charge($SOC_{l_{i,j}t}$) at node j after passing through link $l_{i,j} \in A_t$ on route of trip t, and it can not exceed its maximum SOC:

  if node i is not the origin of trip t:

$$SOC_{l_{i,j}t} = min(SOC_{max}, SOC_{l_{s,i}t} + \frac{e^{ERS}_{l_{i,j}} - e_{l_{i,j}t}}{BAT_t}), \forall l_{i,j}, l_{s,i} \in A_t, t \in T, i \neq O_t$$

$$(4.12)$$

if node i is the origin:

$$SOC_{l_{i,j}t} = min(SOC_{max}, SOC_{max} + \frac{e^{ERS}_{l_{i,j}} - e_{l_{i,j}t}}{BAT_t}), \forall l_{i,j} \in A_t, t \in T, i = O_t \tag{4.13}$$

- Total energy consumption of trip t(e_t): it is related to the energy consumption ($e_{l_{i,j}t}$) on each link of its selected route:

$$e_t = \sum_{l_{i,j} \in A_t} e_{l_{i,j}t}, \forall t \in T \tag{4.14}$$

- Toll cost for using ERS(TOC^{ERS}_t) of trip $t \in T$. The logistics companies also need to pay the road charge for the usage of highway depending on the distance of link ij ($d_{l_{i,j}}$) the Etruck will travel.

$$TOC^{ERS}_t = \sum_{l_{i,j} \in A_t} toll_2 * x_{l_{i,j}} * d_{l_{i,j}}, \forall t \in T \tag{4.15}$$

- Toll cost when using battery only(TOC^{BAT}_t) of trip $t \in T$:

$$TOC^{BAT}_t = \sum_{l_{i,j} \in A_t} tolll_1 * (1 - x_{l_{i,j}}) * d_{l_{i,j}}, \forall t \in T \tag{4.16}$$

- Upper and lower bounds of SOC of battery. Since for battery, there would be the highest and lowest allowed charging state which are fixed for a specific battery type. The SOC of Etruck on each link of each trip when transversing a series of links to reach its destination should always be within this range:

$$SOC_{min} \leq SOC_{l_{i,j}t} \leq SOC_{max}, \forall l_{i,j} \in A_t, t \in T \tag{4.17}$$

5. Data

This chapter elucidates the intricacies of the data employed as inputs within our model for the purpose of conducting a comprehensive case study. Specifically, we delve into the delineation of parameters, freight data, geographical city information, and the intricate highway network.

5.1. Data Precision

For a more profound comprehension of the dataset, it becomes imperative to establish the units, temporal attributes, and spatial refinement.

Units of Data To lend quantitative support to the tactical decision-making process, we will harness a year-based origin-destination (OD) freight demand matrix. Within the original dataset, each OD's freight demand manifests as total goods flux, quantified in tonnages. However, we shall translate this into truckflows with meticulous precision, in concordance with the truck vehicle model (refer to the subsequent section). Monetary values, including costs, will uniformly be expressed in euros, thus allowing their harmonious consideration. Further, parameters associated with energy and electricity shall adhere to the units of kw/kwh. Finally, other pivotal metrics, spanning distance and time, are elegantly denoted in km and hours, respectively.

Temporal Precision Given that our endeavor pertains to a monumental infrastructure investment project encompassing the strategic planning of an Electric Road System (ERS) network, the determination of key temporal elements is of paramount significance. The project's genesis, operational span, and diverse scenarios wield profound implications for the eventual outcomes. Our model is ingeniously structured to dissect the investment trajectory across its operational years, delineating the project's inception and operational phases—a topic artfully expounded upon in section 6.2.1.

Spatial Elaboration In the realm of freight transport modeling, the spatial fabric unfolds across varying tiers of aggregation, ranging from the intimate precincts of households to the expansive scope of cities, states, and entire nations. Within this mosaic, our model finds its anchorage in the realm of road freight transportation in four nations: Germany, Netherlands, Belgium, and Luxembourg—magnificently traversing their highways. Consequently, our spatial framework gracefully rests at the intersection of city and state levels, harmoniously encapsulating the essence of these entwined domains.

5.2. Network and freight demand data

5.2.1. Freight demand

As elucidated in the preceding segment, our network framework operates at the level of cities and states, effectively capturing the intricate tapestry of urban and regional landscapes. Within this intricate weave, cities in the quartet of Germany, Netherlands, Belgium, and Luxembourg stand as the emblematic nodes signifying the epicenter of demand.

Notably, the very sinews of this network are the links that bind these cities, outlining a tangible manifestation of the envisioned highway network—this being the very terrain upon which the Electric Road System (ERS) is destined to materialize. It is here that we draw from the wellspring of the ETI-plus dataset[70]. A dataset of profound import, it encapsulates the dynamic currents of goods demand, coursing between the European Union member states and several other nations encompassing Morocco, Turkey, Russia, Norway, Switzerland, and the United Kingdom. The focal locus of this dataset finds its expression at the NUT-3 level—an administrative stratum congruent with towns and small cities.

Within the European fold, administrative hierarchies unfold in triadic tiers in compliance with the edicts of the European Union. These tiers are distinguished as NUTS-1 (representing regions), NUTS-2 (embodying main and capital cities, alongside provinces), and NUTS-3 (encompassing towns and small cities). However, a sobering revelation emerges: certain NUTS-3 regions evince rather modest freight demand volumes earmarked for transportation. In a judicious bid to streamline our model, mitigate computational intricacies, and facilitate a strategic foundation for infrastructure planning, we harness the art of data clustering.

For the nexus of Belgium, Netherlands, and Luxembourg, the crucible of freight demand vested in NUTS-3 level cities is seamlessly clustered around the provincial capital city, in harmony with the NUTS-2 level delineation. A nuanced paradigm unfolds for Germany, due to its expansive expanse. Within its territorial embrace, the freight demand—whose contours are delineated at the NUTS-3 level—converges around several pivotal main cities, as circumscribed by the NUTS-2 definition for each state. This configuration presumes that the entirety of trucks from each province or state emanates from these clustered urban nuclei.

The culmination of these intricate maneuvers bequeaths unto us an aggregated freight dataset, a tapestry woven to encapsulate all road freight transpiring within these four nations—orchestrated exclusively between the primary cities that grace their highways. It is the very crucible of NUTS-2 level cities that emerges as the apotheosis of our aggregated demand nodes. Owing to the temporal confines of our dataset, exclusively cast for the year 2030, our inaugural year aligns itself with this temporal horizon.

An illustrative tableau of this freight demand's Origin-Destination (OD) matrix adorns Table 5.1. To illustrate, as the chronicle of 2030 unfurls, the metropolis of Antwerpen beckons for the transportation of 513,026 tons of commodities, destined for the embrace of Brussel.

	Arr. de Bruxelles -Capitale / Arr. van Brussel-Hoofdstad	Arr. Antwerpen	Arr. Hasselt	...
Arr. de Bruxelles -Capitale / Arr. van Brussel-Hoofdstad	0	199495	90661	...
Arr. Antwerpen	513026	0	3216366	...
Arr. Hasselt	196469	3793278	0	...
...	...	...	...	0

Table 5.1.: freight demand OD matix in tonnages in 2030

The aggregated data above is only about the regional and long haul demand expressed in tones and needs to be translated into number of heavy-duty battery-electric trucks(HDBETs), since they are the target users that will use the ERS for national and international road transport. However, the fact is that in 2030(the base year of the project) not all the HDTs will be the battery-electric trucks and only some of the fleets will be electrified. Therefore, a electrification share rate should also be adopted. The percentage of BETs in 2030 is highly uncertain which is predicted to be 30%-50% by following the development plans of some key European OEMs[67]. In this case, **the market share of 50**% is selected.

Moreover, I use the **average payload factor of 14 tons** according to the information of Mercedes Benz HDTs[47] to convert the goods volumes to number of trucks moving on the road on the basis of freight trip estimation model[75], as described in equation below:

$$m_t = \frac{U_t * BET_{share}}{payload} \tag{5.1}$$

where m_t is the converted freight demand (in vehicles) of trip(OD) t as explained in section 5.3.1, U_t is the freight demand (in tones) of trip t before conversion, BET_{share} is the market share of BETs and $payload$ is the payload factor.

In addition to the truck flows per OD trip, the number of Etrucks that will use ERS also needs to be estimated. We assume that a truck will operate 250 times(ywd) a year based on research[62]. Therefore, number of trucks operating per OD trip is calculated by using its truck flows(m_t) divided by average trips per truck per year(ywd) as formulated in the objective function.

5.2.2. Network

Another pivotal input matrix is the Origin-Destination (OD) distance, representing the linkages or connections between nodes of demand or, equivalently, the interconnecting distances within the highway network amid demand nodes, or cities. Nevertheless, it is crucial to acknowledge that the presence of highway links between all OD node pairs is contingent upon the intricate configuration of the actual highway network within the four nations. Leveraging the comprehensive ETIplus dataset, we can deduce the distance OD matrix by grounding it upon the ascertained aggregated demand nodes. Table 5.2 showcases an illustrative instance of such a distance OD matrix. For instance, the highway link distance linking Antwerpen and Hasselt measures 82 km.

The geographical data pertaining to demand nodes and the actual highway network is extracted using the OpenStreetMap and Networkx software packages. The resultant primary highway networks and demand nodes are visually represented in figure 5.1, wherein the demand nodes are depicted as red nodes and the highway network is illustrated using black links

	Arr. de Bruxelles -Capitale / Arr. van Brussel-Hoofdstad	Arr. Antwerpen	Arr. Hasselt	...
Arr. de Bruxelles -Capitale / Arr. van Brussel-Hoofdstad	0	57	77	...
Arr. Antwerpen	57	0	82	...
Arr. Hasselt	77	82	0	...
...				

Table 5.2.: distance of highway link OD matrix in kilometers

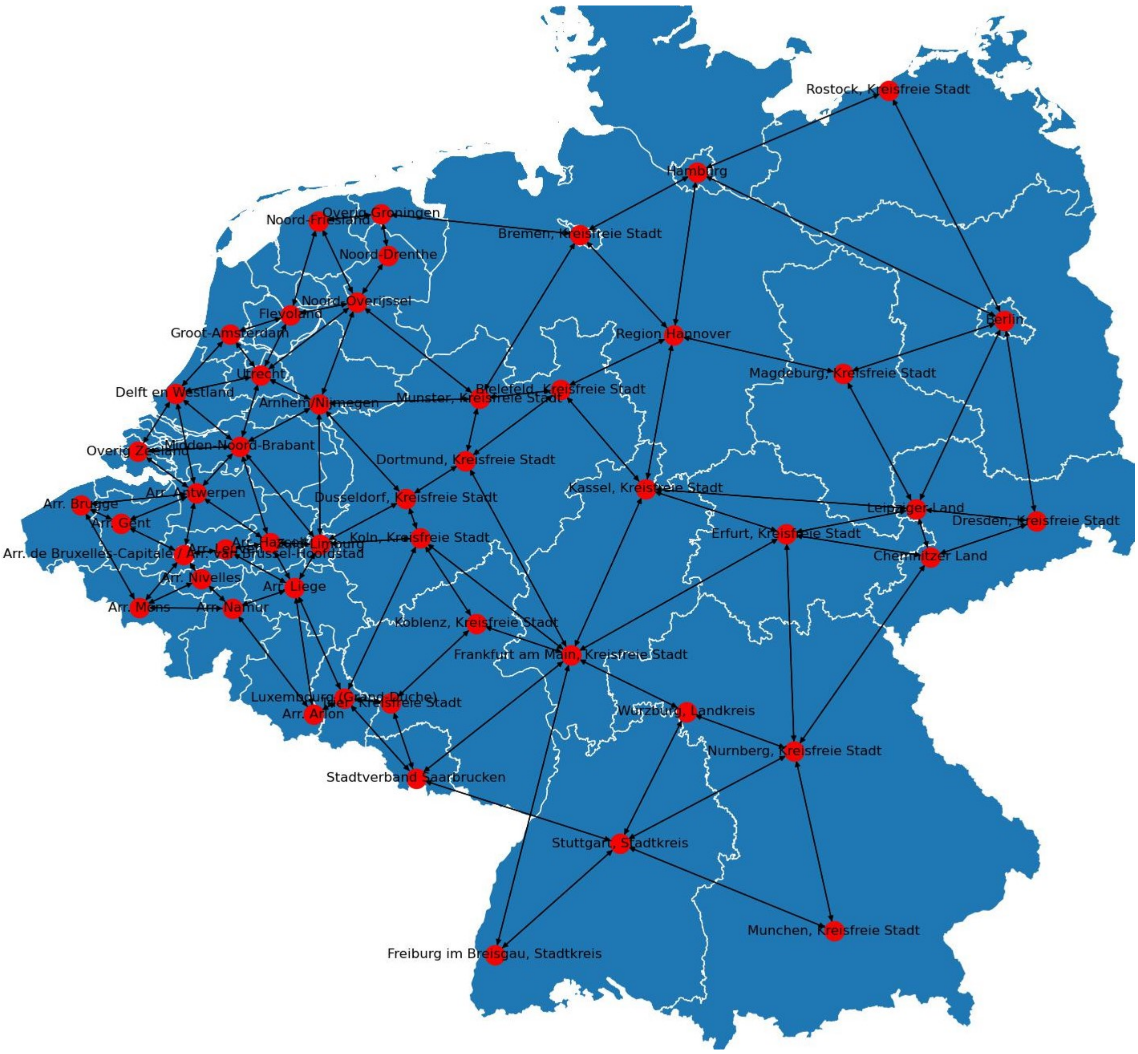


Figure 5.1.: The visualization of highway network in these four countries(own work)

5.3. Parameters

5.3.1. Cost-related

Infrastructure cost

The deployment of Electric Road System (ERS) infrastructure along highways involves two fixed capital costs associated with power wire installation and substation establishment. The overhead contact line necessitates integration with the national power grid, while substations enable conversion of high-voltage alternating current to the voltage compatible with Etrucks. Prior research, as documented in section 2, has yielded varied ERS cost estimates, ranging from 0.5 to 3.1 million EUR per kilometer (bi-directional), as reported by Kühnel[71] in Germany and Taljegard et al.[73] in Norway. Consequently, we adopt an installation cost of 1 million EUR per kilometer (bi-directional) for our investigation. The annual operation and maintenance (O&M) cost is projected at 2% of the initial investment cost, as supported by Taljegard et al.[73]. Additionally, the technical operational lifespan of ERS infrastructure is observed in the literature to span 20-35 years[73, 56], with our research assuming a 25-year operational lifetime. To amortize all investment costs over this duration, a discount rate of 2% is applied[38].

	cost
ERS cost(C_d)	€500,000/km(one direction)
O&M cost(μ)	2%
discount rate(r)	2%
operational life(τ)	25

Table 5.3.: Infrastructure cost-related parameters

Battery cost

Given the dynamic nature of battery prices attributed to mass production and technological advancements, the battery cost is anticipated to reach 150 EUR per kilowatt-hour (kWh) in 2030, aligned with our project's baseline year. This value was confirmed after consultation with sourcing experts with some companies.

	cost
battery price(C_b)	€150/kwh

Table 5.4.: Battery cost

Electricity cost

Users traversing the highway are subject to an electricity cost of 0.22 EUR per kWh during operation, in accordance with data from Aronietis et al.[12], reflecting the average rate in Belgium. Notably, battery-derived energy and ERS-supplied energy are treated as having equivalent costs in our research.

	cost
electricity price(C_e)	€0.22/kwh

Table 5.5.: Electricity cost

Toll

Toll fees represent charges incurred by users when utilizing the highway. The Dutch Ministry is formulating plans to introduce a Heavy Goods Vehicle (HGV) toll for vehicles exceeding 3,500 kg, akin to practices in Belgium and Germany. The typical rate imposed on diesel-fueled HGVs is approximately 0.15 EUR per kilometer[8]. Furthermore, the toll amount is contingent on the ecological attributes of the vehicles, implying that cleaner trucks warrant reduced toll charges. In our scenario, the Etruck utilizing ERS is deemed a more environmentally-friendly mode compared to battery-powered Etrucks. Consequently, considering the study by Van Mierlo et al.[56], tariffs for emission-free HGVs are anticipated to range from 50% to 75% of the rate applicable to diesel trucks. Thus, a discounted toll rate of 0.1 EUR per kilometer is allocated for Electrified highways, while the standard toll rate of 0.15 EUR per kilometer prevails for conventional highways.

	cost
toll for ERS highway($toll_2$)	€0.1/km
toll for normal highway($toll_1$)	€0.15/km

Table 5.6.: Toll cost

5.3.2. Vehicle-related

Battery life cycles

The degradation process of batteries is inherently unpredictable. For strategic analysis, this research utilizes the highest average Electric Vehicle (EV) battery total degradation rate per year, which stands at 4.2%, as based on the Nissan Leaf model[1]. This rate accounts for both cycle fade and calendar fade. Given that Etrucks have elevated output energy and operating temperatures compared to regular EVs, the highest total degradation rate per year for EVs is adopted as a conservative estimate for Etrucks[1]. Furthermore, considering optimal conditions, the average fixed calendar rate per year can be less than 1%, hence we choose a fixed calendar rate of 0.8% based on a study by Ali et al.[9].

The battery replacement threshold denotes the point at which owners must replace batteries to ensure adequate power supply. According to discussions with the company and Gorzelany's report[28], the replacement criterion is when battery capacity falls below 60%-70%. Consequently, the replacing threshold is set at 40% (1 - 60%) to allow for the maximum allowable battery degradation rate.

Additionally, a fixed cycle aging rate per year, resulting from battery usage to access/leave highways to/from logistics hubs and while charging at city hubs, is assumed to be 1%. This estimation is based on the short distances involved, as indicated by the ETIdataset[70], where the average distance between city centers and highways is less than 10 km.

	value
maximum total degradation rate per year(DE_{max})	4.2%
fixed average calendar aging rate per year($calf$)	0.8%
fixed cycle aging rate per year caused by using battery to access/leave highway from/to the logistics hubs and charging at hubs in the city($cycf$)	1%
battery replacing threshold (maximum allowed battery degradation)(End)	40%

Table 5.7.: life cycle parameters

Truck energy consumption model

A widely employed vehicle energy consumption model, as described in the model formulation section, is applied. All pertinent technical parameters, based on the Mercedes Benz Actros[47] and DAF truck model, are listed in Table 5.8. This model assumes a fixed weight for the truck, trailer, and payload.

	value
average truck speed(v)	80km/h
aerodynamic drag coefficient(C_a)	0.6
rolling resistance coefficient(C_{rr})	0.005
frontal area of Etruck(A_f)	10.2m^2
air density(ρ)	1.3kg/m^3
gravity(g)	9.8m/s2
weight of truck+trailer+ full payload excluding battery(a_1)	40,000kg

Table 5.8.: energy consumption model

battery characteristics

Drawing on information from battery packs used in Volvo HDBETs[2] and Mercedes Benz Actros electrification research[47], a battery pack holds 90 kWh of total energy. We consider 20 capacity options for HDETs in our scenario, ranging from 90 kWh to 1800 kWh, a decision variable in the model. The smallest battery pack of 90 kWh is adequate for trips between city centers and Ehighways. Detailed battery technical specifications are provided in Table 5.9.

	value
energy of one pack	90kwh
energy density(z)	232wh/kg
maximum allowed SOC(SOC_{max})	0.9
minimum allowed SOC(SOC_{min})	0.1

Table 5.9.: battery parameters

Charging characteristics

Charging power for ERS is subject to ongoing discussion and scaling. However, considering estimates from Siemens Mobility and Scania[58, 29], plausible charging rates range from 100 kW to 750 kW (e.g., 100 kW, 150 kW, 300 kW, 500 kW, and 750 kW). In this study, we adopt a charging rate of 150 kW as our base assumption. Moreover, the transfer efficiency is set to be 90%.

	value
charging power of ERS(P_{ERS})	150kw
energy transfer efficiency(ef)	90%

Table 5.10.: charging characteristics

6. Solution approach

Traditionally, two primary solution methodologies are employed to tackle optimization problems. The first entails employing exact methods through solvers such as Cplex, which derive optimal solutions. Alternatively, metaheuristic methods, capable of seeking optimal or near-optimal solutions within reasonable time frames, provide an alternative approach. For our multi-objective case, a diverse set of Pareto optimal solutions is preferred. This approach grants policymakers insights while considering solution limitations, thereby facilitating informed decisions.

Given the complexity of our highly nonlinear optimization model, exact methods are inadequate. Hence, we employed the genetic algorithm (GA), a well-established evolutionary algorithm. GA efficiently seeks near-optimal solutions within acceptable time frames, addressing our complex problem.

Before applying the GA, the multi-objective function is transformed into a single objective function using the weighted sum method (A Priori). By assigning various weight combinations to the objectives, a comprehensive set of potential solutions can be explored. Balancing the magnitudes of the individual objective functions is crucial. This practice ensures that the combined objective functions remain unbiased by any single objective[50].

In this case, the two objective functions are normalized by dividing them by their respective maximum function values. Normalization facilitates setting weights for the objectives within a uniform range of 0 to 1. The aggregated objective function is formulated as follows:

$$MinF = w1 * \frac{f1}{IC_{max}} + (1 - w1) * \frac{f2}{TTC_{max}} \tag{6.1}$$

where IC_{max} is the amortized maximum infrastructure cost and TTC_{max} is the amortized maximum total transport cost.

The flowchart of genetic algorithm is illustrated in figure6.1, the process will continue until the maximum generation is reached.

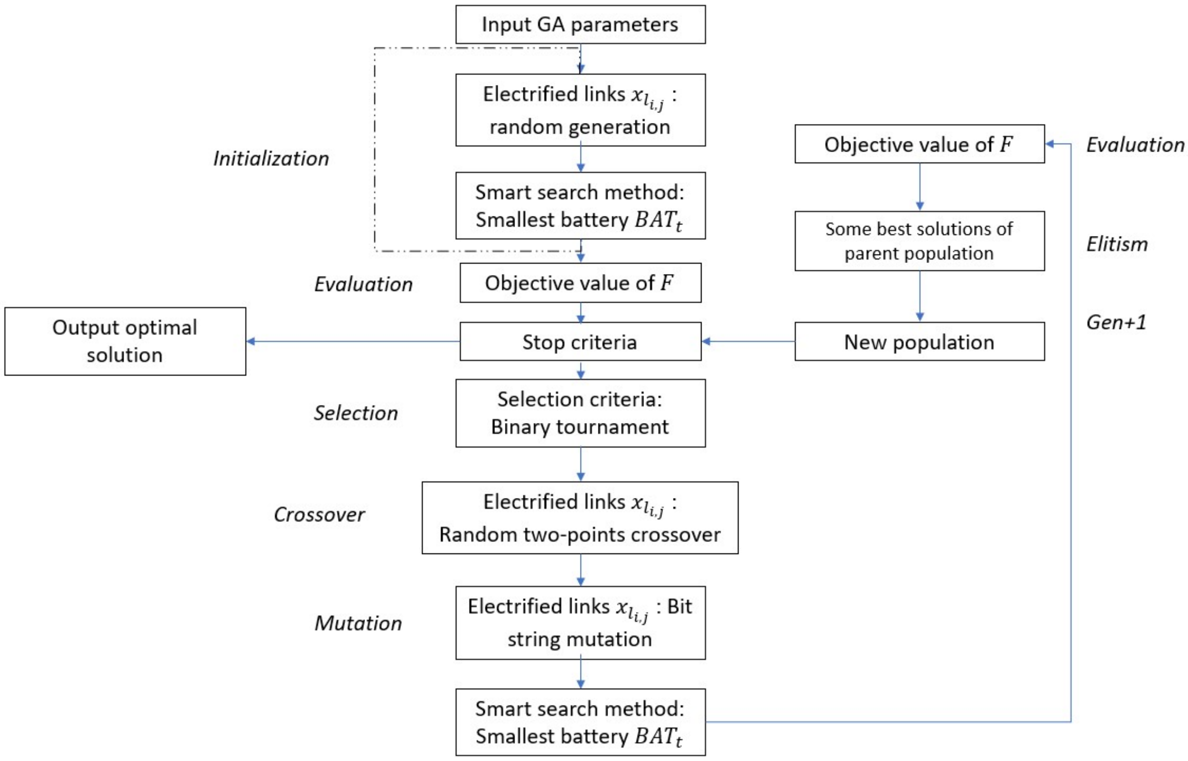


Figure 6.1.: Steps of impoved Genetic algorithm

6.0.1. Initialization

The example chromosome is shown below in figure 6.2, but notably, the real case of chromosome will be much longer than the example. For the first part, the binary variable(0 or 1) is randomly assigned to every directed highway link to represent whether a highway link is electified or not. For the second part, to simplify the computation complexity, the battery size selection of each trip will be obtained by a smart search method proposed in section 7.0.3.

6.0.2. Selection

Tournament selection and Roulette wheel selection are the two most popular selection strategies in GA that had been successfully used in wide variety of applications and proved to be efficient. Considering the complexity,

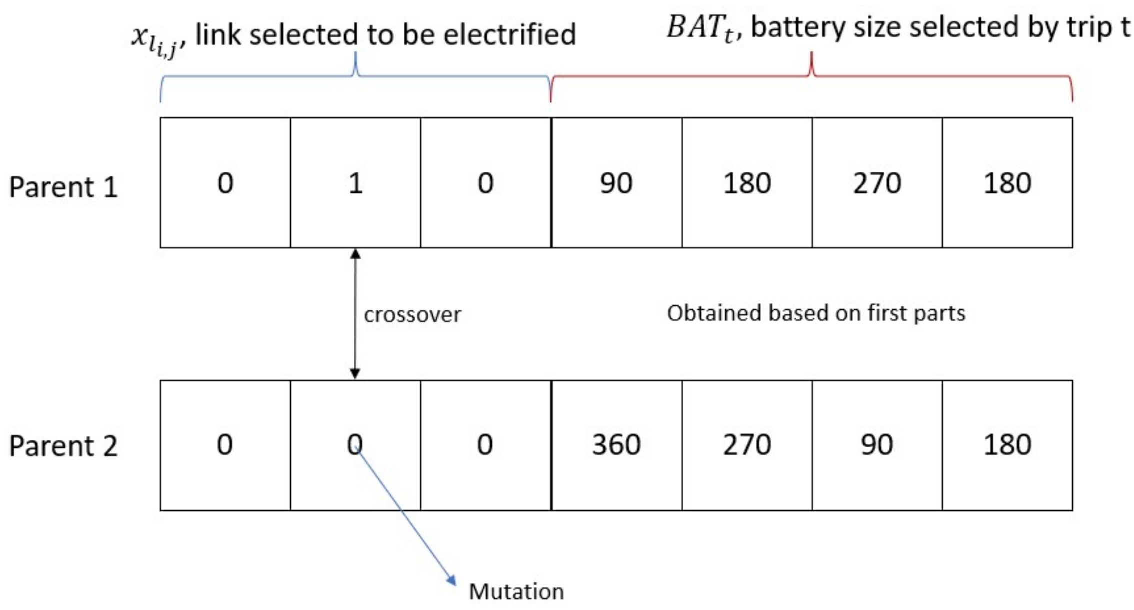


Figure 6.2.: Chromosomes

tournament selection was adopted for our case as it reduces the time complexity[63]. N individuals from the population are chosen randomly, and then they are competing with each other by comparing their corresponding objective value(or fitness value). The individual with the best objective value(fitness value) wins the competition and will be proceed to the next step of GA. In particular, 2 is chosen to be the tournament size in our research as most research did in their study. An example of selection strategy is shown in figure 6.3.

6.0.3. Smart search method

To reduce the computation complexity, a smart search method is designed to calculate the smallest battery size assigned for each trip. So the battery size of each trip(BAT_t) is treated as variables rather than decision variables. Since based on the first parts of chromosome–the availability of ERS on that route, the smallest battery size can be searched, which should meet the constrain (5.18) to ensure that the SOC of battery is always within its allowed range during its transport.

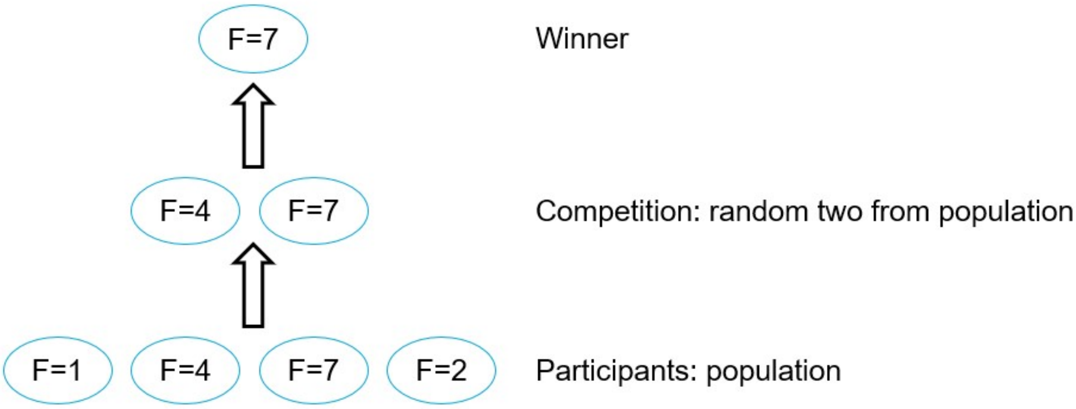


Figure 6.3.: Selection strategy

6.0.4. Crossover and Mutation

Crossover is the most important step of GA, which plays a vital role in influencing the speed and efficiency of searching for the solutions. In our case, the K-point crossover operator, or more specifically, two-points crossover operator is adopted: two random points on the individual chromosome are chosen and the genetic information(genetic slices) is exchanged at these points. The process is illustrated in figure6.4, where the blue slices of parents are exchanged.

Figure 6.4.: Crossover representation

Moreover, mutation operator also shows a significant impact on the performance of genetic algorithm. The bit string random mutation was developed in our study as shown in figure6.5: several genes are randomly selected to change.

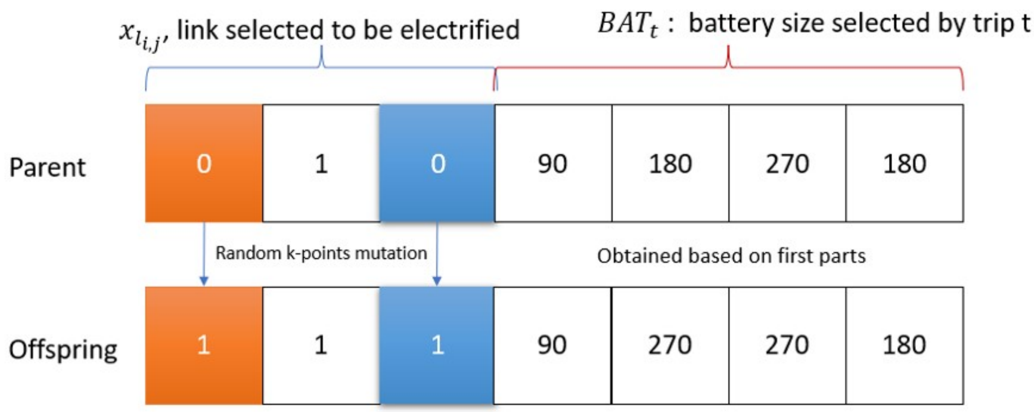


Figure 6.5.: Mutation representation

6.0.5. Elitism

The genes in the selected chromosomes are changed after crossover and mutation. So it is possible that all the parent populations are replaced by the off-springs although the off-springs perform worse than their parents. This also means that some good solutions of current generation are discarded. To avoid this situation, Elitism operators(Elitist preservation) are introduced[6], which has been proved that the GA with Elitism can result in the global optimal solution. In our study, the Elitism operator is integrated:

- Some best chromosomes in the current population are directly transferred into next generation without any change.

7. Model verification

Before applying the model to the final case study, it's imperative to verify its functionality against a simplified network. Thus, the model is applied to a preliminary network planning scenario, focusing on a segment of the European freight transport corridor. This specific corridor originates from the Rotterdam–The Hague area in the Netherlands and terminates in Munich, Germany, spanning a distance of 1914 km (bi-directional).

The test network, visualized in Figure 7.1, is constructed utilizing Networkx and OpenStreetMap packages. For this test, we have extracted 9 primary demand nodes, representing major cities, from the larger map presented in the previous section. These cities include Delft, Utrecht, Arnhem, Düsseldorf, Köln, Frankfurt, Würzburg, and Munich. To create a comprehensive representation, 16 directed highway links, facilitating bi-directional traffic, connect the nodes within the network.

The freight demand for each Origin-Destination (OD) pair, encapsulating truck flows, is obtained from filtered data as elaborated in the Data section. All remaining model parameters and assumptions are consistent with those applied to the broader case, as elucidated in the previous section.

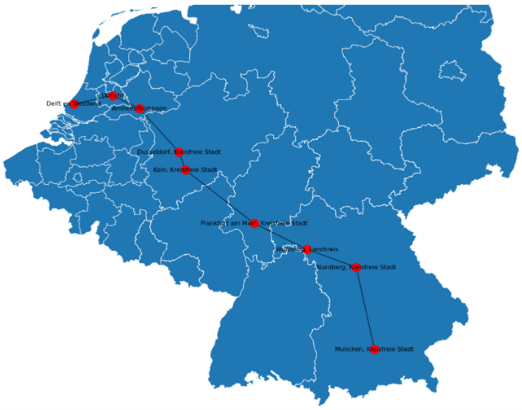


Figure 7.1.: Test network–European freight transport corridor

The Pareto front of the test result is shown in the following figure7.2 by trying different combinations of weights which is not in a regular shape due to the small size of test case. As we can find from the figure 7.2, with the implementation of ERS on the corridor(more and more highway links are electrified), the total transport cost per year(battery cost, energy cost and toll cost) can be significantly reduced. For instance, with a investment cost of around 70 billion Euros per year in building 1914km ERS, a huge reduction of 29% in total transport costs from 0.66 billion Euros to 0.47 billion Euros per year can be obtained, especially for battery cost, which is decreased by 82.5% when the corridor is fully electrified.

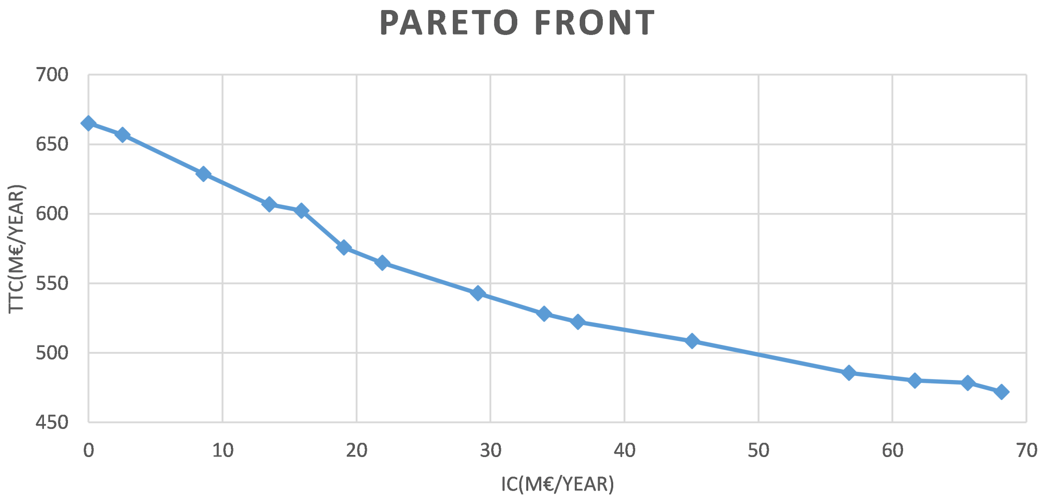


Figure 7.2.: Pareto front of test network

Furthermore, from Figure 7.3, a distinct trade-off between infrastructure cost and annual battery cost emerges. As the electrification of more highway links along the corridor progresses, the battery cost demonstrates a downward trend. Notably, the total battery savings can potentially reach around 0.12 billion Euros per year when comparing the outcomes of a scenario with no Electric Road System (ERS) against the full electrification of the 1,914-km corridor, assuming unlimited budget for ERS deployment. However, when budgetary constraints are considered, the break-even point becomes a significant consideration. This point corresponds to the lowest value of the total system cost (Infrastructure Cost + Battery Cost), indicated by the red point in the graph. This implies that the accumulated battery savings optimally offset the infrastructure construction cost. Therefore, the break-even design that represents the most advantageous solution involves electrifying 1,594 km of

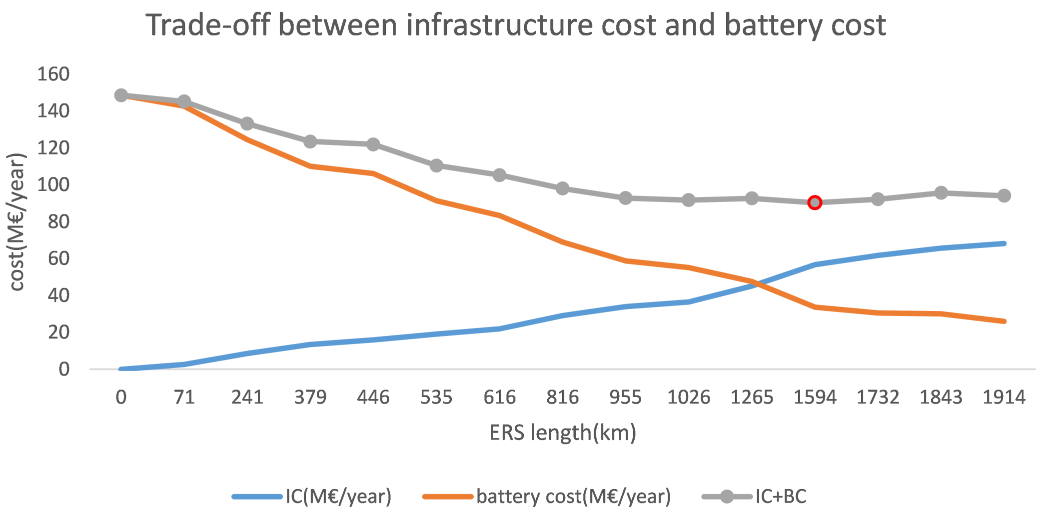


Figure 7.3.: trade-off between battery cost and infrastructure cost

the highway. This configuration is depicted in Figure 7.5, where only specific highway links – those between Arnhem and Dusseldorf, and Frankfurt and Koln – are excluded from electrification, accounting for 17% of the corridor length. This design choice aligns with the input of truck flows. Notably, the truck flows per year per kilometer on these two unselected links are relatively low. Consequently, the resultant battery savings would inadequately offset the expense of ERS implementation on these segments. This observation underscores the robustness of the model results in accordance with our expectations.

Furthermore, Figure 7.4 illustrates a nuanced relationship between infrastructure cost and total transport cost. This relationship exhibits a less pronounced trade-off due to the substantial influence of energy cost and toll cost, which dominate the composition of total transport cost. Consequently, the implementation of Electric Road Systems (ERS) has a limited impact on these components. However, the gray line depicting the total system cost (Infrastructure Cost + Total Transport Cost) consistently declines as the length of ERS increases, showcasing a positive trend. This outcome suggests that, particularly when considering the implementation of ERS on a busy European freight transport corridor, there is an inherent advantage in constructing more ERS infrastructure. Notably, this advantage is contingent upon the government's ability to reduce toll fees for Etrucks utilizing electrified highways. The consistent reduction in total system cost signifies a beneficial dynamic. Despite the presence of upfront infrastructure expenses, the sav-

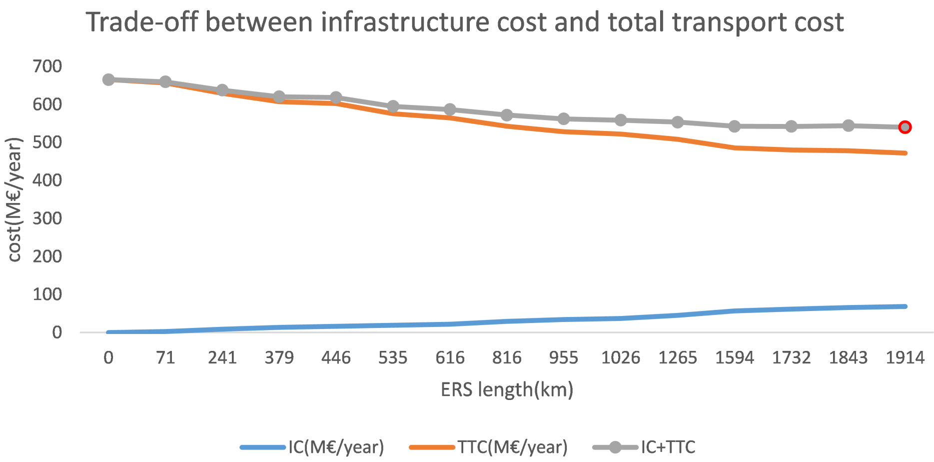


Figure 7.4.: trade-off between total transport cost and infrastructure cost

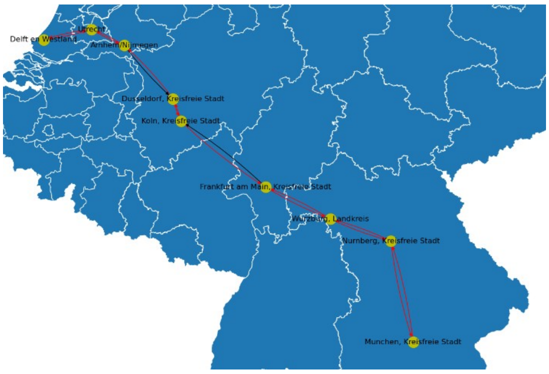


Figure 7.5.: Break-even network design(red: electrified link)

ings generated from lowered total transport costs outweigh the costs of ERS construction. This trend persists due to the high truck flows on the corridor. Consequently, if the government can facilitate reduced tolls for Etrucks leveraging electrified highways, the construction of additional ERS infrastructure remains a viable and profitable proposition.

8. Case study–highway network in NL, BE, DE and LU

In this chapter, the proposed optimization model and solution approach were applied to address the Electric Road System (ERS) network design for the highway network spanning the Netherlands, Germany, Luxembourg, and Belgium (depicted in Figure 8.1). As introduced in the preceding chapter, all pertinent data for this case study has been presented.

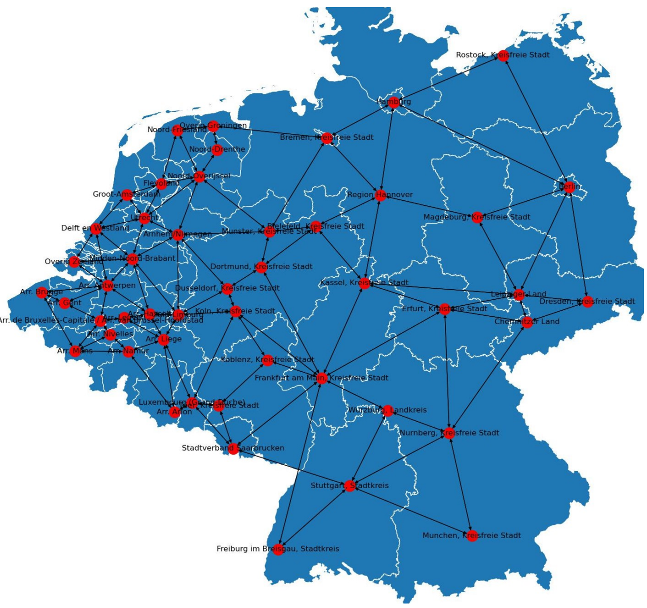


Figure 8.1.: The visualization of the highway network in these four countries(own work)

The improved genetic algorithm, outlined in previous sections, has been implemented in Python to facilitate the optimization process. The algorithm's parameter settings were meticulously chosen, aligning with the guidelines detailed in Chapter 7 and summarized in Table 8.1. Given the chromosome's length of 208 (reflecting the 208 directed highway links within the network), the probabilities of crossover and mutation are deliberately set at sufficiently high levels. This decision aims to enhance the exploration of a broad spectrum of solutions, mitigating the risk of premature convergence to local optima during computation.

Parameters	Values
Generations	2000
Population size	100
Crossover probability	0.9
Mutation probability	0.6
Number of Mutation locations	30

Table 8.1.: Improved genetic algorithm parameters

8.1. Result analysis

8.1.1. Overview

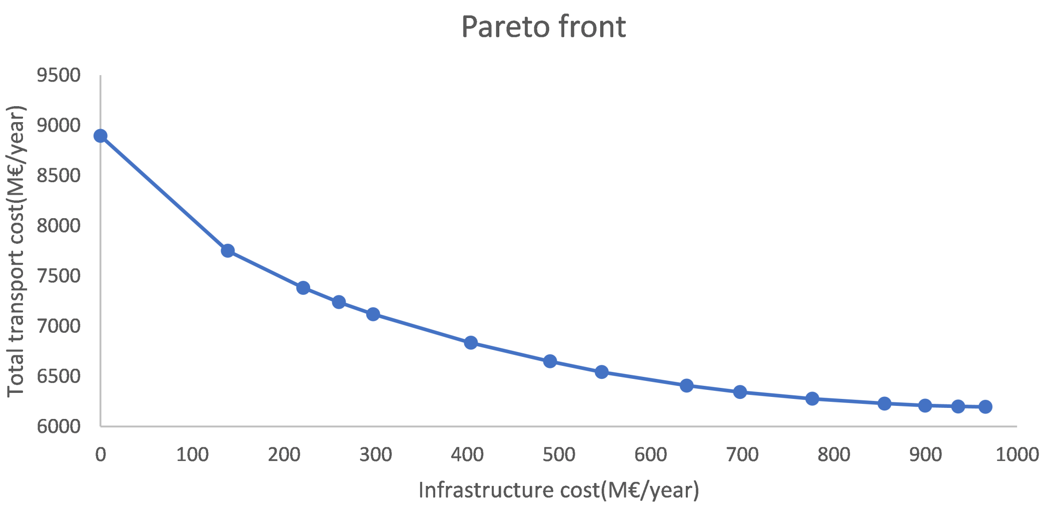


Figure 8.2.: Pareto front

By systematically varying weight combinations, we have successfully obtained a collection of potential optimal solutions, each corresponding to different Electric Road System (ERS) investments (ERS lengths). These solutions are organized into a Pareto front, as visualized in Figure 8.2. Evidently, a well-defined trade-off materializes between the annual total transport cost and the infrastructure investment for ERS deployment across the Netherlands, Germany, Luxembourg, and Belgium. As ERS investment escalates, the overall transport cost borne by logistics companies — encompassing battery cost, energy cost, and toll cost — undergoes significant reduction. This trade-off provides policymakers with an initial overview of how the implementation of ERS can influence total transport cost under diverse budgetary scenarios. For instance, under an unlimited budget, an investment of 0.96 billion Euros per year, facilitating the construction of a fully electrified 27,114-kilometer highway network, leads to an impressive 30.3% reduction in annual total transport cost. Specifically, this reduction corresponds to a decrease from 8.9 billion Euros per year to 6.2 billion Euros per year. Notably, this cost reduction substantially outweighs the ERS investment itself, reinforcing the compelling economic viability of such endeavors.

8.1.2. Trade-off between IC and TTC

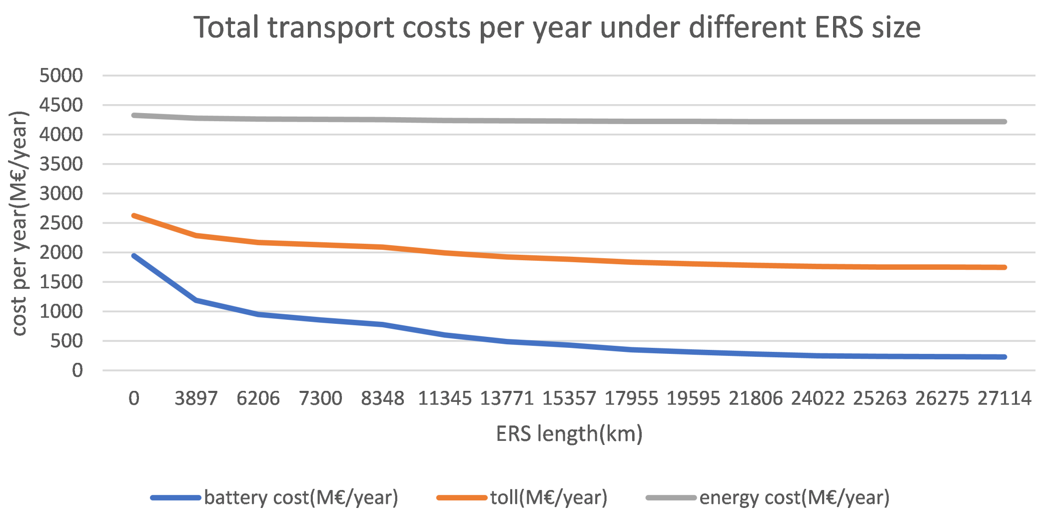


Figure 8.3.: Impact of ERS length on transport cost per category

For a comprehensive insight, each optimal solution within the Pareto set has been individually extracted and is visually represented in Figure 8.3. This illustration captures the alterations in individual cost components encompassed in the total transport cost per year. The overarching trend indicates a consistent reduction in the Total Transport Cost (TTC) as ERS length increases. Notably, the most significant impact of ERS is observed in the re-

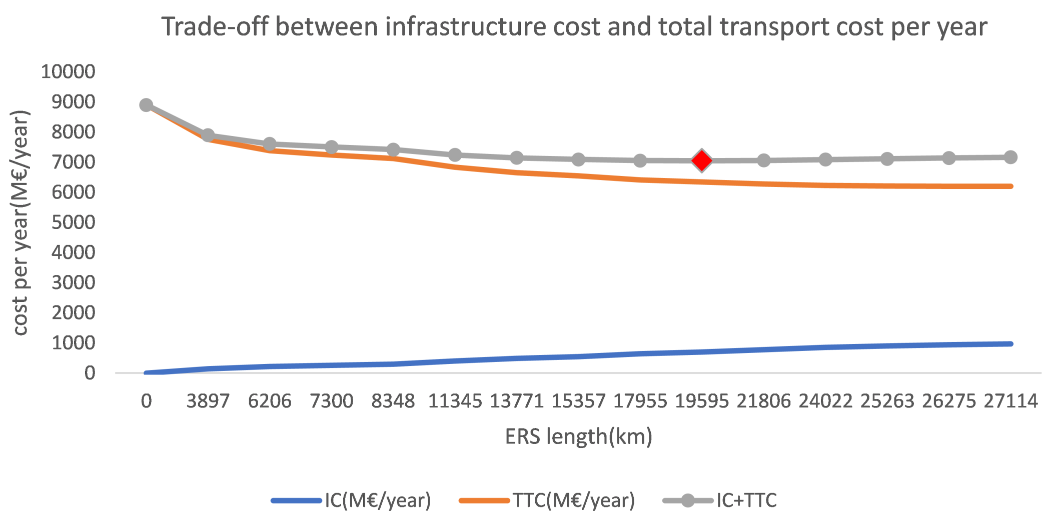


Figure 8.4.: Trade-off between infrastructure cost and transport cost

duction of battery costs. However, the influence of ERS on energy costs and toll costs remains relatively minor. This phenomenon persists despite reductions in onboard battery weight and the application of lower toll rates for using electrified highways, as the battery weight accounts for a very small part of vehicle gross weight. The maximum energy cost reduction observed through modeling is relatively modest, amounting to 2.5%—from 4.3 billion to 4.2 billion Euros annually. This marginal reduction stems from the fact that battery weight, albeit reduced, constitutes only a fraction of the vehicle's gross weight, exerting limited influence on total energy consumption. This observation is reaffirmed by Figure 8.4, which shows a less distinct trade-off between Total Transport Cost (TTC) and Infrastructure Cost (IC). The substantial portion of energy and toll costs within total transport cost prevents total transport cost from being substantially impacted by ERS implementation.

In scenarios constrained by limited investment budgets, prudent decisions are essential to optimize benefits for both the transport system and stakeholders, notably logistics companies (users). Thus, our research introduces the concept of a break-even point. This point, represented by the lowest Total System Cost (Infrastructure Cost + Total Transport Cost) and denoted by the red point in Figure 8.4, signifies the optimal balance. It signifies the point where total transport cost savings for logistics companies most effectively cover the incurred ERS construction cost on the highway network. In this context, the break-even point corresponds to 7.04 billion Euros per year, achieved by electrifying 19,595 kilometers of highway and employing an average battery size of 105 kWh. Beyond this point, the Total System Cost (Infrastructure Cost + Total Transport Cost) increases, even though total transport cost continues to decline. This observation implies that while total transport cost reductions persist, they no longer adequately offset the cost of ERS deployment beyond 19,595 kilometers. Consequently, the economic justification for further ERS expansion diminishes.

Total TTC Savings

The ERS investment per year (IC), total transport cost per year (TTC) and corresponding net total TTC savings have been calculated and summarized in table 8.2 and figure 8.5.

ERS length(km)	toll(M€/year)	IC(M€/year)	total TTC saving (M€/year)	net total TTC saving(M€/year)
0	262	0	0	0
3897	229	139	1145	1006
6206	217	221	1514	1293
7300	213	260	1656	1396
8348	209	297	1775	1478
11345	199	404	2061	1657
13771	193	490	2246	1756
15357	189	547	2353	1806
17955	183	639	2487	1848
19595	181	698	2553	1855
21806	178	777	2619	1842
24022	176	855	2666	1811
25263	175	900	2686	1787
26275	175	936	2695	1759
27114	174	966	2700	1734

Table 8.2.: Total cost savings per year

Several noteworthy observations emerge: from the perspective of logistics companies (users), the implementation of more ERS along the highway network consistently yields reduced total transport cost per year, with maximum savings of approximately 2,700 million euros per year(see table 8.2). Conversely, for investors, the ERS investment escalates continuously. Thus, striking a balance between these divergent concerns is essential.

The optimal solution lies in the break-even point, where network design maximizes net Total Transport Cost (TTC) savings per year. This net TTC saving

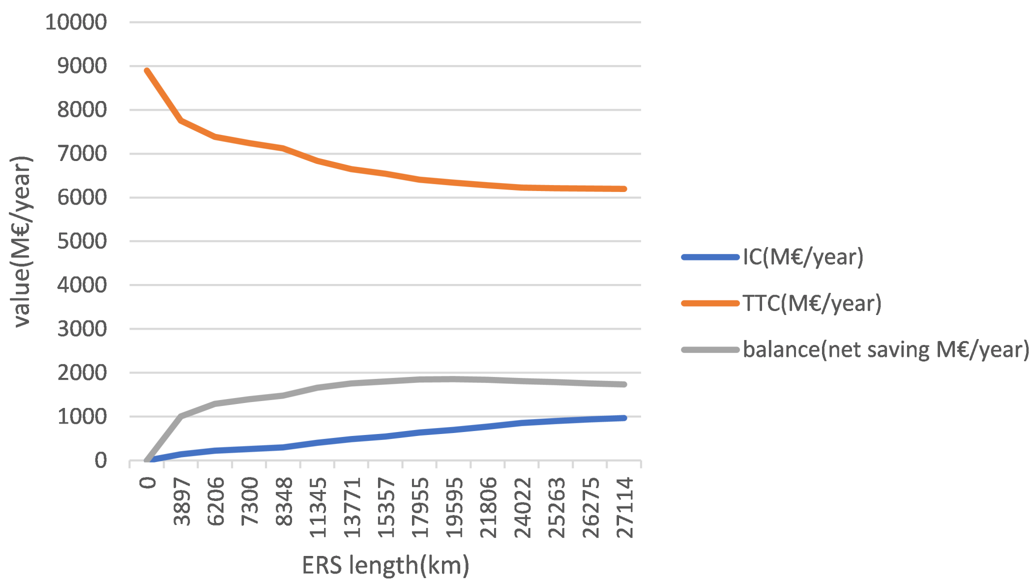


Figure 8.5.: Net total TTC savings per year

represented by grey line in figure 8.5 is obtained by deducting ERS investment from total TTC saving. Opting for the highest net TTC saving ensures that TTC savings realized through ERS implementation adequately offset the expenses of ERS construction. This strategy benefits various stakeholders within the trucking industry and contributes to a balanced trade-off.

From a governmental standpoint, this approach aligns well with strategies that enhance benefits for multiple stakeholders, while also promoting a balanced equilibrium. This assertion particularly holds when considering the current truck technologies, transport patterns, and prevailing conditions. Consequently, the conclusion supports the preceding findings: the optimal network design, marked by the break-even point in figure 8.4, encompasses 19,595 kilometers of electrified highway and yields net total TTC savings of 1,855 million euros per year. The two costs(IC and TTC) balance out at 19,595 km of ERS length(see figure 8.5). However, it's important to note that this design is contingent upon the government's implementation of a lower toll for the usage of electrified highways, specifically 0.05€/km less than that for conventional highways. This toll reduction serves as a subsidy, influencing the annual revenue of road authorities, which would drop from 2.6 billion euros without ERS to 1.8 billion euros under the break-even design. This subsidy would then be directed towards supplementing ERS implementation and supporting logistics companies operating BETs with pantographs.

Finally, the break-even ERS network design with 19,595 kilometers of electrified highway considering TTC is shown in figure 8.6 where red links indicating that link has been electrified:

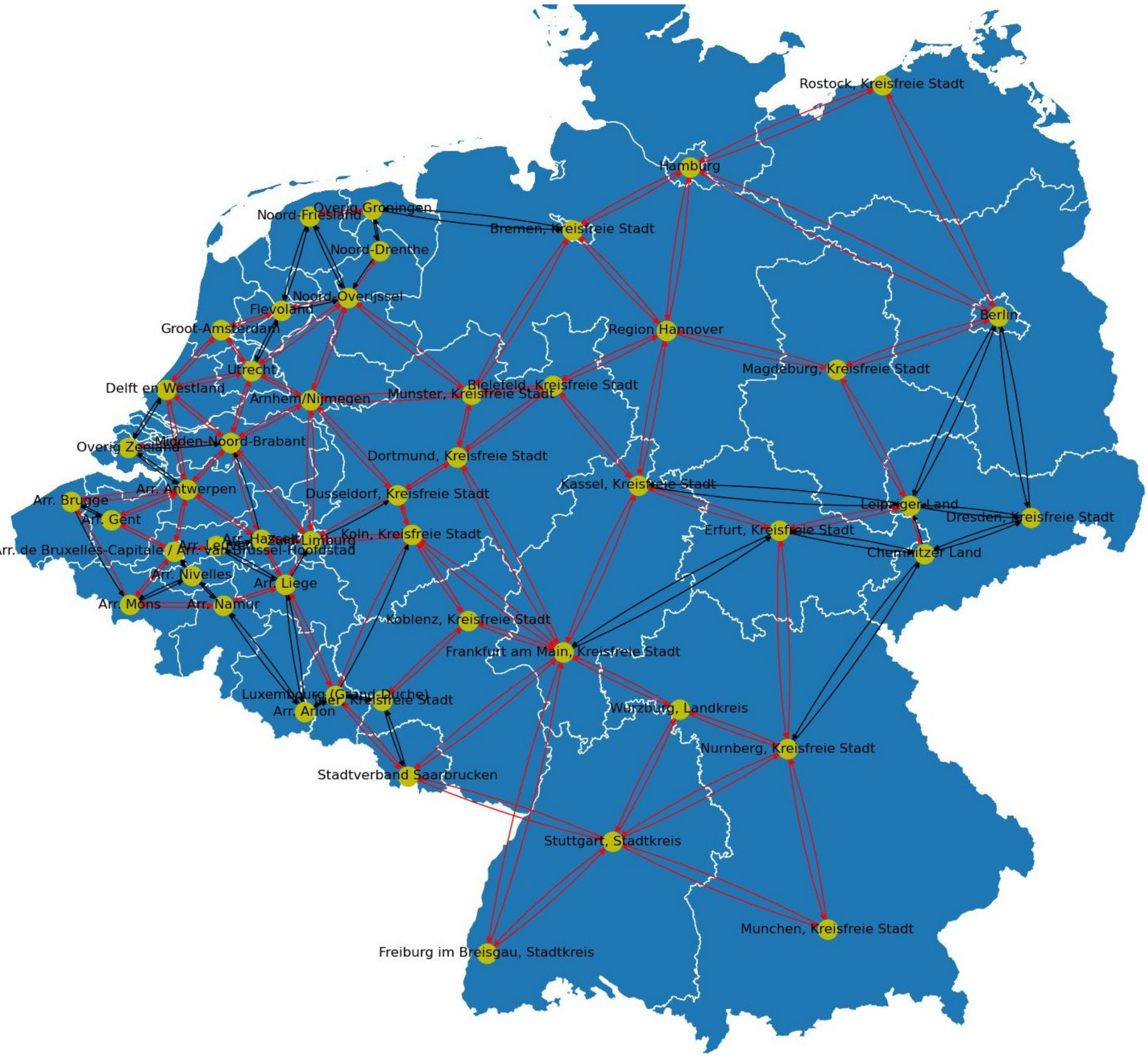


Figure 8.6.: Break-even network design considering TTC

8.1.3. Trade-off between battery cost and infrastructure cost

Figure 8.8 underscores the significant impact of ERS implementation on battery cost reduction. This section delves into an in-depth analysis of battery savings only as the change in energy and toll cost reduction are very small, showcasing a discernible trade-off between battery cost and infrastructure cost, as depicted in Figure 8.7. Different levels of investment in ERS construction yield substantial reductions in annual battery costs.

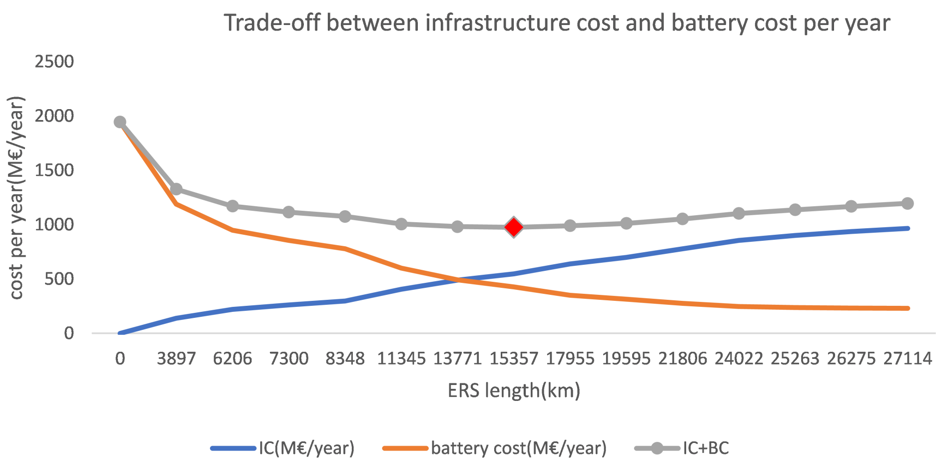


Figure 8.7.: trade-off between battery cost and infrastructure cost per year

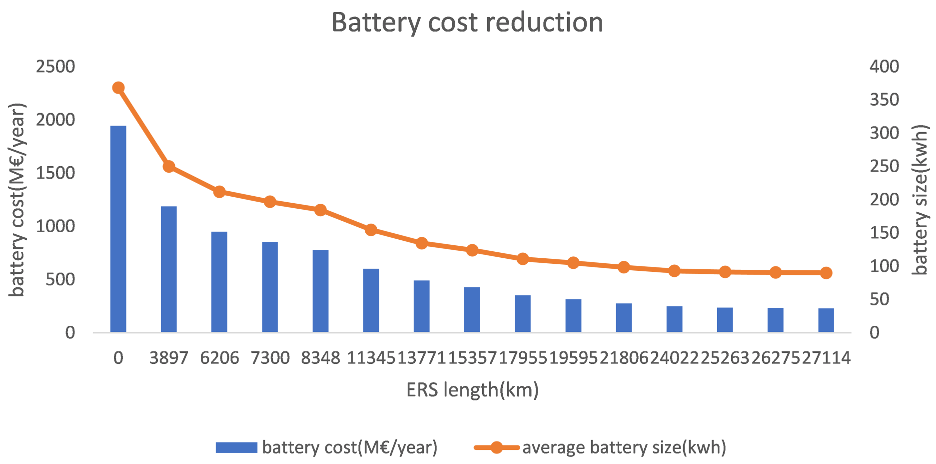


Figure 8.8.: Battery cost and size reduction

If the investment budget for ERS is unrestricted, the total annual battery cost without ERS plummets from 1.94 billion Euros to 0.23 billion Euros with a fully electrified highway network. Moreover, the average onboard battery size diminishes alongside the expansion of the ERS network. For instance, the initial maximum average onboard battery size of 370 kWh—when no ERS is implemented—shrinks to 90 kWh when the highway is entirely electrified. This reduction in average onboard battery size is indicative of a battery weight reduction and subsequently lower energy consumption for Etrucks.

Yet, in scenarios where investment budgets are restricted, a planning strategy must be formulated to reconcile the interests of diverse stakeholders. Another break-even point—focusing solely on battery cost—emerges as an optimal solution, irrespective of toll and energy costs (and the absence of governmental subsidy). This battery-oriented break-even point is represented by the red point in Figure 8.7. This point signifies the lowest Total System Cost (Infrastructure Cost + Battery Cost), symbolizing a scenario where battery savings from users optimally offset the expenses of constructing ERS. Importantly, this point represents the minimum total cost that simultaneously minimizes battery and infrastructure costs. Beyond this point, further ERS expansion triggers a situation where the reduction in battery costs achieved through ERS adoption no longer adequately offsets the incurred costs of ERS construction. Thus, without governmental subsidies (specifically, toll reductions per kilometer), the most beneficial strategy involves electrifying 15,375 kilometers of highway with an infrastructure investment of 0.55 billion Euros per year and an average onboard battery capacity of 124 kWh. Simultaneously, battery costs decrease by 78%, plummeting from 1.9 billion Euros to 0.43 billion Euros annually—equating to a staggering battery saving of 1.6 billion Euros per year.

Total battery savings

To provide a more comprehensive perspective, the ERS investment per year (IC), battery cost per year (BC) and net battery saving per year are analyzed and summarized in Table 8.3 and figure 8.9. This analysis echoes the previous section's findings, reaffirming that electrifying 15,375 kilometers of highway represents the most suitable design from a government standpoint. This design adeptly balances the investment in ERS infrastructure and battery savings, harmonizing the interests of various stakeholders within the ERS project.

ERS length(km)	total battery saving per year(M€/year)	IC(M€/year)	net battery saving (M€/year)
0	0	0	0
3897	756	139	617
6206	995	221	774
7300	1089	260	829
8348	1166	297	869
11345	1343	404	939
13771	1453	490	963
15357	1517	547	970
17955	1594	639	954
19595	1630	698	932
21806	1668	777	892
24022	1697	855	841
25263	1707	900	808
26275	1712	936	776
27114	1714	966	749

Table 8.3.: net total battery cost savings per year

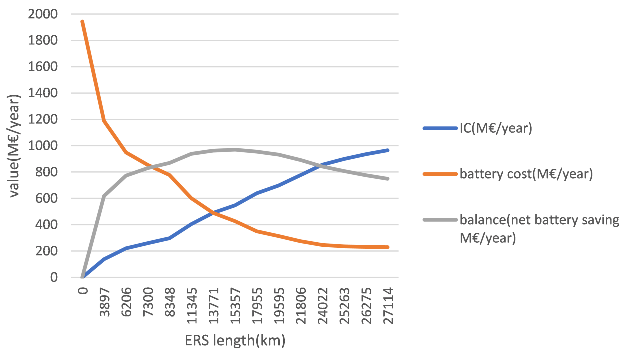


Figure 8.9.: Net total battery savings per year

From a government's perspective, this design choice optimizes the investment in ERS infrastructure and aligns it with battery savings, achieving an optimal net total battery savings per year. Specifically, this planning strategy yields 1,517 million Euros of battery savings per year, signifying the highest net total battery saving. This result underscores that after offsetting the cost of ERS infrastructure, the battery cost reduction reaches a pinnacle of 970 million Euros annually, rendering other net battery savings relatively less impactful. The two costs(BC and IC) balance out at 15,375 km of ERS length(see figure 8.9). Consequently, this solution can be considered the most worthwhile for ERS planning, as it maximizes net benefits while simultaneously catering to the interests of various stakeholders.

Impacts on battery lifespan

One of the notable advantages of Electric Road Systems (ERS) is its potential to enhance battery lifespan. This improvement stems from the fact that when Heavy-Duty Battery Electric Trucks (HDBETs) operate on electrified highways equipped with ERS, they can bypass the battery and draw power directly from the overhead contact line for propulsion. Consequently, the charging and discharging cycles experienced by the battery are reduced, contributing to an extended battery lifespan. Additionally, in scenarios where the chosen route is fully outfitted with ERS infrastructure, BETs may never need to use the onboard battery, as they can rely exclusively on grid power until reaching their destination.

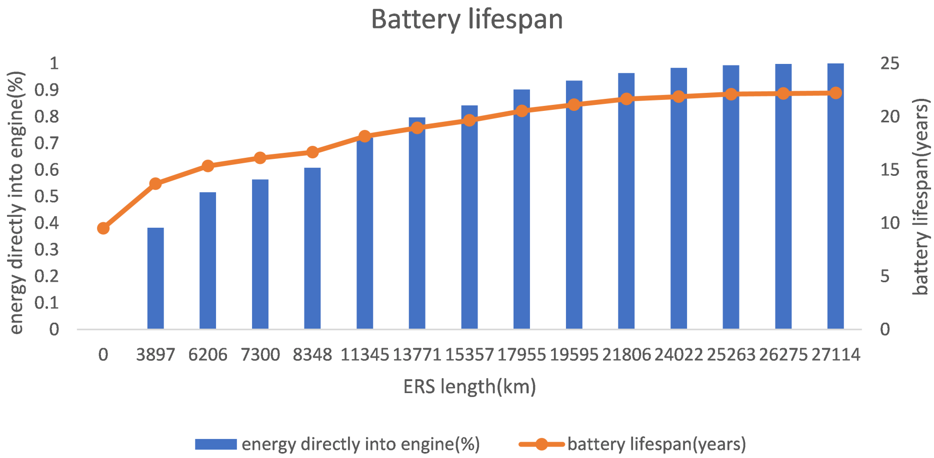


Figure 8.10.: Battery lifespan and energy transmission

This phenomenon is depicted in Figure 8.10, showcasing how, as the ERS network expands, a growing proportion of energy consumption by HDBETs is met by ERS rather than the battery. This energy directly bypasses the battery and powers the engine during intercity transport on electrified highways. Consequently, the battery utilization rate decreases, leading to an increase in battery lifespan. For instance, considering the break-even point design with 15,357 kilometers of electrified highway, approximately 84.3% of HDBETs' energy consumption per year is supplied directly by ERS, resulting in a substantial increase in battery lifespan. This effect is significant, as it extends the average lifespan under normal driving conditions from around 10 years (without any ERS) to 19 years.

This improved battery lifespan is advantageous for both logistics companies and Original Equipment Manufacturers (OEMs). For logistics companies, there are two primary benefits. Firstly, a lower battery utilization rate correlates with fewer quality-related battery problems. Secondly, due to the extended battery lifespan, companies incur lower battery replacement costs each year. From the perspective of OEMs, a prolonged battery lifespan is favorable, especially since they typically provide battery warranties for a set number of years when selling the trucks. Consequently, the possibility of decoupling the value of the battery from that of the BETs arises, as ERS technology can potentially enable batteries to outlast the operational lifespan of the trucks themselves.

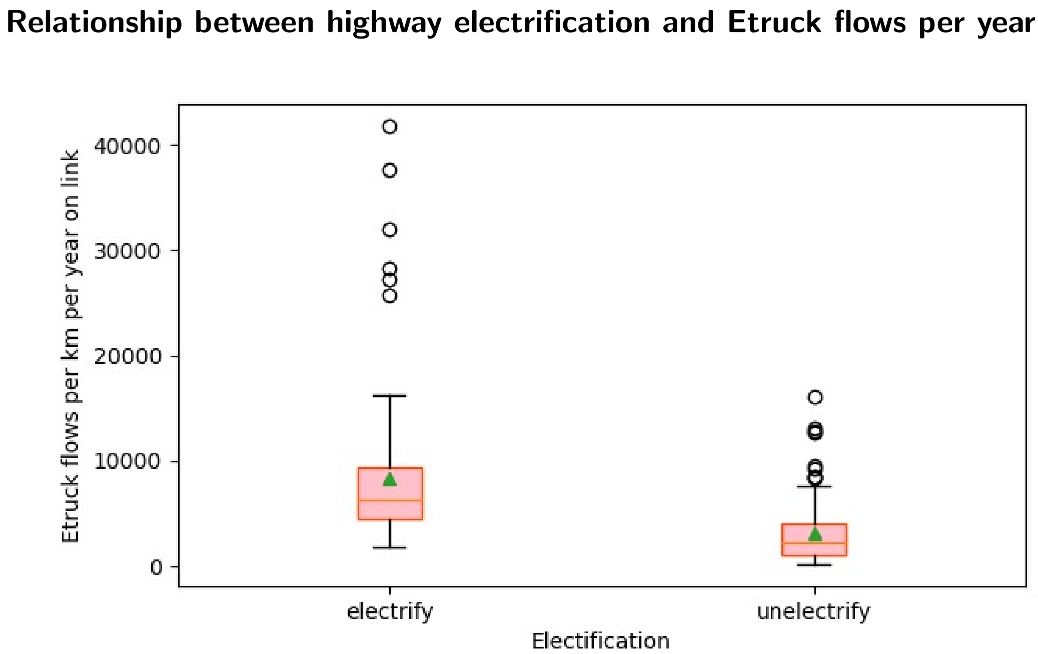


Figure 8.11.: Relationship between highway electrification and its Etruck flows per year for break-even design considering battery cost only

The correlation between the decision to electrify highways and their corresponding annual Etruck flows per kilometer is a crucial factor in the optimization model's decision-making process. This relationship is depicted in Figure 8.11, with triangles indicating average values. Notably, the Etruck flows per kilometer per year on a given link should be sufficiently high to justify its electrification. Upon analyzing the chart, it is evident that electrified highways exhibit a significantly higher average truck flow per kilometer per year compared to unelectrified highways. The average truck flow on electrified highways stands at 8,251, approximately three times greater than the average on unelectrified highways (2,783). Furthermore, even the lowest truck flows on electrified links are nearly equivalent to the average truck flow per kilometer per year on unelectrified highways.

This observation highlights the strategic consideration behind selecting highways for electrification. The optimization model tends to prioritize highways with substantial Etruck flows per kilometer, ensuring that the infrastructure investment in ERS aligns with the potential benefits generated by higher usage and energy demand.

Finally, the break-even network design considering BC only with 15,357 kilometers of electrified highway is shown in figure 8.12, where red links indicating that link has been electrified:

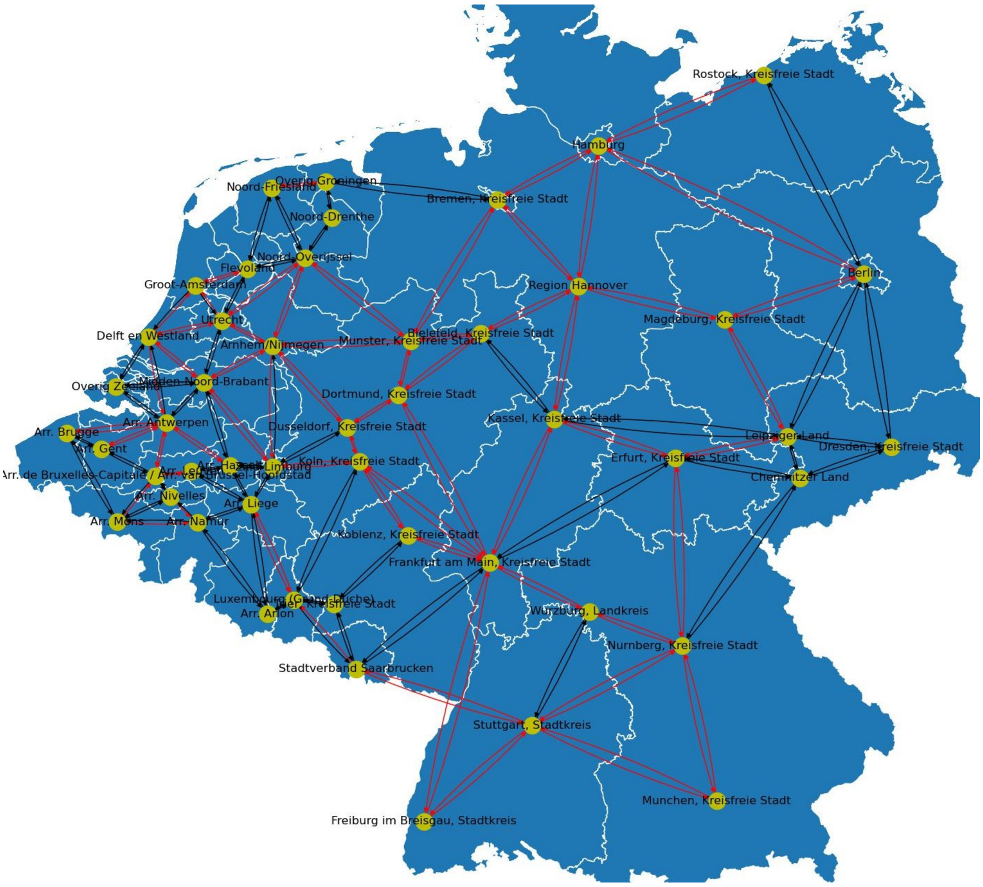


Figure 8.12.: Break-even network design considering trade-off between BC and IC

8.1.4. Impacts on energy market

The implementation of ERS will undoubtedly impact the energy market and the vehicle charging industry. Figure 8.13 illustrates the energy demand from ERS per year based on varying lengths of the ERS network.

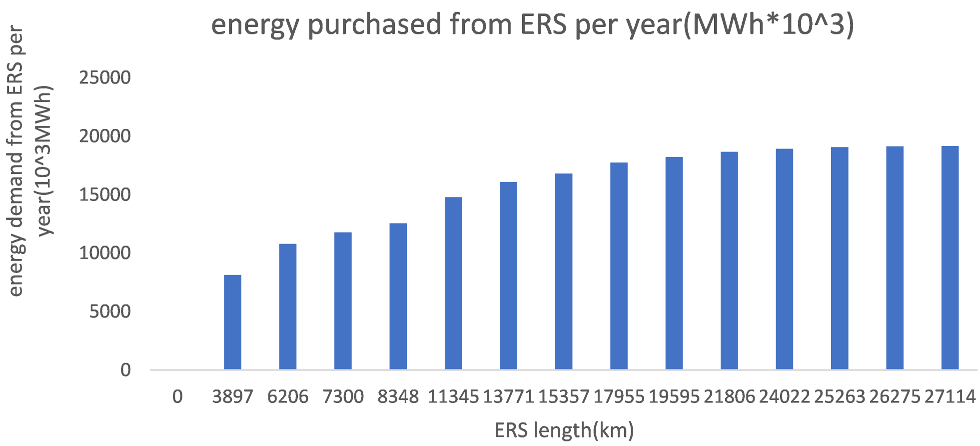


Figure 8.13.: Energy demand from ERS per year

As the ERS network expands and more Heavy-Duty Battery Electric Trucks (HDBETs) adopt this technology, the energy demand from ERS will naturally increase. For instance, in the case of the break-even design that considers battery cost only (refer to Figure 8.12) with 15,357 kilometers of electrified highway, ERS will deliver around 168 billion kWh of electricity to trucks annually. This equates to a daily energy demand of approximately 4.6 million kWh by the year 2030.

Considering the potential profit of selling electricity via ERS to Etrucks, which is estimated at 0.14€/kWh[12] (compared to the base price of electricity at 0.08€/kWh from the electricity company), a substantial business opportunity arises in operating ERS infrastructure in these four countries. The potential profits from operating the ERS infrastructure, given the break-even design, could amount to as much as 2.3 billion Euros per year.

Moreover, it is worth noting that three busy highway links with the highest energy demand in the break-even design have been identified. These links include the highway from Frankfurt to Freiburg, as well as both directions of the highway between Freiburg and Stuttgart. These highways exhibit high energy demand due to their lengthy stretches and heavy truck traffic flow.

8.2. Discussion

8.2.1. Results implications

Our study uncovers an interesting balance between the money spent on Electric Road System (ERS) infrastructure and the yearly costs of transporting goods. With no budget constraints, investing 0.96 billion Euros each year in electrifying 27,114 kilometers of highways led to a remarkable 30.3% drop in yearly transport costs, from 8.9 billion Euros to 6.2 billion Euros. This also resulted in a substantial 76% reduction in the size of the batteries onboard the trucks. What's even more impressive is that for all the solutions we found, the cost savings per year were consistently higher than the annual ERS expenses, proving its excellent economic feasibility.

We also identified two break-even scenarios where the cost savings could effectively cover the expenses of building the ERS. In the first scenario, called the "Comprehensive Break-Even Design," we would electrify 19,595 kilometers of highway each year with an investment of 0.7 billion euros. This would lead to substantial savings of 2.6 billion euros in total transport costs annually, accompanied by a 71% reduction in average battery size. This approach also dramatically reduces annual battery demand by 84%. In the second scenario, referred to as the "Focused Break-Even Design," we'd electrify 15,375 kilometers of highway annually with an investment of 0.5 billion euros. This would result in significant savings of 1.6 billion euros in annual battery costs, with a 78% reduction in annual battery demand. Both of these designs require significant investments in ERS to reach this balance, which can be challenging in practice. However, our model also highlights an interesting observation. Based on our results in figure 8.7 (Centered on Battery Costs Only), there's an immediate cost reduction from the moment of ERS operation until around 5,000 kilometers. After that point, investment costs and battery savings tend to balance out at around 15,000 kilometers of electrified length. So, the sweet spot for network electrification seems to range from 5,000 to 15,000 kilometers. This is something policymakers should consider when planning the initial stages of ERS deployment.

Model also estimates the potential battery lifespan extension: Battery lifespan under normal driving conditions increased from around 10 years to 19 years with 15,375 kilometers of electrified highway that leads to 84% ERS-direct energy supply(84% of energy consumption on the highway will be powered by ERS dirctly rather than battery).

Finally, looking ahead to 2030, we estimated the energy demand along highways due to ERS. With a 50% market share of Heavy-Duty Battery Electric Trucks (HDBETs) in these countries, the ERS energy demand could reach 168 billion kWh annually. This highlights the need for government attention to ensure a sufficient energy supply to support this growing sector.

8.2.2. Sensitivity analysis

In this section, a sensitivity analysis regardin some key parameters(battery price, market share and ERS cost) in research are conducted. We specifically consider the break-even designs, where the two conflicting objective functions—battery cost and ERS investment cost—are given equal importance. These combined objectives are applied within our proposed Genetic Algorithm (GA) to minimize the total system cost (IC+BC). In table 8.4, the variation of parameters in a format of $(max, min, \mathbf{interval})$ in the analysis was presented.(Note: market share(BET_{share}) was introduced in Chapter Data)

Sensitivity test	$C_b(euro/kwh)$	BET_{share}	$C_d(euro/km)$
Test on battery price C_b	(100, 200, **25**)	0.5	50,000
Test on market share BET_{share}	150	(0.3, 0.5, **0.05**)	50,000
Test on ERS cost C_d	150	0.5	(50,000, 200,000, **50,000**)

Table 8.4.: Sensitivity test

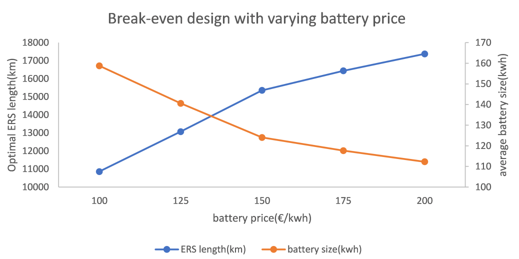


Figure 8.14.: varying battery price

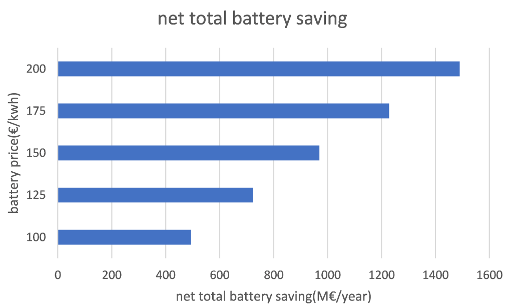


Figure 8.15.: cost-benefit analysis

Initially, the primary focus was directed towards the dynamic fluctuations in battery pricing within the market. This was meticulously analyzed, with reference to figures 8.14 and 8.15, revealing a notable outcome. As battery prices oscillated between the range of 100 to 200 units, a corresponding extension of approximately 7,000 kilometers and 30% reduction of onboard battery size in the break-even design were observed. Concurrently, the net total battery savings exhibited a remarkable tripling effect, elevating from 500 million to 1,500 million euros. Consequently, it becomes evident that as battery prices ascend, the integrated optimization model endeavors to increase the electrification of additional highway segments, subsequently mitigating the reliance on batteries within the system. This strategic maneuver serves as a countermeasure to the escalating battery costs. In essence, the prevailing high battery prices in the market render the protraction of Electric Road Systems (ERS) implementation across these four countries a more economically viable prospect.

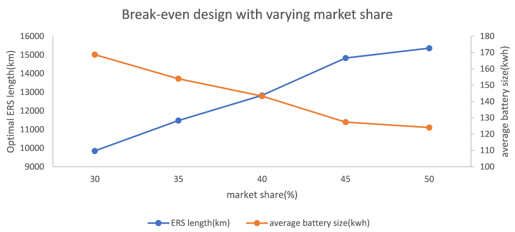


Figure 8.16.: varying market share

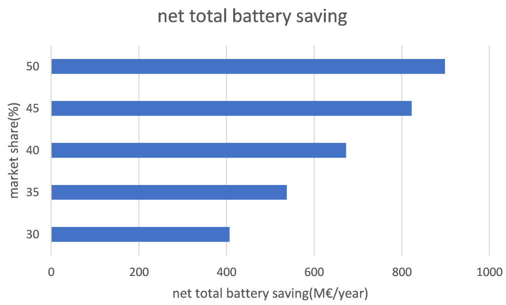


Figure 8.17.: cost-benefit analysis

A similar trend was discerned during the sensitivity analysis of the Battery Electric Trucks (BETs) market share, as visually depicted in figures 8.16 and 8.17. It is evident that a higher market share yields greater advantages in the context of constructing an extensive ERS network. The net total battery saving doubles (from 400 million to 900 million euros) when market share of BETs varies from 0.3 to 0.5.

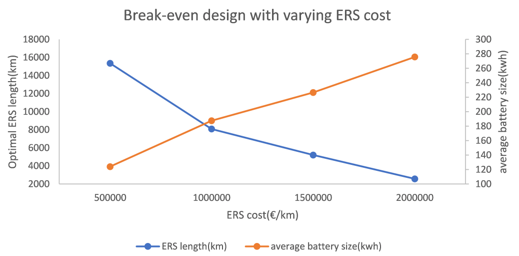


Figure 8.18.: varying ERS cost per km

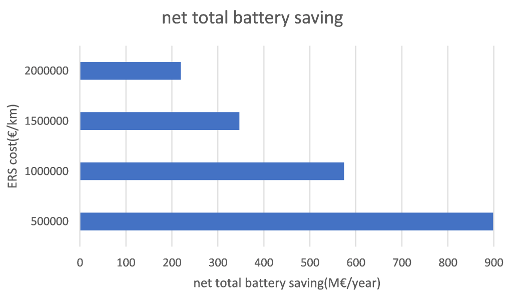


Figure 8.19.: cost-benefit analysis

Lastly, attention was directed towards the examination of ERS construction costs per km. In stark contrast to the influence of battery prices and market share, an inverse relationship was established, as illustrated in figures 8.18 and 8.19. With the escalation of ERS expenses per kilometer, the model exhibits a propensity to curtail the total extent of electrified highway infrastructure within the system. The repercussions of variation of ERS cost per km on the optimal ERS length and net total battery savings are substantial. A threefold surge in ERS cost per kilometer would result in a staggering 83% reduction in the optimal ERS length and a concomitant decline of 76% in net battery savings. This underscores the notion that higher ERS costs per km render the implementation of ERS in this region less feasible, making the acquisition of larger batteries a more prudent economic consideration.

9. Reflection

This chapter presents the answers to each sub research question and the main research question. Then, the limitations and future work about this research are discussed.

9.1. Answer to the sub-questions

To answer the main research question, 6 sub-questions are answered first. Below are the answers:

- What are the determinants of these costs considered in model including infrastructure and battery cost?

  The factors influencing the costs in our model, including infrastructure and battery costs, have been systematically analyzed and presented in both Chapter 2 (literature review) and Chapter 6 (Data). In the case of infrastructure costs, we consider the expenses associated with constructing the Electric Road System (ERS) and its operational maintenance over its predefined lifespan. The length of the highway chosen for electrification through the optimization model plays a pivotal role in determining these costs. On the other hand, battery costs are intricately tied to the prevailing market battery prices and the total quantity of battery packs required to electrify Heavy-Duty Trucks (HDTs) by the year 2030. Additionally, we apply the annual equivalent cost formula to transform the one-time cost occurring in 2030 into an annual cost, spread over the expected lifespan. Notably, in our research, the battery cost is also interconnected with the calculated battery lifespan, which we assume to be positively correlated with the electrification rate of the routes selected by users under average driving conditions, as discussed in Chapter 5.

- What other factors should be incorporated into model in addition to battery and infrastructure cost?

In addition to battery and infrastructure costs, we also integrate other significant factors into our model, namely toll and energy costs. These considerations are extensively covered in Chapter 2 (literature review) and Chapter 6 (Data). Our research aligns with the common practice in freight transport modeling, where tolls, time costs (representing driver wages), and energy (fuel) costs are typically incorporated. Given the intricate nature of route choice behaviors and the computational complexity involved, our case study prioritizes practicality by focusing on the shortest path for each trip, leading to a fixed time cost for every trip. In terms of toll costs, the value varies based on the vehicle's environmental attributes. In our scenario, Electric Trucks (Etrucks) utilizing the ERS are regarded as more environmentally friendly than battery-powered Etrucks. As evidenced by study provided in chapter Data, toll rates for emission-free Heavy Goods Vehicles (HGVs) are expected to range from 50% to 75% of those applicable to diesel trucks. Consequently, we apply a discounted toll rate of 0.1 EUR per kilometer for electrified highways in our analysis. Regarding energy costs, they are closely linked to the gross vehicle weight of Heavy-Duty Battery Electric Trucks (HDBETs). With the implementation of the ERS, which effectively reduces the onboard battery size due to its charging capabilities, the maximum annual reduction in energy costs observed in our modeling stands at 2.5%. This holistic integration of factors ensures that our model comprehensively addresses the intricate cost dynamics associated with the implementation of the Electric Road System for heavy-duty transport.

- How to model the trade-off so that an optimum can be determined?

  To navigate the intricate trade-offs inherent in the Electric Road System (ERS) implementation, our approach considers the diverse array of stakeholders involved. The primary challenge lies in identifying the most suitable highway segments for electrification, which uncovers the pivotal conflict highlighted in Chapter 1 and Chapter 3: determining whether to channel investments into constructing ERS to complement batteries or to directly invest in battery acquisition. This trade-off quandary is elegantly formulated into our optimization model to explore the optimal solution. The comprehensive details of this formulation can be found in Chapter 5: Model Specification. Our model, structured to address this trade-off and converge on an optimum solution, employs two conflicting objective functions. The first objective function is tailored to minimize the amortized infrastructure cost along with its ongoing Operations and Maintenance (O&M) expenses. The second objective function aims to minimize the annual total transport cost, encompassing factors such as battery, energy, and toll costs. These functions encapsulate the crux of the trade-off between ERS infrastructure and battery investment. In the pursuit of solutions that effectively balance these contrasting objectives, our approach yields a diverse set of Pareto optimal solutions, showcasing the impacts of ERS implementation considering budgets limitation. Furthermore, our investigation identifies break-even solutions(minimum system cost: IC+TTC), which possess the potential to harmonize these two objective functions under specific conditions. These break-even solutions offer a practical way to strike a balance between ERS infrastructure investment and battery-related expenses. To extract these optimal solutions, the decision variables at the core of our optimization model encompass the strategic placement of ERS infrastructure and the determination of battery sizes for each individual trip. To effectively execute this model, meticulous preparation of relevant input data and parameter settings is essential, ensuring the alignment of real-world considerations with the analytical findings of our research. This comprehensive approach, carefully balancing conflicting objectives and integrating input data, empowers us to identify the optimal ERS network configuration that mitigates costs and maximizes benefits across various stakeholders involved in the heavy-duty transport sector.

- How to solve the model(What is the suitable solution approach)?

  To address the intricate trade-offs and determine optimal solutions, a tailored solution algorithm is introduced in Chapter 7: Solution Approach. This algorithm, specifically designed for the context of our case study, builds upon the foundation of a genetic algorithm (GA) and incorporates an elitism strategy to enhance its effectiveness.The primary objective is to illustrate a comprehensive spectrum of Pareto optimal solutions that capture the interplay between different factors. This approach aims to assist policymakers in comprehending the potential impact of ERS implementation while accounting for the complex multi-objective nature of the case. Policymakers can then make informed decisions based on their priorities and resource availability. The algorithm's incorporation of an elitism strategy enhances its efficiency and accuracy in identifying promising solutions within the solution space. By providing a holistic view of the trade-offs, this approach equips stakeholders with a robust understanding of the potential impacts of implementing ERS infrastructure.

- What is the result when applied to a case study of Western European area? What is a good network for these four countries?

  The case study's comprehensive analysis is presented in chapter 9, showcasing a diverse spectrum of Pareto optimal solutions. These solutions address the optimal annual total transport cost, which includes battery, energy, and toll expenses. These costs vary based on investments made in Electric Road Systems (ERS) infrastructure. Notably, the most favorable outcome reflects a yearly investment of 0.96 billion euros, resulting in 27,114 kilometers of fully electrified highways and an annual transport cost of 6.2 billion euros. However, the study also identifies limited energy cost reduction due to ERS implementation, with a maximum reduction of 2.5%. This observation suggests that energy costs are not significantly affected by reductions in battery weight.

  Viewed from a governmental standpoint, the optimal ERS network design corresponds to the break-even point, where total savings in transport costs to logistics companies cover the expense of constructing ERS on the highways. In alignment with assumptions in the Model Specification, a recommended network design entails investing 0.7 billion euros annually to establish 19,595 kilometers of electrified highway. This approach assumes that around 0.8 billion euros of yearly tax income can be allocated as subsidies for ERS supplementation. As a result, the annual transport cost reduces by 28.8%, yielding substantial savings (up to 6134€/year per truck) and a decrease in average battery size from 370 kwh to 105 kwh. In scenarios where government subsidies are absent (lower toll per km), an alternative break-even network design involves electrifying 15,375 kilometers of highway, leading to a 78% reduction in battery costs. This design results in a significant net battery gain per truck per year (3206€) following the coverage of ERS construction costs.

  The study also highlights the potential to extend the battery lifespan of Electric Trucks (Etrucks) through decreased battery utilization rates, particularly evident in large-scale highway electrification scenarios using ERS under average driving conditions. For example, electrifying 15,375 kilometers of highway could enable 84.3% of BETs' energy consumption in 2030 to be directly supplied by ERS during highway operations. This strategic integration results in an estimated battery lifespan extension of nine years. Furthermore, a 15,375-km ERS length corresponds to a substantial energy demand of up to 4.6 million kwh per day along the highway

The case study also conducts a sensitivity analysis on battery prices, uncovering their impact on the break-even network design. The optimization model consistently seeks to electrify more highways to counterbalance increasing battery costs. This observation underlines that higher battery prices correlate with greater battery savings for logistics companies following ERS implementation. Consequently, the study concludes that the optimal ERS network size is contingent upon prevailing battery prices to a certain extent.

- What recommendations and considerations can be made for different stakeholders in ERS project based on the result of our case study?

  Government

  Aligned with EU emissions reduction goals and insights from leading OEMs, a 50% BET market share is envisioned by 2030. Subsidizing electrified highway use could lead to larger break-even network designs, fostering BET adoption. This strategic intervention, particularly in the initial stages, would amplify cost savings for logistics companies employing ERS. If feasible, extensive ERS deployment across the four countries is justifiable, given consistent battery savings exceeding ERS investment.

  Addressing prevalent concerns, ERS nullifies range limitations for heavy-good transport by enabling continuous grid power supply during highway operation. Additionally, the prospect of battery shortage amid robust EU vehicle electrification propels ERS as a prudent solution. By reducing battery demand by up to 78% with a 15,375-km electrified highway network, ERS mitigates dependence on battery imports, augmenting local industry and curbing supply chain vulnerabilities. Policymakers must acknowledge the sensitivity of ERS savings to battery prices, ERS expenses and battery electric trucks market share, necessitating a meticulous market analysis.

  Furthermore, ERS promotes sustainability by marginally lowering annual energy consumption, relieving energy production pressures. Reduced battery demand alleviates resource consumption, enhancing emissions reduction efforts.

  Logistics companies

  Logistics companies, poised as the primary beneficiaries of Electric Road Systems (ERS), occupy a central role in the focus of this research.

The symbiotic relationship between ERS and logistics companies unveils an array of advantages. Foremost, the allure of reduced yearly total transport costs, encompassing tolls, energy, and battery expenses, beckons. This financial mitigation heralds economic viability. Furthermore, a diminished battery utilization rate ushers in a reduction in technical issues plaguing onboard batteries. This reduction, in turn, curtails ancillary costs linked to repairs and maintenance. Moreover, the downsized onboard battery configuration translates to augmented carrying capacity for carriers, in marked contrast to conventional Battery Electric Trucks (BETs). This augmentation resonates as a distinct operational advantage, poised to amplify efficiency. A salient challenge encountered by BETs resides in energy transfer and storage efficiency. The inherent inefficiencies during transmission and storage result in energy wastage, signifying an additional financial overhead for companies. However, the advent of ERS engenders a paradigm shift. Our findings illuminate that approximately 84.3% of the energy requisites for Heavy-Duty Battery Electric Trucks (HDBETs) can be directly channeled into the engine via pantograph. This robust energy transfer efficiency—90%—crucially mitigates the hitherto latent costs associated with energy loss during transmission and storage.

Truck manufacturers

Trimming the need for batteries emerges as a strategic advantage for European Original Equipment Manufacturers (OEMs). Currently, most batteries for their Battery Electric Trucks (BETs) are imported from outside Europe. Take DAF as an example – this well-known truck maker sources its batteries from CATL, a Chinese supplier. This reliance on external sources accentuates the value of lessening battery demand for European OEMs. Extending the battery lifespan also aligns with OEMs' interests. The necessity of offering warranties for trucks equipped with batteries over several years brings financial implications into focus. Interestingly, the idea of separating battery and electric truck businesses gains traction, as batteries tend to outlive trucks in terms of use. This concept carries the potential for solid business prospects. Furthermore, a significant business opportunity lies in investing in the creation and operation of charging infrastructure for Electric Road Systems (ERS) across the four targeted countries. Notably, companies like DAF and Paccar (DAF's parent company) play a pivotal role in this domain, extending their reach to encompass charging facilities for BETs. The insights revealed in Chapter 9 vividly highlight the energy demand arising from the 15,357-km ERS in 2030, totaling an impressive 168 billion kWh. With each kilowatt-hour of electricity potentially yielding €0.08 in profit, the projected yearly returns from energy sales effectively cover the annual operational costs of ERS. This financial alignment enhances the appeal of investing in ERS charging infrastructure for OEMs, culminating in a promising intersection of sustainable operations and financial gains.

9.2. Answer to the main research question

Our overarching research question, "How to determine the optimal ERS network, given the trade-off between infrastructure and battery costs?" is meticulously addressed across our study. Distilling the findings from each subquestion, we discern actionable insights that effectively address our main research inquiry.

When considering the optimal ERS network, two distinct scenarios warrant attention:

Unlimited Budget or Battery Shortage Concerns: In situations where budget constraints are absent, or concerns about battery resource shortages emerge, opting for extended ERS networks emerges as a robust strategy to complement BET operations. By building longer ERS networks, the mitigation of battery-related limitations becomes a feasible solution, enhancing the viability of electric trucking operations.

Limited ERS Budget: In instances where ERS budgetary considerations are paramount, the concept of a break-even design emerges as a compelling proposition, predominantly from a governmental perspective. This design expertly navigates the trade-off dynamics between infrastructure expenditure and total transport costs (primarily battery expenses). This equilibrium translates to optimized net savings per truck annually, post-cost amortization for ERS establishment. Delving into the specifics, two distinct break-even designs are advanced:

a. Comprehensive Break-Even Design (Including Toll, Energy, and Battery Costs): With support from road authorities, electrifying 19,595 kilometers of highway presents a viable course of action. This design yields a significant reduction in total transport costs while maintaining governmental subsidies, underpinning the robustness of ERS adoption for BETs.

b. Focused Break-Even Design (Considering Battery Costs Only): In scenarios where energy cost influence is marginal, electrifying 15,375 kilometers of highway stands out as an attractive proposition. This design not only underscores substantial reductions in battery expenses but also aligns with pragmatic resource allocation.

9.3. Limitations

In this research, we presented an innovative multi-objective optimization model designed to enhance the efficiency of Electric Road Systems (ERS) catering to Heavy-Duty Battery Electric Trucks (HDBETs). Our model, in contrast to prior approaches in the literature, exhibits the capability to accommodate dynamic charging strategies for BETs and places a specific emphasis on reducing battery size. The model's application yielded valuable insights into the potential impact of ERS implementation on cost savings in terms of total transport expenses, with a particular focus on reductions in battery-related costs. This analysis substantiates the economic viability of ERS deployment for HDBETs. As mentioned in the literature, due to lack of HDTs trip or scheduling data, the approach's ability of offering a precise cost analysis and energy/traffic distribution may be limited.

However, it is crucial to acknowledge certain limitations within our study. Firstly, the analysis may overestimate the energy requirements for the year 2030. This overestimation is attributed to the utilization of a conventional energy consumption model that relies on current technical parameters. By 2030, significant advancements in truck technology are expected, including improvements in battery density and overall energy efficiency. Consequently, actual energy consumption by HDBETs might be lower than projected.

Additionally, we might have underestimated the potential cost savings. The assumption that all BETs are operating with maximum cargo loads could lead to an underestimation of the number of trucks in service. Furthermore, the analysis focused exclusively on direct point-to-point transportation, neglecting scenarios where a single trip involves multiple stops or when trucks are operating empty, which could impact the cost savings.

A critical aspect pertains to our prediction of a battery price of 150 Euros per kilowatt-hour by 2030. This projection might be conservative, considering ongoing advancements in battery technology and the anticipated scale of mass battery production in the future. Consequently, the cost reduction potential in battery expenses could be lower than anticipated.

One of the most significant challenges lies in our estimation of battery lifespan. Our model employs a simplified linear battery lifespan estimation approach, assuming a positive correlation between route electrification rates and battery durability. This approach assumes constant minimum cycle fade rates and calendar fade rates at average levels under typical driving conditions. However, in reality, battery degradation is influenced by a multitude of factors, including depth of discharge, environmental conditions, and current levels. This introduces a degree of uncertainty in our lifespan estimations, which should be considered as providing a general trend rather than precise predictions.

Furthermore, we did not incorporate constraints related to network capacity or power grid limitations in our model. The interactions between power grid capacity and highway capacity are intricate and challenging to estimate accurately based on current conditions. Nonetheless, our energy demand analysis offers valuable insights into the potential energy requirements along the highways in 2030. It should be noted that the estimation of energy demand along the highway segments may be conservative due to potential limitations in energy supply.

9.4. Future work

According to the limitation proposed, future work is suggested to cover these aspects:

Network Capacity and Power Grid Constraints: A key limitation resides in the omission of power grid limitations and network capacity in our model. Interactions between power grid and highway capacity, complex and challenging to estimate given current conditions, merit future attention. Incorporating flow capacity constraints and power supply dynamics could yield a more comprehensive understanding of ERS feasibility.

Battery Lifespan Estimation: The simulation of battery degradation, a complex task even for experts, holds critical significance. While our research proposes a lifespan estimation model under average conditions, deeper exploration considering factors such as state of charging and voltages could enrich our insights. Incorporating real-world data on Catenary BETs' battery lifespans would add nuance to our findings.

Network Structure and Truck Flow: Aggregated data as input may inadvertently affect infrastructure planning. To address this, future research can consider barriers like tunnels, bridges, and inclines that impact ERS implementation.

Expanded Vehicle Flow Consideration: Our current focus on Heavy Duty Trucks (HDTs) underestimates the potential of other vehicle types utilizing ERS. Expanding our model to encompass various vehicle types could yield a more holistic understanding. Incorporating international truck flows and customer expectations further refines our predictions.

User Willingness to Adopt ERS: A critical yet unexplored dimension is users' willingness to adopt ERS. Addressing the variability in user preferences for ERS utilization, which may not be uniform, could enrich our findings and guide policy recommendations.

Enhancing Environmental Considerations: Beyond optimizing transport and infrastructure, considering broader environmental implications like emission reductions and resource conservation could enhance the robustness of our model.

Additional ERS Technologies to Explore: This study exclusively delved into ERS-OC, characterized by superior charging power and transfer efficiency compared to ERS (induction). Future investigations could apply the proposed model to assess the viability of alternative ERS technologies.

In summary, our study, while comprehensive, presents opportunities for deeper exploration and refinement. By addressing these limitations and expanding our research horizons, we can contribute further to the effective implementation of ERS networks in heavy transport systems.

A. Appendices

A.1. Results of chapter 9

IC(€/year)	TTC(€/year)	average battery size(kwh)	battery cost(€/year)	ERS length(km)	energy purchased from ERS(kwh)
0	8894956344	368.2612	1943709456	0	0
138773024.3	7749987373	249.87334	1187531606	3897	8141954466
220997020.4	7381345782	211.82676	949186554.9	6206	10795212058
259954600.2	7238566272	196.74444	854304967.8	7300	11783788140
297274110	7119471293	184.44354	777531868.6	8348	12559741421
403997936.9	6833547321	154.60118	600752042.8	11345	14784626549
490388328.7	6648551410	134.55921	490492443.1	13771	16065537722
546866136.4	6541978856	124.03861	427202667	15357	16811199207
639381485.9	6408001077	110.96297	349959778.3	17955	17747921298
697782245.4	6341991904	105.08244	314071843.5	19595	18214543733
776516440.1	6276055643	98.4073	275551273.3	21806	18660473826
855428685.8	6228464981	92.918365	246912610.7	24022	18928702224
899620967.9	6208638085	91.294478	236325486.3	25263	19072313302
935658509.7	6200015547	90.465016	232038834.5	26275	19136499542
965535483.6	6195257559	90	229345496.4	27114	19165092095

Table A.1.: Detailed results of the calculation: 1

toll(€/year)	energy cost(€/year)	IC+TTC	IC+BC	energy directly into engine(%)	energy consumption(kwh)
2624387703	4326859185	8894956344	1943709456	0	19667541751
2287431780	4275023987	7888760398	1326304630	0.382096948	19431927215
2170790963	4261368264	7602342802	1170183575	0.515349601	19369855745
2128246027	4256015278	7498520872	1114259568	0.564263732	19345523990
2090405529	4251533895	7416745403	1074805979	0.607740146	19325154070
1992174012	4240621267	7237545258	1004749980	0.720639265	19275551213
1925869522	4232189446	7138939739	980880772	0.79701817	19237224752
1886236905	4228539284	7088844992	974068803	0.842570963	19220633109
1834220017	4223821281	7047382562	989341264	0.902474747	19199187641
1805894095	4222025965	7039774149	1011854089	0.935006105	19191027116
1780727481	4219776889	7052572083	1052067713	0.963987687	19180804041
1764163426	4217388945	7083893667	1102341297	0.98324041	19169949750
1755367267	4216945332	7108259053	1135946454	0.993338151	19167933325
1751501798	4216474914	7135674056	1167697344	0.9978014	19165795062
1749591802	4216320261	7160793043	1194880980	1	19165092095

Table A.2.: Detailed results of the calculation: 2

battery lifespan(years)	battery saving per truck(€)	ERS investment per truck(€)	net battery saving per truck(€)	TTC saving per truck(€)	net TTC saving per truck(€)
9.523809524	0	0	0	0	0
13.70218384	2500.610571	458.9096221	2041.700948	3786.307032	3327.39741
15.35796418	3288.795723	730.8168117	2557.978911	5005.370855	4274.554044
16.12387436	3602.560401	859.6459435	2742.914457	5477.529556	4617.883613
16.66013278	3856.441976	983.0581282	2873.383848	5871.365694	4888.307565
18.15202524	4441.036593	1335.984004	3105.05259	6816.889959	5480.905955
18.94470827	4805.654944	1621.66908	3183.985864	7428.654414	5806.985334
19.65680282	5014.94841	1808.435994	3206.512416	7781.080045	5972.644052
20.5310875	5270.383536	2114.375742	3156.007794	8224.132234	6109.756492
21.11972422	5389.061634	2307.50168	3081.559954	8442.418495	6134.916815
21.6676628	5516.445615	2567.868417	2948.577198	8660.463642	6092.595225
21.87847459	5611.151037	2828.823953	2782.327085	8817.841581	5989.017628
22.11549566	5646.161683	2974.963763	2671.19792	8883.407304	5908.443541
22.17949361	5660.337246	3094.136598	2566.200649	8911.921244	5817.784646
22.22222222	5669.243868	3192.937002	2476.306866	8927.65547	5734.718468

Table A.3.: Detailed results of the calculation: 3

A.2. Proposed improved Genetic algorithm

The proposed genetic algorithm with Elitism strategy has been upload to my github: (https://github.com/XimengLiao/Master-thesis-ERS-network-.git), along with the data used in this study.

Colophon

This document was typeset using $\LaTeX$, using the KOMA-Script class `scrbook`. The main font is Palatino.

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