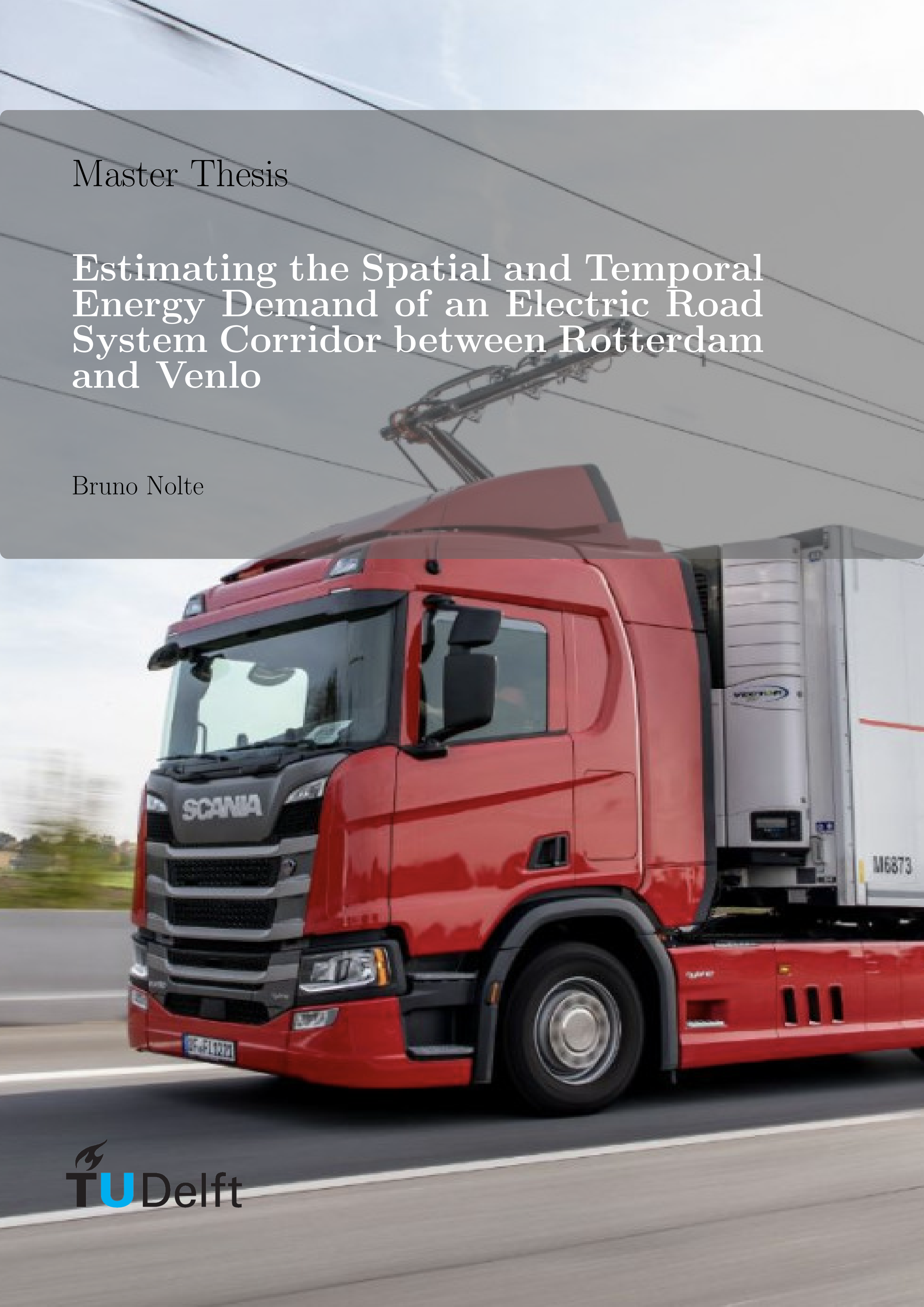
Master Thesis

Estimating the Spatial and Temporal Energy Demand of an Electric Road System Corridor between Rotterdam and Venlo

Bruno Nolte



TU Delft

Estimating the Spatial and Temporal Energy Demand of an Electric Road System Corridor between Rotterdam and Venlo

Master's Thesis

By

Bruno Nolte

In partial fulfillment of the requirements for the degree of
Master of Science in Complex Systems Engineering & Management

Faculty of Technology, Policy and Management
Delft University of Technology

In collaboration with ElaadNL

to be defended on August 22, 2025

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August 2025

Preface

In front of you lies the final version of my thesis, written as the final project of my master's degree in Complex Systems Engineering & Management at Delft University of Technology. Over the last 7 months, so many hours of hard work have been poured into this project and I feel so proud that this is the final product. With this project, my time as a student in Delft comes to an end, and I'm glad it is concluding in this way. I never would have expected that, after my first contact with supervisor Lori, it would ultimately lead to this final result. Lori connected me with the people at ElaadNL, which turned out to be such a pleasant and successful collaboration.

From the end of last year, I knew that I wanted to do a research for my thesis in the green energy sector. I felt like I wanted to contribute to something good and something that might catch traction in the future. Investigating the energy demand of an Electric Road System suited this wish perfectly. Working on this topic felt relevant in today's context of climate urgency and electrification challenges. Personally, it was rewarding to contribute to the transition toward more sustainable mobility. However, the project was not without its obstacles. The biggest challenge was debugging the model provided by Jasper Bakker, who's work I used as a starting model. With a relatively limited background in programming, I had to invest significant time in understanding the code and structure of the simulation model that my work built upon. Debugging and adapting existing Python code demanded persistence and a methodical approach. Through trial and error, and many iterations, I gradually developed both the confidence and the competence needed to complete the work. As the project progressed, I became increasingly more confident with coding and now that I have finished the research, I can truly say that I am equipped with decent programming skills.

In addition, I developed a much deeper appreciation for the transport sector and the fascinating transition to electric trucks. Perhaps most importantly, I experienced how rewarding it is to work independently on a complex project, from initial scoping to the final result. After spending so many hours getting familiar with the topic and doing research, I truly believe in the benefits of ERS and the role it might have in future freight transport.

I also want to take my time to thank some important people that helped me during the process of doing this research and writing this report. First of all, Ron van Duin, Ivo Bouwmans and in particular Lori Tavasszy for their guidance during the project. They provided me with valuable feedback and were always open for questions. Without their support the final product would never have been of the aspired quality. I also want to thank the people from ElaadNL, in particular Jeroen Janssen and Nazir Refa for their warm welcome at the company and the guidance throughout the project.

For now, I wish the reader a pleasant time reading my work and I hope to inspire others to do more research in this field.

Bruno Nolte
July 24, 2025
Amsterdam

Executive Summary

Medium- and heavy-duty vehicles make up just 5% of the vehicle fleet but contribute over 25% of transport-related greenhouse gas (GHG) emissions. With transport responsible for around 27% of global GHG emissions, the European Union has proposed a 90% reduction in truck emissions by 2040. Electric trucks offer a low-emission solution, but barriers such as battery cost, limited range, and insufficient charging infrastructure hinder large-scale adoption.

Electric Road Systems (ERS) present a promising alternative by allowing trucks to charge while driving, potentially reducing battery size and cost. Yet, the spatial and temporal impacts of ERS on the electricity grid remain underexplored. Existing studies often focus on isolated trips, rely on assumptions for adoption estimates, and lack detailed analysis within the Dutch context. This study uses tour-level freight transport data for over 4 million trips across the Netherlands and neighboring regions. Unlike trip-based approaches, this dataset captures complete truck tours, offering a more realistic view of logistics behavior. Each trip includes detailed information on origin, destination, timing, and vehicle type. The analysis uses the high-resolution NRM zoning system, which divides the study area into nearly 7000 zones, allowing for precise spatial modeling of transport flows and ERS adoption potential, especially for international freight movements along the Rotterdam–Venlo corridor. To guide this investigation, the following main research question is addressed:

"What is the expected temporal and spatial distribution of energy demand of an Electric Road System along the Rotterdam-Venlo corridor?"

Before looking at the data from a tour perspective, it is first determined for every single trip whether it would be viable for ERS adoption. For a trip to be viable, it must meet three criteria:

1. **Distance from Network (α)**: Both the origin and destination zones must lie within a maximum distance from the ERS corridor. This ensures that trucks with small batteries can reach the network.
2. **Percentage of Trip on ERS (β)**: A sufficient portion of the total trip distance must be covered on the ERS. If the ERS usage is too low, adoption is not worthwhile.
3. **Maximum Detour (γ)**: The total route (including access to ERS) must not deviate too far from the direct origin-destination path. Trips requiring excessive detours are excluded.

Only trips that meet all three conditions are considered part of the trip adoption potential. The values of the criteria for three different scenarios are given in Table 1.

	Tight	Moderate	Flexible
α	50 km	80 km	110 km
β	70%	60%	50%
γ	1.3	1.4	1.5

Table 1: Scenario parameter overview

After applying all selection criteria, a set of trips was identified eligible for ERS use. However, assessing only individual trips overestimates adoption potential. Therefore, entire truck tours—consisting of multiple trips by the same vehicle—were evaluated for battery feasibility.

Two types of tours were distinguished:

1. **Tours with one ERS trip**: Only one trip uses the ERS. The model checks if the battery can support the pre- and post-ERS distances based on a 150 kWh battery.
2. **Tours with multiple ERS trips**: The tours include multiple ERS-eligible trips. Here, battery consumption before, during, and between ERS segments is tracked.

A battery simulation was developed to evaluate whether trucks can complete their full tour using ERS charging. Tours that cannot meet battery constraints are excluded from the adoption potential. To estimate where and when energy is needed, the corridor was divided into 98 segments of 2 km. For

each 15-minute interval, the model calculates truck positions and charging status, assuming a constant speed of 80 km/h. Trucks always use 150 kW for traction; those still charging draw an additional 150 kW. The result is a high-resolution, time-based map of ERS power demand along the corridor—critical input for grid planning and infrastructure design.

The values of the two parameters c and $P_{ERS\text{-}charge}$ are varied to observe how energy demand develops under stricter or more favorable conditions, given in Table 2.

	Tight	Moderate	Flexible
c	2.175 kWh/km	1.875 kWh/km	1.575 kWh/km
$P_{ERS\text{-}charge}$	120 kW	150 kW	180 kW

Table 2: Tour variable overview

After testing all the trips in the dataset to the criteria from Table 1 and Table 2, a final set of tours was generated that would hypothetically make use of the ERS network, as they comply with the defined conditions and battery constraints. The results of the tour adoption potential are presented in Table 3.

	Tight			Moderate			Flexible		
Tours	**Tight**	**Moderate**	**Flexible**	**Tight**	**Moderate**	**Flexible**	**Tight**	**Moderate**	**Flexible**
Tours in trip adoption potential (M/year)		3.00			4.28			5.78	
Final number of tours in tour adoption potential (M/year)	1.88	1.91	1.97	2.63	2.76	2.85	3.29	3.52	3.73
Percentage of total freight flow (%)	3.4	3.5	3.6	4.8	5.0	5.2	6.0	6.4	6.8

Table 3: Tour adoption in all scenarios

After linking ERS-adopting trips to their full tours, the annual number of ERS-adopting tours was found to be 3.0 million for the Tight scenario, 4.3 million for Moderate, and 5.8 million for Flexible. These totals are lower than the number of adopting trips, indicating that many tours contain multiple ERS-eligible trips. Tour adoption increases with more favorable (flexible) technological assumptions.

Figure 1 and 2 show the difference in ERS adopting trips in the *trip* adoption potential (right) compared to the *tour* adoption potential (left). The colored lines visualize the trips that comply with all the criteria and are therefore included in the adoption potential in three scenarios (green = flexible, blue = moderate, purple = tight). The difference between the figures before and after removing the non-ERS-adopting tours, relates to the exclusion of tours in which the battery runs empty.

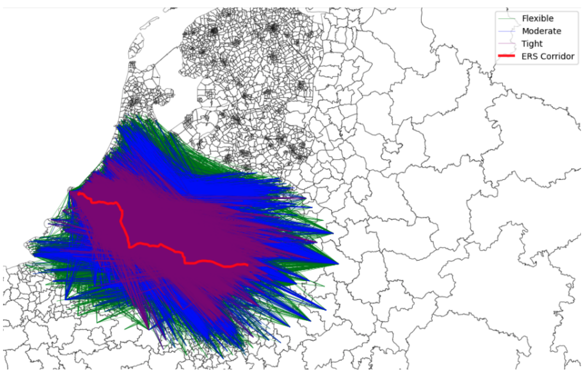


Figure 1: ERS-using trips from tours in the tour adoption potential

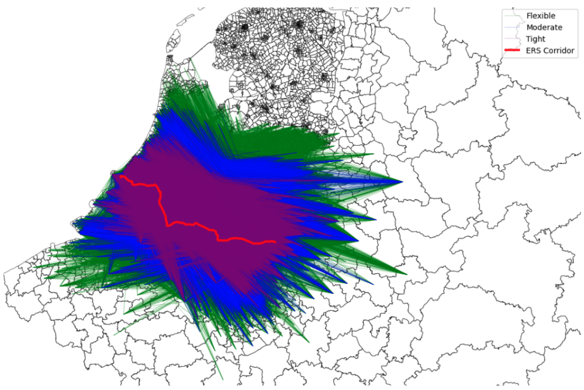


Figure 2: ERS adopting trips between zones in the trip adoption potential

After identifying the tours included in the adoption potential for each scenario, a final set of tours is now left that can complete their route using ERS without battery depletion. For each of these tours, the battery level at ERS entry is known, based on the simulated pre-ERS travel.

The final step is to calculate energy demand, which is analyzed in two ways: (1) Spatial energy demand and (2) Temporal energy demand.

The spatial analysis shows that the highest daily energy demand occurs in the western corridor section, particularly between kilometers 20 and 40 near Rotterdam. Segment 15 (km 28–30) peaks at over 35,000 kWh per day. Demand decreases toward Venlo, with segment 98 showing around 5,000 kWh/day.

The peak power analysis also highlights the Rotterdam area, with a maximum load of 3,420 kW on segment 12 (km 22–24). Segments 10, 15, and 20 also show high loads, while values drop substantially further east.

The temporal energy demand analysis reveals distinct daily fluctuations along the ERS corridor. Demand peaks between 7:00–11:00 AM, with smaller surges from 4:00–6:00 AM and 2:30–7:30 PM. These peaks are concentrated in the western corridor, particularly between kilometers 20–50, indicating an eastward movement of trucks during the day. Demand is consistently low between 9:00 PM and 4:00 AM. These patterns are visualized in the combined spatial-temporal heatmap (Figure 3).

This aligns with typical logistics flows, where activity builds near Rotterdam in the morning and spreads southeast. Propulsion needs drive the peaks, while charging demand remains relatively stable throughout the day.

Segments 12 and 15 show the highest power demand, with sharp increases from 6:00 AM and sustained high usage through the afternoon. After the evening peak, demand declines and stays low overnight. These results offer valuable insight into the timing and intensity of ERS power loads.

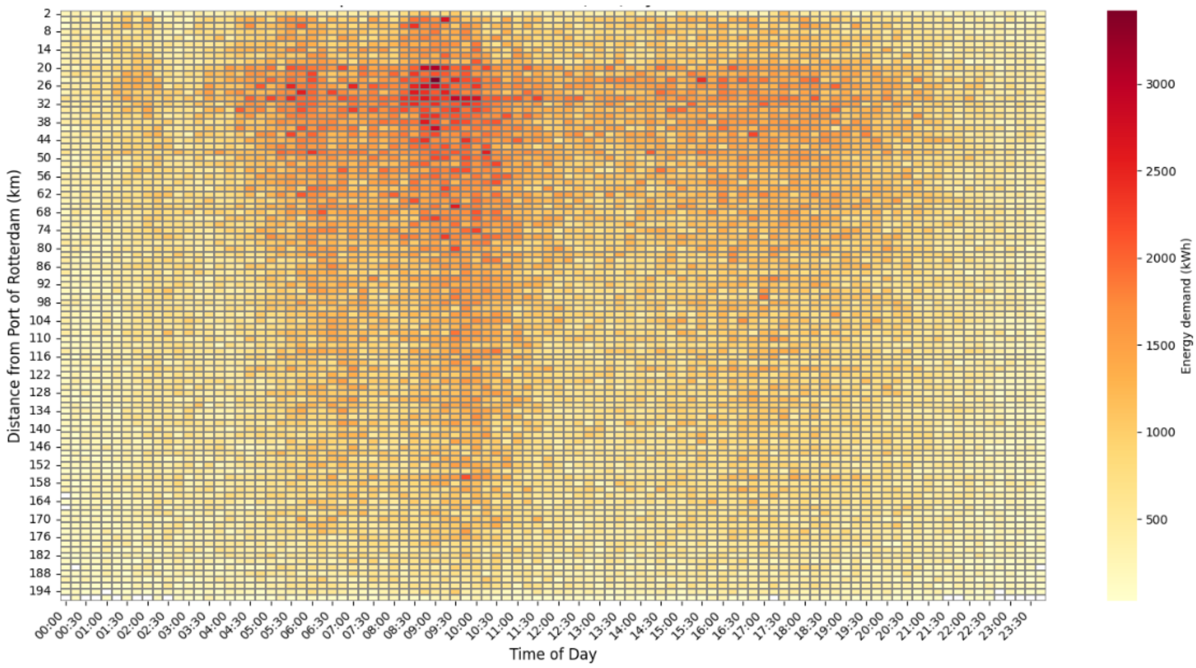


Figure 3: Heatmap of ERS Power Demand (kWh) by Segment and Time (Moderate scenario)

The results show that applying battery constraints at the tour level significantly lowers ERS adoption compared to trip-level analysis. Over 35% of potentially eligible trips were excluded due to range limitations. This highlights the importance of accounting for battery capacity, charging access, and full route structure to avoid overestimating the adoption potential. While a single-corridor approach limits adoption, a broader ERS network with overlapping routes and more charging opportunities could reverse this effect, making ERS use more feasible, especially when combined with static charging. Spatial analysis revealed that energy demand is highest between kilometers 20–50 near the Port of Rotterdam, a key logistics hub where many trucks enter with low battery. These trucks often use this section for both propulsion and charging. Eastbound traffic dominates the corridor, leading to an asymmetric energy pattern with demand concentrated in the west.

These findings provide ElaadNL, the Ministry of Infrastructure & Water Management, and grid operators with crucial insight into when and where energy is needed, enabling more efficient grid planning and infrastructure investments. Even though only 5% of freight flow is expected to adopt ERS under moderate assumptions, the results inform decisions on ERS feasibility versus alternatives like fast chargers.

Key limitations include the use of straight-line distances, simplified routing assumptions, static 2018 data projected to 2040, and an optimistic adoption rate. Real-world factors like traffic, prices, or driver behavior were not included.

To conclude, this study estimated the spatial and temporal energy demand of an ERS corridor using tour-level data. In the moderate scenario, 5% of freight flow, about 2.8 million tours annually—adopted ERS. Demand peaked near Rotterdam (segments 10–20), with the highest energy use at segment 15 and peak power at segment 12 (9:00 AM). Three daily demand peaks were observed. Scenario analysis showed that battery efficiency has a major impact, while charging power plays a smaller role.

Future research should integrate real routing data, weekend activity, adoption behavior without depot charging or with congestion data. Tour-level analysis should become standard in ERS planning to better capture charging needs and guide infrastructure decisions.

Contents

1 Introduction

In this section, the problem and the objectives of this study are outlined. First, the problem statement is described. Next, the research objectives are mentioned. Subsequently, the main research question is described, along with the sub questions. Then, the case study used for this research is introduced and finally the structure of the report is outlined.

1.1 Problem Statement

Even though only representing 5% of the total vehicle fleet, medium and heavy-duty vehicles are a major concern in the transportation sector due to their contribution of over a quarter of the sector's green house gas (GHG) emissions [1]. Transport is a major part of today's society and with a share of as much as 27% to the total GHG emissions it is one of the largest polluting sources in the world [2]. Not only environmentalists, but also governments are now taking rapid action to reduce emissions. As one of the main contributors, the transport sector is being subjected to strict scrutiny to ensure it complies with the short and long-term regulations [3]. To put ambition into reality, the European Union proposes for a substantial 90% reduction in truck emissions by 2040 [4]. An ambitious goal that underscores the urgency of the EU to decarbonize the transport sector, especially the emission share by trucks. This necessitates systemic change in freight transport technologies.

Despite these ambitions, major technical barriers remain. ElaadNL recently predicted a swift increase in market share of electric trucks in the Netherlands, as can be seen in Figure 4. However, currently this share is still less than 2% [5]. Fossil fuel driven vehicles are still very dominant and this is mainly because of the lower costs, longer driving range, and ease of refueling conventional vehicles [6]. For example, (affordable) electric vehicles that are on the market today typically have a range of around 300 km [7]. Larger batteries could be a solution to tackle this problem, but big batteries are currently expensive and extremely heavy. Larger battery packs also impose additional cost and additional weight which reduces vehicle energy efficiency and which, in mass-limited payload scenarios, can result in additional vehicles required to perform the same transport task [8]. Such 'big-battery' trucks need to be supplied with battery capacities of the order of 500–1000 kWh, and a supporting network of high-powered static chargers potentially including those which meet the 'Megawatt Charging System' (MCS) standard (1000+ kW) [8]. Besides, the bigger the battery, the longer it takes to charge [9]. Ideally, the sector would benefit from smaller batteries that offer sufficient range and can be recharged quickly. Whether such a combination is technically and economically feasible in the future is difficult to say.

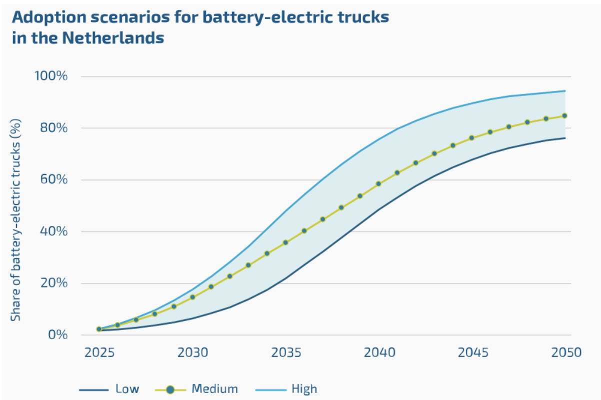


Figure 4: Number of electric trucks forecast by ElaadNL [5]

However, one potential solution to address this challenge has recently gained attention: Electric Road Systems (ERS). These systems offer the possibility for freight trucks to charge while driving through wireless power transfer, on-ground power supply, or overhead catenary cables [10]. Figure 5 shows what the latter looks like. This way, the trucks could potentially carry smaller batteries due to the ability to charge dynamically along the major roads. This leads to associated reductions in vehicle costs, embodied carbon emissions, and vehicle weight. De Saxe et al. [8] even state that the reduction in battery sizes over a national fleet of HGVs (Heavy Goods Vehicle) will likely far outweigh any additional embodied carbon in the ERS infrastructure.

Still, ERS is very under-investigated, but the advantages (at least on paper) are clearly visible. ElaadNL predicted a market share increase to 36% in 2035 and in a "high scenario" even to nearly100% in 2050 for electric trucks in the Netherlands (Figure 4) [11]. All these trucks would need energy to charge their batteries, which would massively impact the energy grid. The same research estimates the total energy demand by trucks in 2050 to be 11.1 TWh per year. To put that into perspective: that is about 10% of the total current yearly electricity demand in the Netherlands [12]. This emphasizes the need for improvement of the charging infrastructure. While ERS shows potential to overcome key barriers in freight electrification, its feasibility in terms of energy demand, remains underexplored. In particular, little is known about how ERS adoption would affect the electricity grid along key freight corridors.

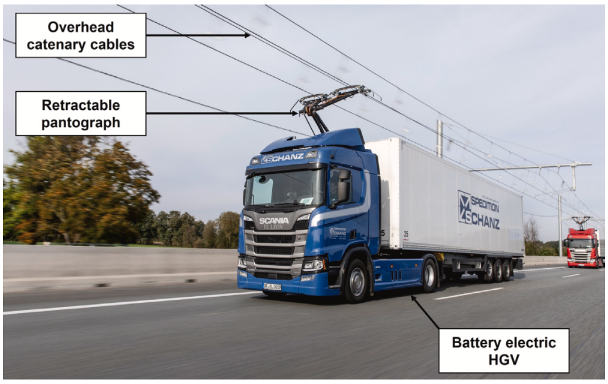


Figure 5: An overhead catenary implementation of ERS [13]

1.2 Research Objectives

Electric Road Systems represent an interesting alternative to support the transition toward a fully electric truck fleet by 2050. However, a comprehensive analysis of the energy demand implications of potential ERS corridors in the Netherlands is crucial to support evidence-based policy development and infrastructure planning. There is little research done in this field and grid operators will have to know what impacts they can expect in order to prepare for the dynamic charging infrastructure. A logical starting point for such an investigation is the Rotterdam–Venlo corridor, one of the most heavily utilized freight routes in the country. Along the corridor, demand patterns are likely to differ spatially and temporally. The magnitude of these impacts is still unknown. Thus, a quantification of the energy demand by an ERS corridor is much needed. This study aims to quantify the spatial and temporal energy demand patterns of an ERS corridor between Rotterdam and Venlo.

A quantitative research approach is chosen for this study as it allows for systematic analysis of numerical data to explore the relationship between ERS and energy demand. Previous studies show varying results on ERS energy patterns, and this method helps test such findings using statistical tools. For the Rotterdam–Venlo corridor, extensive traffic flow data is available, making it suitable for quantitative analysis. This method enables the identification of spatial and temporal patterns in energy demand, based on forecasted freight traffic flows for the year 2040. These forecasts provide the necessary input to estimate the number of electric trucks using the ERS and their charging behavior over time. However, the approach relies heavily on the quality and representativeness of the data used.

1.3 Research Questions

Based on the research objective introduced above, the following main research question is formulated:

"What is the expected temporal and spatial distribution of energy demand of an Electric Road System along the Rotterdam-Venlo corridor?"

To systematically work towards answering the main research question, this study utilizes sub questions that are phased and chronologically structured to lead to a comprehensive answer to the main question. Each sub question represents its own phase, builds upon the previous phase, and forms the foundation for the next. This enables a structured understanding of the demand patterns along the corridor. The key tasks, goal of the question, link to other questions, and tools/methods used are outlined in Table 4. The following sub questions have been formulated:

1. **What is the freight volume and transport flow along the Rotterdam-Venlo corridor?**
2. **What is the ERS adoption potential for all the *trips* performed by heavy trucks per year?**
3. **What is the ERS adoption potential for all the *tours* performed by heavy trucks per year?**
4. **What are temporal and geographical demand patterns along the corridor?**

Sub question	Key Tasks	Goal of Question	Link to Previous Questions	Tools/Methods Used
SQ1: What is the freight volume and transport flow along the Rotterdam-Venlo corridor?	Obtain and preprocess BasGoed data; Analyze freight volumes and temporal trends; Perform spatial analysis of freight movement along the corridor.	To establish the baseline truck movement data and identify how freight traffic varies spatially and temporally.	–	Literature review; Secondary data analysis; Geospatial analysis; Python
SQ2: What is the ERS adoption potential for all the *trips* performed by heavy trucks per year?	Identify key adoption criteria; Estimate ERS adoption; Develop adoption scenarios; Visualize trips that use ERS in a map.	To determine a set of trips that are likely to adopt ERS if available.	Uses freight flow data from SQ1 to determine which trucks are eligible and willing to use ERS.	Literature review; Secondary Data Analysis; Scenario modeling; Python
SQ3: What is the ERS adoption potential for all the *tours* performed by heavy trucks per year?	Identify impact of battery constraints; Estimate ERS adoption; Analyze impact of different parameter values; Visualize tours that use ERS in a map.	To determine the final set of tours that would adopt ERS based on set of conditions.	Uses truck and route characteristics from SQ1 and trip adoption potential from SQ2 to estimate final set of ERS-adopting tours.	Modeling in Python.
SQ4: What are temporal and geographical demand patterns along the corridor?	Scale up truck demand to full corridor demand; Analyze peak demand periods; Map energy demand hotspots.	To identify peak demand periods and spatial variations in energy consumption along the route.	Uses energy consumption factors (SQ3) and freight flow data and adoption rates (SQ1 & SQ2) to determine hotspots and estimate demand curve.	Secondary data analysis; Python

Table 4: Sub questions, key tasks, goal of the question & link to other questions

1.4 Case Study

Not every route or road network is suitable for the deployment of an ERS infrastructure. The suitability depends on traffic volume and the anticipated utilization by electric trucks. A viable business case must be developed. Economies of scale apply to the adoption of ERS, meaning that the energy price paid by users can be reduced if there are many users. This, in turn, shortens the payback period of the infrastructure [14]. Therefore, potential ERS deployment is expected to focus on high-traffic freight corridors.

One such corridor is the route between Rotterdam and Venlo, accommodating many trucks originating from the Port of Rotterdam and destined for the Ruhr region in Germany [15]. The corridor's strategic position and international relevance make it a strong candidate for future ERS development. Two primary paths connect Rotterdam to Venlo: a northern and a southern route. In this study, the southern route is selected, consistent with prior ERS modeling efforts ([16]), and is visualized in Figure 6.

Figure 6: Rotterdam-Venlo route [17]

1.5 Intended Contributions

By using unique and realistic tour-level truck data, novel insights can be obtained on actual energy demand patterns, going beyond the conventional trip-based methods. By incorporating tour-level data and estimating the ERS-adopting tours, this research will improve the accuracy of spatial and temporal energy demand forecasts for ERS corridors (Section 2 gets into this in more detail). This is particularly important for understanding how energy is consumed over time and across locations, as the battery state-of-charge is not reset between trips but accumulates throughout the tour. This research provides the first detailed analysis of ERS-induced energy demand patterns in the Netherlands, offering localized insights that are essential for Dutch grid operators and policymakers. Besides, it will be the first analysis of energy demand on an ERS corridor that uses tour-level data for its estimation. The results can support infrastructure and energy planners by identifying when and where peak demand occurs along the corridor, aiding in the design of effective load management and grid reinforcement strategies.

1.6 Structure of the Report

The structure of this report is as follows. Section 2 presents a literature review in which state-of-the-art literature is analyzed and compared based on overarching themes. This review identifies knowledge gaps, which serve as a starting point for this research and introduce the gap this report aims to address.

Following the literature review, Section 3 outlines the model description. In this chapter, it is explained step by step how to answer the research question. The chapter begins by outlining the components that make up energy demand. It then describes the model used to determine trip adoption potential, which serves as the basis for calculating the tour adoption potential. Following this, the procedures for estimating temporal and spatial energy demand are explained. The chapter concludes with a sensitivity and scenario analysis and a discussion of the key assumptions underlying the study.

In Section 4, the results are presented. These correspond to each of the elements previously discussed in the model description chapter. Section 5 contains the discussion of the results. Here, battery constraints are examined, the effect of using tour-level data on adoption potential, and the spatial and temporal energy demand are analyzed. The implications of the study for ElaadNL are also discussed, along with its limitations.

Finally, Section 6 presents the conclusion and ends with several recommendations for future research.

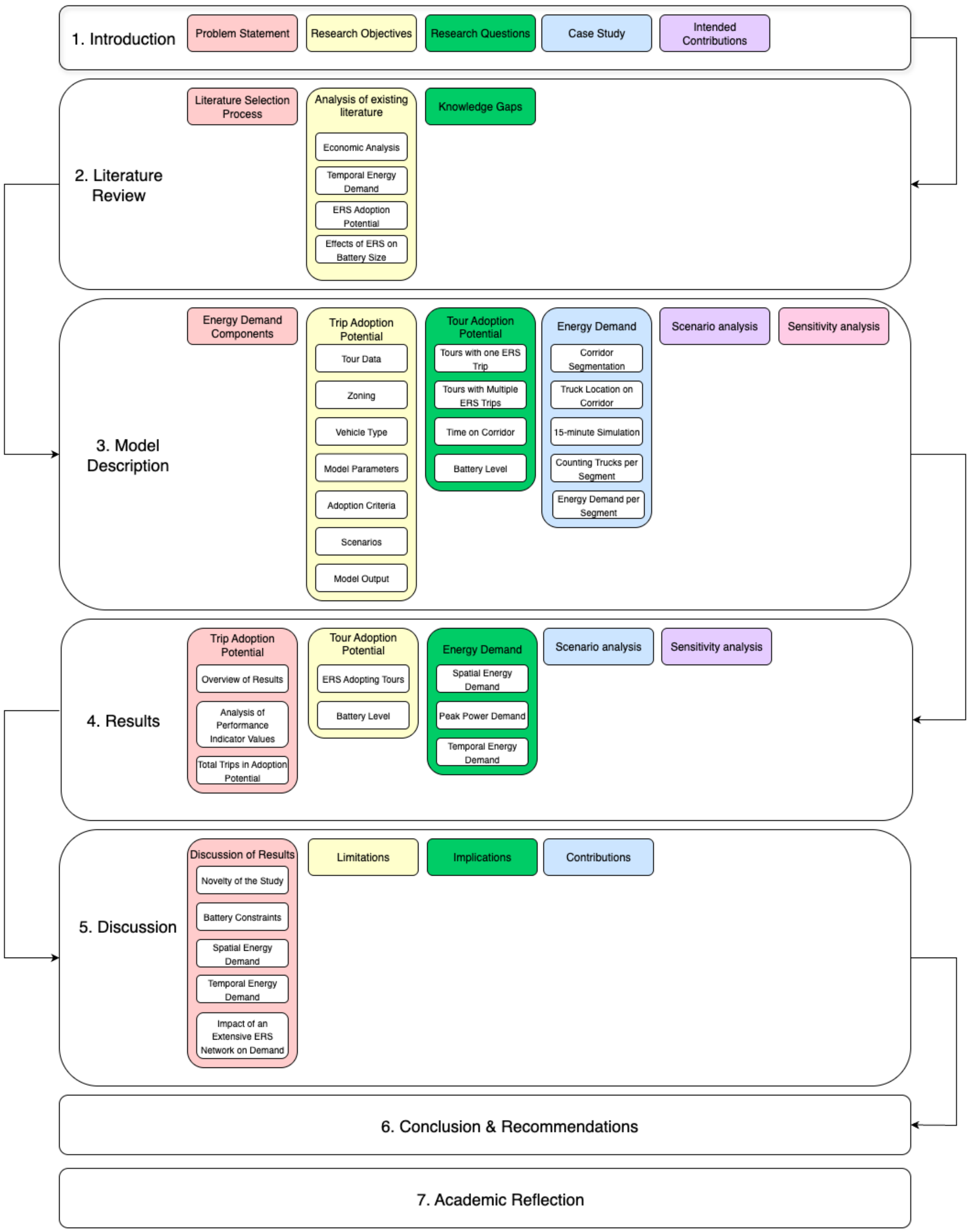


Figure 7: Structure of the report

2 Literature Review

This chapter reviews the current state-of-the-art scientific papers on Electric Road Systems. First, the literature selection process will be described. Then the chosen literature will be analyzed by applying a synthesis on these studies. A broader perspective will be obtained on the subject and finally an under-investigated knowledge gap will be identified.

2.1 Literature Selection Process

Before the start of the project, loads of relevant literature was obtained via the supervisor of this research, who is already familiar with the topic. From this literature, a selection was made that focuses predominantly on the energy demand and adoption of ERS. Additionally, Scopus was consulted to find more literature on ERS which resulted in the addition of one relevant article. ElaadNL also provided one relevant source to review. The search and selection process of the literature is visualized in Figure 8. It shows which search terms were used, how many references were found, and which selection criteria were used to scope down towards a feasible number of articles. Eventually, 10 sources were selected for the literature review.

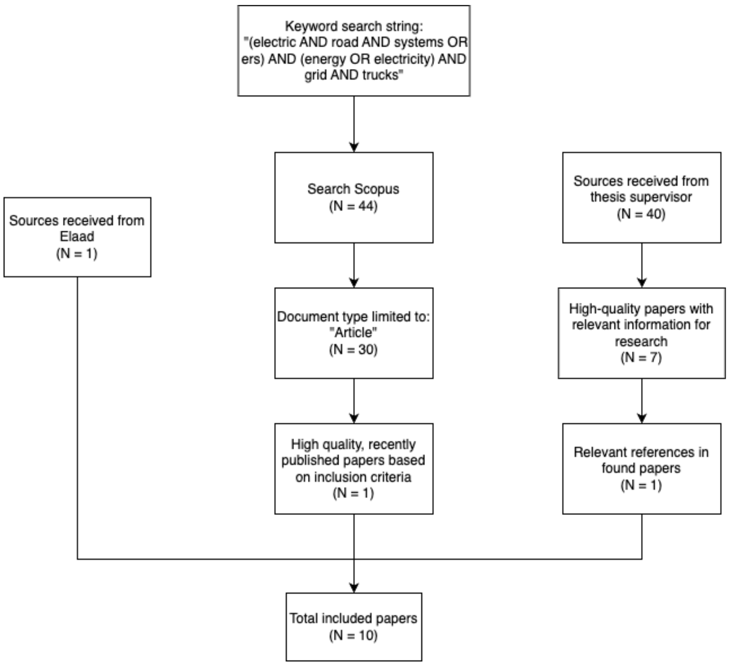


Figure 8: Literature search criteria

2.2 Analysis of Existing Literature

For the relevance of this study, it is important to examine what new insights can be offered through the analysis that will be conducted. ERS is a relatively new phenomenon, but despite this, considerable research has already been done and several papers on this topic have been published, including on the energy demand it generates. In order to identify the knowledge gap in the current literature, several relevant reports are analyzed to determine what these sources have in common, but more importantly, what they overlook or fail to address. The selected sources are categorized based on their overarching theme and are discussed below per theme.

Economic Analysis

Within the literature, different perspectives are used by authors to analyze and assess ERS. One of these is examining the economic impact of ERS by outlining the costs and benefits. Examples are Rogstadius [14], who investigates the socio-economic impact of adding ERS to the mix, Yeow et al. [18] who perform a cost analysis on savings through ERS and assesses its potential in the US and Deshpande et al. [19], who perform a cost-benefit analysis to identify locations where ERS is economically viable. There seems to be a consensus among authors that on the long term ERS is profitable and will outperform other charging methods based on costs versus benefits. Deshpande et al. [19] found that up to 47% of the total road freight in England, 72% in France, 38% in India, and 57% in South Africa could be electrified using ERS with a 20-year break-even period. In a study by Rogstadius [14], he found that one of the key drivers of the success of ERS is the user fee that is set to charging on the infrastructure. In the article, he states that if the fee is set low enough, 80-90% of heavy truck traffic (driven km) within the network has economic incentives to charge dynamically. The author states that in Sweden, maximum utilization is reached when the total price of dynamic ERS charging is at most just above the cost of private depot charging, approximately €0.3/kWh. This emphasizes the importance of a fee that transport operators need to pay to make use of the system. In the article by Yeow et al. [18], the authors do not specifically mention a break-even period in the same way as the other articles, but concludes that despite high upfront costs, ERS may be cost-competitive with long-range batteries, plug-in charging, and diesel trucks if they are used on roads with high traffic volumes.

Temporal Energy Demand

Although ERS is a relatively new phenomenon, some research has already been conducted, and a substantial body of literature exists on the topic. However, there is a lack of studies that investigate the characteristics of the energy demand of an electric road system. Only several authors have studied the energy demand of an ERS network ([20], [21], [22], [18]). For example in a study by Taljegard et al. [21], the authors investigated the spatial and dynamic energy demand on a highway in Norway. They used a method to calculate the energy demand of a heavy truck utilizing the ERS infrastructure. They assume a 100% electrification of the road traffic and used average daily traffic data measured at 770 checkpoints along the route they investigate. Their findings include variations in energy demand distribution throughout the day, week, and year. For instance, there is a clear difference in energy demand between weekdays and weekends, with the highest demand occurring between 3 PM and 5 PM. However, this source assumes a 100% electrification of traffic, which is not what the current traffic distribution looks like. Additionally, the authors have shown that an ERS load profile that includes the traffic (passenger cars, trucks and buses) on all main roads in Norway would increase the hourly peak power demand on the dimensioning hour of the system by approximately 7%, and that heavy vehicles account for almost half of this increase.

In the study by Jelica et al. [20], they investigate the hourly electricity demand when electrifying light and heavy vehicles with ERS on the roads that connect the three largest cities in Sweden. The study uses two datasets: (1) the road traffic volumes per hour during a period of 1 year; (2) and the traffic volumes per day for an average day. The study found similar patterns in hourly demand, with peak demand occurring between 1 PM and 2 PM. In addition, the study found that the implementation of ERS on the roads connecting the cities will increase yearly national energy demand by 4%, but will decrease the national transportation energy demand by 9%. If just implementing ERS on these roads can achieve this level of reduction, expanding the network could lead to even greater national energy savings. Also, the authors assume a complete adoption of electric trucks, which is not representative for current traffic flows. Similar to Taljegard et al. [21], the study by Jelica et al. [20] also found a peak power increase in electricity demand, but by 11%, compared to the existing peak power demand of the Swedish national electricity system.

Yeow et al. [18] investigated and compared several green transport methods based on system costs and reduction in GHG emissions. They used projected nationwide truck freight demand data for 2050, which includes freight tonnage between origin-destination pairs within the contiguous U.S. 10.000 OD pairs were eventually used. They found that ERS shifted peak power demand to the middle of the day, when projected average grid emissions are lowest (matched with solar power generation), and away from high electricity costs in the evening. Interestingly, this paper suggests that electricity costs savings due to time-of-day charging were negated by energy loss from lower dynamic wireless power transmissions (DWPT), grid-to-wheel efficiency (10%) and pantograph aerodynamic drag (8%). Therefore, eRoads benefits could be maximized by improving DWPT transfer efficiency and reducing aerodynamic drag from the pantograph with eRoads. In contrast to Jelica et al. [20], Yeow et al. [18] found that ERS shifted the energy demand to the middle of the day (12 PM - 3 PM), instead of at the end of the working day (4 PM - 5 PM). This is possibly due to the different locations of the study (U.S. vs. Sweden).

In a paper on road traffic's future energy and power needs by Rogstadius [22], the peak power demand for heavy trucks is found to be between 2 PM and 4 PM. The author visualizes clearly how the demand curve changes with the implementation of ERS and how different months have different energy demands. He found that only in winter the demand is different and that due to the use of ERS the peak demand is no longer at night but rather during the day and that the peaks are much lower than without the option of dynamic charging. However, the study uses assumptions on the distribution of charged energy based on previous simulations also by Rogstadius [23] that indicate that 55% of charging by heavy duty vehicles will be done with ERS. It is likely that this assumption does not hold for the distribution in the Netherlands, since the simulations by Rogstadius [22] are from a Swedish model.

ERS Adoption Potential

A study by Bakker et al. [16] on the adoption potential of ERS in the Netherlands estimates the number of heavy truck trips that would utilize ERS charging following the deployment of an ERS corridor between Rotterdam and Venlo. The study bases its estimations on three key factors: the maximum feasible distance without ERS (which determines the required battery size), a minimum percentage of travel along the ERS corridor, and the maximum detour a trip would take to access ERS infrastructure. Using these criteria, the research assesses the number of trips between two zones that fall within the ERS adoption potential. The study's output includes the total distance traveled on the ERS network and the percentage of total transport flows that fall within the adoption potential. The authors suggest that future research could build upon these findings by investigating energy consumption patterns. Additionally, they acknowledge a lack of detailed information on specific vehicle routes, which poses challenges in understanding how truck operators would actually utilize ERS in practice. To bridge this gap, they recommend that future studies integrate high-resolution freight flow data with precise route information to gain deeper insights into adoption behavior.

Effects of ERS on Battery Size

The study by Bakker et al. [16] refers to a paper by De Saxe et al. [8] that thoroughly investigates the energy demand of ERS corridors in England and how it affects battery sizes in different scenarios. It provides crucial insights into how the power demand of ERS can be computed and which factors contribute to the total demand. The study found that the addition of an ERS was shown to reduce the required battery capacity in all static charging scenarios relative to a scenario with no ERS. Battery capacity reductions of 41%, 62%, and 75% were calculated for ERS topographies of length 2750, 5500, and 8500 two-way km respectively averaged over all journeys. While the results were promising for ERS, it is unclear whether a single corridor network would obtain similar results in terms of battery downsizing.

In a study by Liao et al. [24], the authors examine the optimal network for ERS catering to BETs (Battery Electric Truck). They present a model that offers new insights about the potential impact of ERS implementation on cost savings in terms of total transport expenses, with a particular focus on reduction of battery-related costs. They found that the ERS investment costs can be balanced with cost reduction, up to a network length of around 20,000 km. The results of this study align with the findings from De Saxe et al. [8] that significant savings in battery size follow from widely adopted ERS networks. The article shortly touches upon the energy demand associated with ERS deployment levels. However, the smallest ERS deployment level is 3800 km and thus is not representative for a single ERS corridor. Additionally, they assume a predefined constant charging rate for ERS per unit of time, which in reality depends on several variable factors, the authors state.

Rogstadius also looked at battery sizing [23] [14]. He examined the cost savings associated with battery usage. His findings indicate that the overall consumption of battery resources by heavy trucks in Sweden is likely to decrease with the implementation of ERS. He states that battery capacity per BET will decrease by approximately 65% on ERS-equipped routes and that ERS contributes a reduction in long-term annual BET battery demand by up to 50%. This reduction occurs for two main reasons, he states: first, battery cycling decreases since propulsion energy no longer has to flow through the traction battery, reducing wear and tear. Second, ERS allows logistics operations to function with smaller battery packs, which in turn slows down battery aging over time. However, there is also literature that states that smaller batteries age faster [25].

Study	Aspects	Topic	Case Studies
[22] Rogstadius (2023)	Temporal energy demand	Forecasts future energy and power needs for ERS vehicles per type of charging infrastructure.	Sweden
[14] Rogstadius (2024)	Economic feasibility	Analyzes the utilization of a future ERS network in Sweden.	Sweden
[18] Yeow et al. (2024)	Economic feasibility & Temporal energy demand	Assesses the environmental and economic impacts of different electrification strategies for long-haul heavy-duty trucks in the U.S. by 2050. Compares large batteries, fast chargers, and electrified roadways.	USA
[19] Deshpande et al. (2023)	Economic feasibility	Formulates the cost breakeven period for ERS infrastructure, considering costs and income for providers. Uses freight movement data to identify viable locations.	India, France, South-Africa, England
[20] Jelica et al. (2018)	Temporal energy demand	Analyzes the hourly electricity demand associated with implementing electric road systems in Sweden.	Five Swedish roads with highest traffic flows
[21] Taljegard et al. (2017)	Temporal energy demand	Assesses the energy demands of Norway's E39 highway under various electrification scenarios, analyzing spatial and temporal variations in power needs.	E39 Highway, Norway
[23] Rogstadius (2023)	Effects on battery size	Investigates whether ERS for heavy-duty trucks is viable for aligning with EU GHG reduction targets.	Sweden
[16] Bakker et al. (2024)	ERS adoption potential	Studies the potential for adopting ERS for heavy freight trucks, focusing on network design impacts in early development stages.	Netherlands
[8] De Saxe et al. (2023)	Effects on battery size	Develops a vehicle simulation model to calculate battery capacity requirements for UK logistics journeys with different ERS network sizes.	United Kingdom
[24] Liao et al. (2024)	Network analysis	Explores the economic viability and optimal design of ERS for heavy-duty trucks, addressing high battery costs and limited charging infrastructure.	Netherlands, Germany, Luxembourg, Belgium

Table 5: Literature Review

2.3 Knowledge Gaps

Despite challenges, ERS clearly offers potential future benefits. As previous studies have shown, ERS can help smoothen the energy demand curve by shifting charging loads from the evening, when electricity prices and grid usage are typically high, to daytime hours when trucks can charge dynamically while in motion [21]. This shift has the potential to mitigate peak loads at depots and flatten overall demand patterns. However, it has also been demonstrated that ERS can substantially increase hourly peak loads on specific segments of the electricity grid [20]. After analyzing the existing literature, several knowledge gaps have been identified that are not touched upon in previous studies.

First and foremost, a critical shortcoming in existing literature is the failure to account for the tour-based structure of truck operations. A significant portion of trucks have multiple destinations per day, completing several trips within a single day. These trips should not be viewed as separate, as they collectively form the tour that a truck completes. For example, Bakker et al. [16] estimate the number of trips that would use an ERS network, but only looks at individual trips. In addition, the datasets used by Taljegard et al. [21] and Jelica et al. [20] provide average daily traffic patterns, and estimate the energy demand based on measured traffic data on highways, without looking at the tour structure of the traffic. By analyzing truck tours rather than individual trips, valuable insights can be gained regarding the battery state of charge, and consequently, the energy demand on the ERS corridor. This approach provides a more realistic representation of actual energy demand than analyses that only consider individual trips or average traffic patterns.

Secondly, expect for the study by Bakker et al. [16], all the studies use current traffic flow patterns and assumptions on electrification to estimate the number of trucks that would adopt ERS. To provide trustworthy results, an calculation-based estimation of the ERS-adopting tours must be generated first before calculating the energy demand. An estimation of the number of tours that will use ERS is crucial for the total energy demand and should be a main part in the calculation.

Lastly, while several studies have investigated the energy demand impacts of electric freight infrastructure in countries such as Sweden, Germany, and Norway, there is a notable lack of research on ERS-induced demand patterns in the Dutch context.

So, this study will calculate the spatial and temporal energy demand of an ERS corridor, by using a unique tour-level dataset that captures more than 2 million heavy-duty vehicle trips per week in the Netherlands and neighboring countries. The data includes precise data on origin and destination zones, sequence of trips, and departure times. Never before has a study been performed with such precise zoning data, using nearly 7000 unique zones, in combination with the tour dataset. By integrating tour structures into ERS modeling, this study provides a novel and operationally realistic estimation of the ERS-adopting tours and subsequently the energy demand of an ERS corridor in the Netherlands.

3 Model Description

In this section, the model used to find the energy demand of an ERS corridor is discussed. First, the components that contribute to energy demand are analyzed. Next, the trips that will be included into the trip adoption potential are determined by cleaning and analyzing the data and testing the trips to several criteria. Subsequently, the leftover trips are used to determine the tour adoption potential by testing the tours to their battery level. Then, the energy demand will be determined per timestamp per corridor segment. Lastly, a scenario and sensitivity analysis will be conducted.

3.1 Energy Demand Components

Understanding the energy demand of an ERS corridor requires an analysis of both the number of trucks that would use the infrastructure and the energy those trucks would consume. This chapter begins by examining the factors that influence the demand for dynamic charging on a potential ERS route. Figure 9, provides a simplified conceptual model of the factors that influence the energy demand profiles of trucks. The two factors that lead to energy demand are road freight activity and energy consumption, supported by the infrastructure characteristics. The infrastructure has no direct impact on the demand profiles. It affects how much of the theoretically calculated energy demand can actually be delivered by the ERS. That is why those arrows are dashed. The first part of this study focuses on the road freight activity category. Later in this research, the energy consumption is analyzed. To determine the energy demand along an electric road system corridor, it must first be known how many trucks would hypothetically make use of the dynamic charging infrastructure if it were constructed. After all, implementing an ERS does not automatically mean that all the trucks on that corridor will use the dynamic charging facilities, since not all trips use the entire corridor to reach their destination. It would make the use of an ERS-truck redundant.

To use the ERS facilities, logistics companies must invest in battery-electric trucks that can actually use the overhead catenary line to charge their battery. This concerns a hypothetical future scenario in which the adoption of such trucks is still uncertain. Therefore, an estimate must be made to obtain an accurate outcome of the number of trucks that will actually use the ERS infrastructure. In other words, the adoption potential of an ERS corridor between Rotterdam and Venlo needs to be estimated. To do this, a method developed by Bakker et al. [16] will be used. This method will be explained in detail in the following sections.

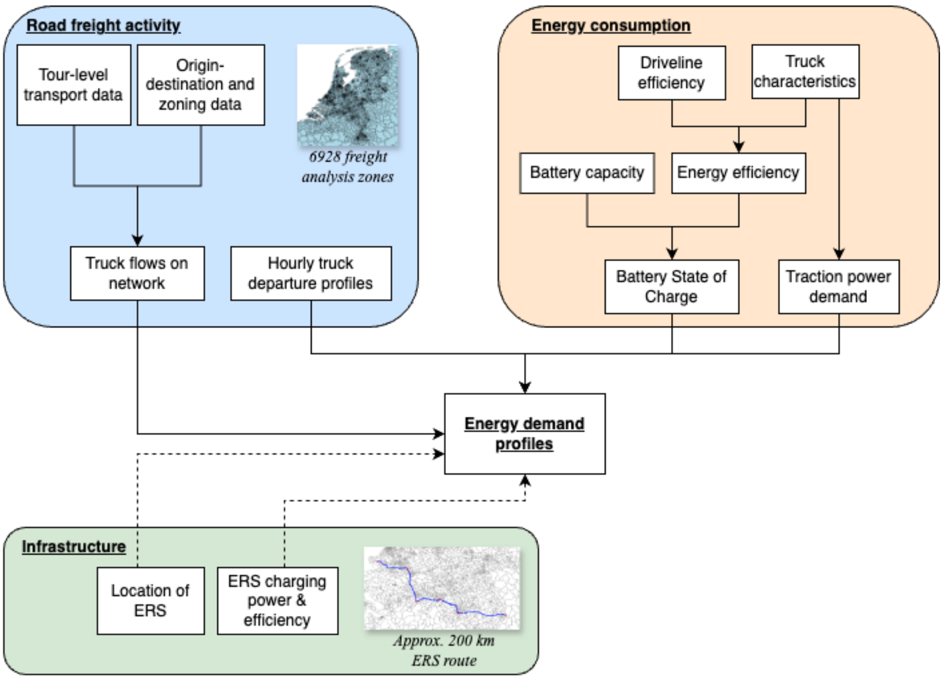


Figure 9: Conceptual Model

3.2 Trip Adoption Potential

The first step in determining the energy demand of an ERS corridor is estimating how many trips between two zones would be performed using ERS. When a trip makes use of the Electric Road System, it is referred to as adopting the ERS. Consequently, this results in a list of trips that would be performed with ERS. This is called the **trip adoption potential**. To identify these trips, various parameters are used as input for the model, which will be discussed later in this section. First, the dataset will be introduced.

3.2.1 Tour Data

To determine which trips would adopt ERS, insight into all the transport flows in the Netherlands must first be obtained. These transport flows are necessary to later estimate which portion of the freight traffic would utilize the ERS infrastructure. Fortunately, there is a model that provides insight into freight flows and goods transport within the Netherlands: the BasGoed dataset. BasGoed stands for "Basismodel voor Goederenvervoer" (Basic Model for Freight Transport). It is a strategic freight transport model used to generate forecasts for road, rail, and inland waterways. The model describes the volume of goods transported by road within the Netherlands and is intended to assess the impact of various measures on freight flows [26]. The primary data source for BasGoed is a yearly road transport survey, which is conducted by the Central Bureau of Statistics (CBS) under the mandate of the European Union (EU Regulation No 70/2012) [16]. Unlike the research by Bakker et al. [16], this research uses the ToursBase2040 dataset, which looks at complete tours instead of individual trips. This dataset is modeled and predicts the transport flow in 2040 based on current data, originating from 2018. Using tour data is more realistic than using only trip data, since most of the trucks have multiple stops during the day and these trips should not be seen as separate. A tour involves multiple stops and sometimes also returns to the depot where the trip originally started from. For example, a tour may begin at point A, make intermediate stops at B and C for loading or unloading, and return to point A at the end of the day. This tour then consists of 3 separate trips (A $\rightarrow$ B, B $\rightarrow$ C, C $\rightarrow$ A). Other tours in the dataset consist of multiple trips but do not end up at the origin zone. Some tours consist of one single trip. The ToursBase dataset contains all sorts of tours and has information on more than 4 million trips, with each trip providing specific details such as the tour it is part of, the origin zone, destination zone, vehicle type, trip and tour departure times, distance traveled, and much more.

The dataset is modeled for 5 days, meaning that the total number of trips in the set represents all tours in the Netherlands during one workweek (5 days). This implies that approximately 4 million trips are made per week. It is assumed that logistics trips are carried out on 256 days per year. If, later in the study, the number of trips or tours per year is to be examined, a factor of 256/5 (= 51.2) should be used to calculate the annual total. To determine the average number of tours or trips per day, division by 5 is applied.

3.2.2 Zoning

To interpret the BasGoed data, various zoning systems can be used. For this research, the NRM zoning system is applied (Nederlands Regionaal Model - or Dutch Regional Model). This system divides the Netherlands and neighboring countries into roughly 7,000 zones (6928). Most zones are in the Netherlands though, as can be seen in a preview of all the zones in Figure 10. Since many trips in the data originate from the Port of Rotterdam and are destined for the Ruhr Area in Germany, it is critical to include foreign zones as well. The Rotterdam-Venlo corridor is an essential route for road cargo originating from the Port with foreign destinations. It would make the results unrealistic if trips destined abroad were left out, since these trips make up an important part of the trips that likely adopt ERS. For each trip in the dataset, it is clearly specified which NRM-zone the trip originates from and which zone it is destined for. By using this highly detailed zoning system, reliable insights can be drawn regarding the routes taken by trips and the potential for dynamic charging on specific trips.

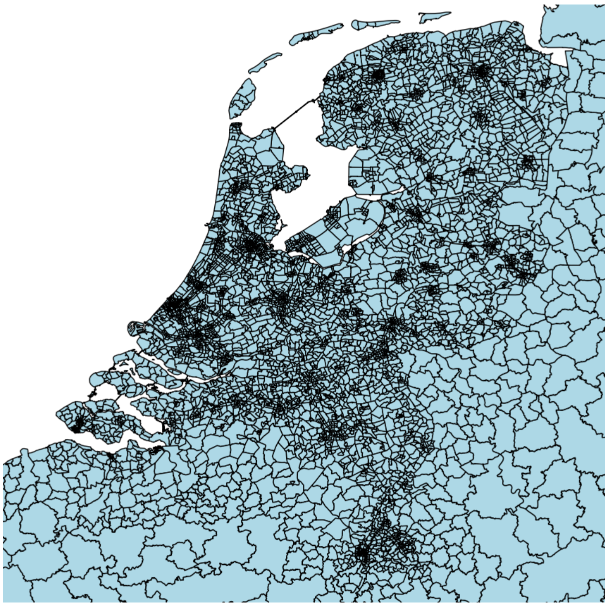


Figure 10: Sample of the NRM zones used for the model

3.2.3 Vehicle Type

As mentioned earlier in Subsection 3.2.1, the dataset contains information on more than 4 million trips. However, not all trips are performed by vehicles that are relevant for this investigation. In the Tour dataset, 11 different vehicle types are incorporated, including: small, medium, and large trucks; small and large trailers; semi-trailers; special transport; LZV (long heavy trucks); vans; light electric vehicles; and scooters. Data for the last two categories were not available, so they were never included in the dataset. In addition, the following categories were also excluded, as these vehicles are not eligible for ERS usage: small trucks, small trailers, and vans. ERS is potentially promising for large vehicles, which currently require very large batteries—one of the main reasons the transition from diesel to electric has barely begun in this segment. Delivery vans, on the other hand, are already widely electrified and operate primarily in urban areas. This study focuses mainly on trucks that cover long distances on highways and are therefore eligible for ERS. After removing the trips performed by the given vehicle types, the total remaining number of trips in the data was 2,679,788 and the number of tours per week was 1,073,829.

3.2.4 Model Parameters

After cleaning the data, it is time to start finding the trip adoption potential by using a quantitative model developed in Python, based on earlier work from Bakker et al. [16]. Table 6 provides a summary of these parameters used in the model.

Type	Parameter	Description	Data type	Unit
Input	Trips between zones	Number of trips between NRM zones	6928 × 6928 matrix	#/week
	Distance between zones	Haversine distance between NRM zones	6928 × 6928 matrix	Kilometer
	Distance over network	Travel distance over the ERS network between NRM zones	6928 × 6928 matrix	Kilometer
	Distance to network	Haversine distance between NRM zones and ERS network	6928 × 1 matrix	Kilometer
Criteria	Distance from network	Maximum distance of origin and destination to the ERS network	Value	Kilometer
	Percentage of trip ERS	Minimum percentage of trip traveled over the ERS network	Value	Percentage
	Detouring for ERS	Maximum amount of detouring in order to travel over the ERS network	Value	Ratio
Output	Percentage of Total Freight Flow	Share of all trips traveled using the ERS network	Value	%
	Total distance traveled over ERS Network	Kilometers traveled over the network	Value	Km/week
	Average distance over network	Average length of a single route over the ERS network	Value	Km/trip

Table 6: Overview of input, experimental, and output parameters for the ERS model

All input of the model are based on the data from the tour dataset introduced earlier. The parameters will be explained shortly:

Trips between zones

Total number of trips between two NRM zones. For this input, a 6928x6928 matrix is constructed, where the first dimension refers to the origin NRM zone and the second dimension refers to the destination NRM zone. The values in the matrix are therefore the total number of trips per week from one NRM zone to the other. If there are 50 trips from zone 1 to zone 2, the value in the cell is 50.

Distance between zones ($D_{i,j}$)

The second input is another 6928x6928 matrix, representing the straight-line (as-the-crow-flies) distance between each pair of NRM zones. These distances are calculated using the Haversine formula based on the latitude and longitude of the centroid of each zone.

Distance to ERS network ($d_{i,i'}$)

The next input is a 6928×1 matrix that calculates the shortest straight-line distance from each NRM zone's centroid to its nearest point on the ERS network. This is also computed using the Haversine formula. It helps assess the accessibility of the ERS network from each zone.

Figure 11 illustrates what this input parameter measures precisely. The distances depicted by the red arrows, are the distances to the network.

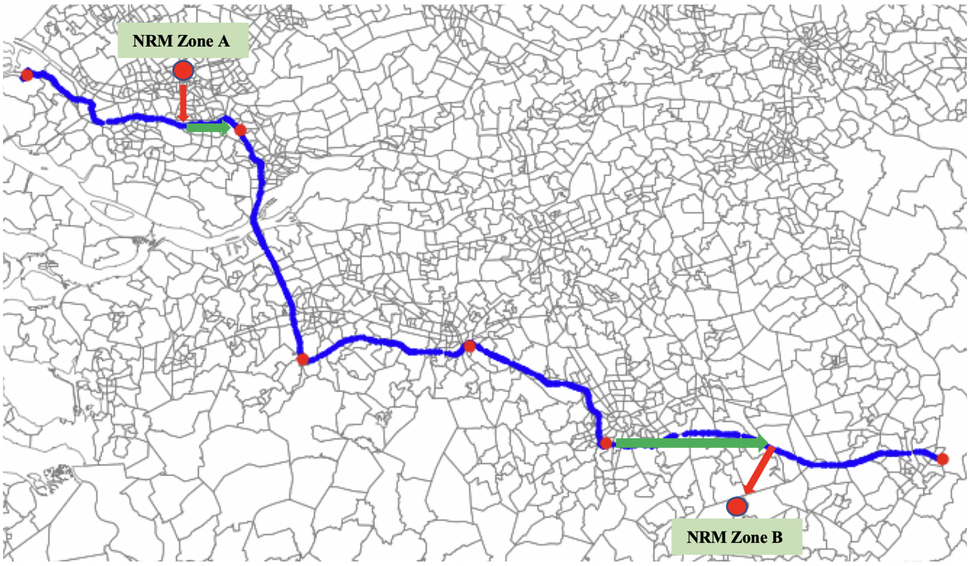


Figure 11: Example of the distance traveled over the network between two zones

Distance over the ERS network ($d_{i',j'}$)
Lastly, this matrix estimates how far each trip between two zones would travel over the ERS network, assuming full detour if necessary. Each trip is forced to use the ERS network for this input, even if it would require a lot of detouring to do so. Calculating this distance for each NRM zone pairing requires several steps, which are discussed briefly here.

The ERS network is defined by several reference points (e.g., intersections). See Figure 12, where the reference points are marked with red dots. For each zone, the nearest point to the network and the closest reference points are identified. Since the distance to the network for every zone was calculated earlier and the closest reference point for every origin zone and destination zone are known(Figure 11), it is possible to find the fastest route and the distance of this route. This distance is again stored in a matrix. The result is a 6928x6928 matrix with the ERS-specific travel distances for each zone pair. So, the distance over the ERS network consists of the distance from the closest point on the network to the closest reference point (green arrows in Figure 11) and the distance over the network between the reference points.

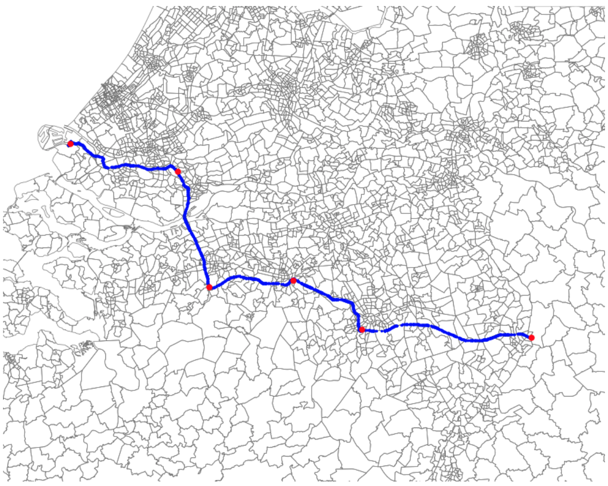


Figure 12: Reference Points on ERS Network

It is now known for each zone: (1) the distance to every other zone; (2) the number of trips to every other zone; (3) the distance to the network; (4) and the distance a trip to another zone covers over the network. These parameters will be tested to a set of criteria to see whether that trip would potentially make use of the ERS and would thus be included in the trip adoption potential. These criteria are introduced in the next subsection.

The notations of the different distances over/to/from the ERS network are summarized in Table 7.

Notation	Description
$D_{i,j}$	Distance between the centroid of zones i, j
$D_{i,j}^{ERS}$	Distance of the total trip between zones i, j that travels over an ERS network
$d_{i,i'}$	Distance between the centroid of zone i and its closest entry point to the ERS network
$d_{i',i*}$	Distance between the entry point and the closest reference point on the ERS network
$d_{i*,j*}$	Distance of the shortest route between the originating and destination reference points over the ERS
$d_{j*,j'}$	Distance between the closest reference point on the ERS network and the exit point closest to zone $j \in Z$
$d_{j',j}$	Distance between the exit point of the ERS network and the centroid of zone j

Table 7: Distance notations and descriptions

3.2.5 Adoption Criteria

In order to assess whether a trip falls within the adoption potential, it must be tested according to a set of criteria. All identified trips from the dataset are evaluated against these criteria to determine which trips ultimately meet all conditions. If a trip falls within this potential, it means that the trip would utilize dynamic ERS charging, assuming the necessary infrastructure is available. By estimating the number of such trips, insights can be gained into the number of tours that would eventually adopt ERS. This, in turn, allows for the calculation of the energy demand at a later stage. The criteria are explained below.

Distance from network (α)
The first criterion assesses the maximum allowable distance from both the origin and destination zones to the ERS network. After all, one of the benefits of dynamic charging is the small battery size, but this also means that O-BETs (Overhead Battery Electric Truck) have limited capacity and are dependent on the ERS and can only travel short distances on just their battery. This means the depot (or wherever the trucks were located when starting their trips) and the destination can only be that far from the ERS network. If the origin or destination zone is 200 km away from the closest network entry, and the truck (with a small battery that allows for dynamic charging) can only drive 80 km on battery energy solely, this trip would not be a match for ERS adoption. Using the distance-to-network matrix (from the input), each NRM zone pair is evaluated: if both zones (origin and destination) are within a specified threshold distance from the network, the pair of zones complies with this first condition. If the trip complies with this condition, it is marked with binary value 1, as can be seen in equation (1) below. For clarity, Figure 11 shows what the distance from the network represents precisely (red arrows).

$$c_{i,j}^{1} = \begin{cases} 1, & d_{i,i'}, d_{j',j} \leq \alpha, \\ 0, & \text{otherwise} . \end{cases} \tag{1}$$

Percentage of trip with ERS (β)
The second criterion concerns the proportion of a trip's total distance that is covered using the ERS network. Adopting ERS, and therefore investing in O-BETs, is only interesting if a large proportion of the trip is covered using the ERS infrastructure. If a truck operator can only use the ERS network for a short distance, it is probably not beneficial to use O-BETs with small batteries. Only if the spent distance on the network is "large enough" is the transition to dynamic charging beneficial. This criterion aims to set the limit for when the spent distance on the network is large enough. This criterion is operationalized by calculating the total trip distance for each NRM zone pairing as the sum of three components (Figure 11: the ERS network distance (from the distance-*over*-network matrix) and the distances from both the origin and destination zones to the network (from the distance-*to*-network matrix). The share of the trip traveled on the ERS is then determined by dividing the ERS network distance by the total trip distance. If origin zone A and destination zone B are both 50 km from the network, and the trip between A and B uses 20 km of ERS corridor, this trip would not comply with this condition. If a trip complies with this criterion, it gets assigned a binary value of 1 once more, visualized in the formula below (2).

$$c_{i,j}^{2} = \begin{cases} 1, & \frac{d_{i',j*} + d_{i*,j*} + d_{j*,j'}}{D_{i,j}^{\text{ERS}}} \geq \beta, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Required detouring for ERS (γ)

The third criterion concerns the detour a trip has to make to utilize the ERS network. An example detour is given in Figure 13. The idea behind this condition is that in many cases, traveling over the ERS network results in less-than-optimal routes, as the ERS network only covers a single corridor from Rotterdam to Venlo. There is likely a limit to the extent to which a potential user is willing to detour to make use of the ERS network. This may depend on the benefits of using ERS technology over alternatives. For example, if ERS technology is much cheaper than the alternatives, the potential user may be more willing to detour to make use of the ERS network [16]. To quantify the allowed detour, a ratio is calculated between the total trip distance (distance on network + access distances) and the direct, straight-line distance between zones. If this ratio falls below a predefined threshold representing the maximum acceptable detour, the NRM zone pair complies with the criterion and gets assigned a binary value of 1 again. Figure 13 visualizes what distances are compared with each other.

$$c_{i,j}^{3} = \begin{cases} 1, & \frac{D_{i,j}^{\text{ERS}}}{D_{i,j}} \leq \gamma \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Bakker et al. [16] add an important side note: traveling by road always leads to longer distances than the Haversine distance. Hence even without traveling over the ERS network, there is a certain degree of detouring going by this operationalization. They found a mean value of 1.22 for a sample of city pairings in the Netherlands. To account for this, a threshold is chosen which is higher than this mean value.

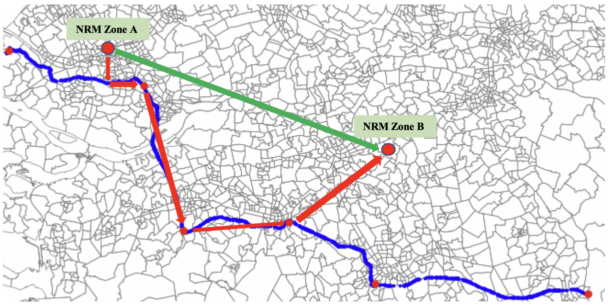


Figure 13: Example of required detouring

Since this study uses an NRM zoning system with as many as 6928 zones, the density of zones is high. This zoning provides precise and reliable results, but it also introduces certain complexities. Some zone centroids are only a few kilometers apart (see Figure 14). Because the model uses a mandatory route over the ERS network to determine the distance between two zones, it sometimes reports that a trip between zones located only a few kilometers apart covers several tens of kilometers over the ERS network. This is, of course, not realistic and needs to be avoided. To eliminate this issue, a filter is introduced that requires a minimum distance of 5 km between two zone centroids for a trip to qualify for ERS usage. This serves purely to eliminate erroneous trips between closely located zones over the network.

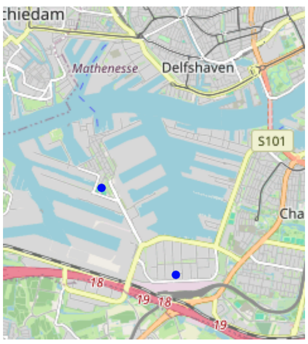


Figure 14: Close centroids

Concluding, every trip is evaluated against these three criteria and is considered part of the adoption potential if all the criteria are met. This trip then has been assigned three 1-values through the criteria formulas. $A_{i,j}$ can now be defined as the binary identification of whether a trip adheres to all the three criteria as follows:

$$A_{i,j} = c^1_{i,j} \cdot c^2_{i,j} \cdot c^3_{i,j} \tag{4}$$

Symbol	**Description**
α	maximum distance (km) allowed to travel from and to the ERS network
β	minimum fraction of the total distance that must be traveled within the ERS network
γ	maximum ratio of detouring allowed if ERS network is used
R	set of the three adoption conditions
c^r_{ij}	binary indicator of whether freight flow F_{ij} adheres to Condition $r \in R$
A_{ij}	binary indicator of whether freight flow F_{ij} adheres to all three conditions

Table 8: Adoption conditions notation

3.2.6 Scenarios

The criteria established in Section 3.2.5 are experimental, and their actual values are not known. This means values must be assigned to these parameters manually. Since predicting the true values is difficult, multiple values are assigned to each parameter. These values are shown in Table 9. The table illustrates that three scenarios are used: Tight, Moderate, and Flexible. In a Tight scenario, the minimum/maximum values of the criteria are strict, which will result in fewer trips adopting ERS. For example, freight flow is only considered part of the adoption potential if it requires not more than 80 kilometers of travel before entering the ERS network or after exiting it. In a Flexible scenario, this maximum distance to/from the network is already 110 km. By applying different values for the criteria, a wide range of results is obtained, providing a clear understanding of how sensitive the outcomes are to variations in the parameter values.

	Tight	Moderate	Flexible
α	50 km	80 km	110 km
β	70%	60%	50%
γ	1.3	1.4	1.5

Table 9: Scenario parameter values

To determine the maximum distance from a zone to the network (α), the distance an O-BET can travel on battery power solely, without using dynamic charging, must be considered. Since a major advantage of O-BETs is that they use smaller batteries, the chosen distance for this criterion should not be too large. Battery capacities and efficiencies of electric trucks vary significantly. Some modern BETs already offer ranges up to 400 km on a single charge [27]. However, for O-BETs, a more modest battery size of 150 kWh is assumed, as also adopted by [28]. There is no clear consensus in the literature on the energy consumption rate of O-BETs. Estimates range from 1.30 to 2.24 kWh/km. For example, Lin et al. [29] uses an average of 1.8 kWh/km, while Jelica et al. [20] reports a consumption rate of 2.24 kWh/km. In contrast, ElaadNL's Outlook Logistics forecast assumes a significantly lower value of 1.1 kWh/km [30]. In this study, assumptions are aligned with De Saxe et al. [8] and Speth & Gnann [31], who model the ERS system as delivering 150 kW of power for traction (this will be discussed in more detail in Section 3.5). Given a constant speed of 80 km/h, this translates to an energy consumption rate of $150/80 = 1.875$ kWh/km (assuming no energy losses in the system). Since this power assumption is also used in later parts of this research, 1.875 kWh/km is adopted as the standard consumption rate. Using a 150 kWh battery size and this consumption rate, the battery-only driving range is 150 kWh divided by 1.875 kWh/km = 80 km. This value is used as the threshold α-value for the moderate scenario. For sensitivity purposes, this threshold is varied by ± 30 km, setting it to 50 km in the Tight scenario and 110 km in the Flexible scenario.

To determine the β value, the maximum distance to the network (α) is used. Consider a zone that is as far away from the network as allowed (80 km). Then it has the battery capacity to reach a destination that is also 80 km away from the network (considering the truck is fully charged when leaving the network). This means the trip travels 160 km without ERS. The Rotterdam-Venlo corridor is approximately 200 km long. This means that approximately 55% of travel is done on the corridor, in an extreme example of maximum distance from the network. Since this is an extreme example, where the distance to and from the network is at its maximum and the entire ERS corridor is utilized, it represents a worst-case edge condition. In more realistic scenarios, many origin and destination zones will be located significantly closer to the network, resulting in shorter off-network distances. Moreover, not all trips will traverse the full length of the corridor. Therefore, the share of the trip that takes place on the ERS in typical cases will often exceed 55%. To reflect this, the value for β in the Moderate scenario is set at 60%, which represents a realistic but still challenging threshold. It ensures that the ERS is used for the majority of the trip, without excluding trips that make efficient use of the infrastructure but do not reach the theoretical maximum. A 10% increase and decrease of the β value is used for the Tight and Flexible scenario.

Since the haversine distance between zones are used, there is already a detour ratio compared to the actual connection between zones (a mean value of 1.22 for a sample of city pairings in the Netherlands, as discussed Section 3.2.5). Therefore, a value of 1.30 is chosen in the Tight scenario, a 1.4 ratio in the Moderate scenario and 1.5 ratio in the Flexible scenario.

3.2.7 Model Output

After implementing all the criteria in the model designed by Bakker et al. [16] and testing the trips between zones to these criteria, several results are obtained, which are described below. These performance indicators will give an impression of the volume of the trips in the trip adoption potential.

Percentage of total freight flow
The first output of the model is the percentage of total freight flow that uses the ERS corridor. This performance indicator captures the freight flows that meet all three conditions as a percentage of the total freight flows between all zones, and is computed by dividing the trips that comply with all the criteria by the total number of trips. This percentage shows how many trips fall within the adoption potential compared to the total number of trips in the dataset.

Total distance traveled over the ERS network
This performance indicator captures the total distance traveled over the ERS network, in kilometers per year, and can be obtained by summing up all the distances traveled over the network by trips that comply with the criteria. After testing the criteria, a set of trips that fall within the adoption potential remains, and by summing the distances traveled over the network (from the distance-over-network matrix), the total distance traveled over the ERS network is obtained.

Average distance over the ERS network
Lastly, this performance indicator captures the average distance in kilometers that trips travel over the ERS network, and is computed by dividing the total distance traveled over the network (that was computed already) by the total number of trips that fall within the adoption potential (and thus comply with the criteria).

Total number of ERS-adopting trips
Most importantly, the number of trips that are performed with ERS and are therefore included in the adoption potential. These trips will be used later to determine the number of tours included in the tour adoption potential. This will be explained in the next section.

3.3 Tour Adoption Potential

For each individual trip, it is now known whether it would use dynamic charging on the ERS, based on the specified criteria. However, since each trip is part of a tour, as described in Section 3.2.1, the complete tour must now be considered to determine whether it can actually adopt ERS. A trip may meet the criteria, but the tour it belongs to may still be unsuitable for ERS adoption.

For example, consider a tour consisting of five trips, where only the final trip uses ERS. The four preceding trips together cover such a long distance that an O-BET with a smaller battery would never have enough range to complete them, meaning the tour is not eligible for ERS adoption, even though it contains one trip that meets the criteria. This clearly shows that analyzing individual trips alone is not sufficient. To eventually draw realistic conclusions, it is crucial to look at complete tours in determining the adoption potential. For selecting ERS-adopting tours, a distinction can be made between tours with one ERS trip, or with multiple.

3.3.1 Tours with one ERS trip

First of all, a tour must contain at least one trip that uses the ERS. After testing all the individual trips to the criteria, it is known for every trip whether it uses ERS (Section 3.2). And, because it is also known which tour each trip belongs to, it is known which tours contain ERS-adopting trips.

For each tour with one ERS-adopting trip, the cumulative distance of the trips **before** (d_{pre}) the first ERS trip and the trips **after** (d_{post}) the last ERS trip is calculated. This cumulative distance must not exceed the maximum battery range of the truck: 150 kWh (E_{Batt}). The calculation of this cumulative trip distance is based on the distance-between-zones matrix described in Section 3.2.4. To determine the maximum pre-ERS and post-ERS distance, the energy consumption rate (c in kWh/km) of a truck can be used. Together with the cumulative distances of the pre- and post-ERS trips, it is now possible to determine the battery level during the trip. This gives the following equations.

For the total energy required for pre-ERS and post-ERS trips:

$$E_{\text{pre-post}} = c \cdot (d_{\text{pre}} + d_{\text{post}}) \tag{5}$$

This total energy must not exceed the battery capacity, which gives:

$$E_{\text{pre-post}} \leq E_{\text{Batt}} \tag{6}$$

Some tours consist of one trip, and in some cases, this one trip is covered over the ERS network. In such cases, the criteria from Section 3.2.5 apply (max. detour, max. distance from network, etc.). This trip would automatically fall within the tour adoption potential, since it already was included in the trip adoption potential.

3.3.2 Tours with multiple ERS trips

It gets a bit more complex for tours with multiple ERS trips. When a tour consists of multiple ERS trips, it is not enough to consider only the pre- and post-ERS distances — the distance of the trips between the ERS trips must also be taken into account. For example, a tour may start with an ERS trip and end with an ERS trip, but the total distance of the trips in between may still exceed the battery range of the truck. Therefore, in addition to the pre- and post-ERS distance, the **intermediate non-ERS distance** (d_{inter}) must also be considered. This gives the following equation:

$$E_{\text{non-ERS}} = c \cdot (d_{\text{pre}} + d_{\text{inter}} + d_{\text{post}}) \tag{7}$$

Which must be within the battery limit:

$$E_{\text{non-ERS}} \leq E_{\text{Batt}} \tag{8}$$

3.3.3 Time on Corridor

An important factor that influences the battery level is the total time a trip spends on the ERS corridor. When a trip uses a considerable part of the corridor, the truck has the opportunity to fully recharge its battery. However, if a trip uses a smaller section of the corridor, the truck may exit the corridor with a partially charged battery. This is important information, as the battery level will be used to examine whether a trip is able to reach its destination. Since one of the criteria for selecting trips within the trip adoption potential already considers a minimum percentage of the trip that must occur on the corridor

(β), many trips indeed cover a significant portion of it. Nevertheless, there are still some cases where the distance traveled over the corridor is too short to fully recharge the battery. Therefore, it is important to map the time spent on the corridor, or the distance traveled divided by the truck's constant speed (80 km/h). In this research it is assumed that the truck has a constant speed (v_{constant}) of 80 km/h and road congestion is not taken into consideration. This and other assumptions will be addressed in Section 3.7. So, a truck that travels 80 km on the corridor, for instance, will spend one hour on it. This gives the following equation.

$$\text{Time on ERS (hours)} = \frac{D_{ij}^{\text{ERS}}}{v_{\text{constant}}} \tag{9}$$

To determine the time each trip spends on the ERS corridor, the distance-over-network matrix is used that was constructed earlier, containing the ERS travel distance between all pairs of NRM zones. This matrix represents the kilometers traveled over the ERS corridor for each origin–destination pair. Time spent on the ERS is then computed by dividing the ERS travel distance by the constant travel speed. The resulting values represent the time (in hours) that trucks spend on the ERS corridor during the trip. The time spent on the corridor was only computed for the trips within the adoption potential. Origin-destination pairs with no trips in the adoption potential were assigned a time value of zero.

The output is a 6928x6928 matrix that shows, for each origin-destination pair how much time is spent on the corridor and will be used to estimate the truck's battery level upon exiting the corridor.

3.3.4 Battery Level

In order to know whether the battery range is sufficient to reach post-ERS zones, some assumptions need to be made regarding the capacity of the ERS infrastructure to charge the trucks battery. De Saxe et al. [8] state that when a vehicle is connected to a section of ERS, and the battery state-of-charge (SoC) is below 100%, the ERS will simultaneously charge the battery while providing traction power. They assume a fixed charging rate of $P_{ERS-charge}$ = 150 kW and $P_{ERS-traction}$ = 150 kW, such that the total power drawn from the ERS is approximately 300 kW during motorway cruising. This is in line with design specifications indicated by manufacturers and similar assumptions in recent studies [32] [33]. Since the ERS provides power for traction as well, the battery can charge without getting depleted simultaneously. So, a truck uses energy from the overhead catenary line for traction as well as for charging its battery. Assuming the ERS provides enough power for all the trucks connected and the trucks have a battery capacity of 150 kWh, a truck charges from empty to full battery in an hour.

Since it is known for every trip in the adoption potential how long it spends on the ERS corridor (time-on-corridor matrix), the battery level can be determined when the trip leaves the corridor.

To evaluate the battery levels of electric trucks traveling along the ERS corridor, a battery simulation model was developed to estimate the battery SoC during entire tours. This simulation enables a detailed understanding of when and where a truck charges or depletes its battery while traversing between zones, with and without the aid of the ERS infrastructure. This will help finding tours that are not able to complete their route with a smaller O-BET battery, and are therefore left out of the tour adoption potential. Only tours that can be completed with solely ERS charging will be left over.

To simulate the battery SoC of a tour, the following approach was conducted. A tour consists of trips that either use or do not use ERS. For trips that do not use ERS, the battery is only drained. The truck only consumes energy during this trip, based on the direct, straight line route distance between origin and destination zones (from the distance-between-zones matrix from Section 3.2.4). For trips that are part of the trip adoption potential and therefore use the ERS corridor, the trip is divided into three segments: (1) travel from origin zone to network; (2) travel over the ERS corridor; (3) travel from ERS exit to destination zone.

1. **Travel from origin zone to network**
   The model retrieves the shortest haversine distance from the origin zone to the ERS corridor using the distance-to-network matrix. The energy consumed during this distance is subtracted from the

battery level at the start of the trip ($d_{i,i'}$ multiplied by c). If the battery is depleted before reaching the ERS network, the trip cannot continue and the tour is left out of the tour adoption potential.

2. **Travel over the ERS corridor**
   Once the truck reaches the network, it can recharge. The time spent on the corridor is retrieved from the matrix that was designed in Section 3.3.3, which was precomputed for each origin-destination pair. The truck gains energy during this interval at a constant charging rate of 150 kW, up to the maximum battery capacity (150 kWh).

3. **Travel from ERS exit to destination zone**
   The final segment calculates the energy needed to reach the destination zone from the nearest exit point of the ERS network (again using distance-to-network matrix). This consumption is also subtracted from the battery. This means that the truck will never arrive at a destination with a full battery, since there is always some extra distance it needs to cover from the network to the destination. This is very important, as it might impact the ability of a truck to reach its next destination.

An example of a simulation of a truck's battery SoC, assuming energy consumption rate c of 1.875 kWh/km:

1. *Trip 1 (No ERS): Battery SoC at start = 150 kWh*
   Distance traveled = 62 km
   Battery SoC at destination = 34 kWh

2. *Trip 2 (ERS): Battery SoC at start = 34 kWh*
   Battery level at entry ERS = 6 kWh
   Distance traveled = 90 km
   Battery level at exit ERS = 150 kWh
   Battery level at destination = 143 kWh

3. *Trip 3 (No ERS): Battery level at start = 143 kWh*
   Distance traveled = 17 km
   Battery level at destination = 111 kWh

4. *Trip 4 (No ERS): Battery level at start = 111 kWh*
   Distance traveled = 60 km
   Battery level at destination = 0 kWh (111 - 113)

Throughout the simulation, if the battery level reaches or drops below 0 kWh, the tour is marked as battery-depleted. In such cases, all subsequent trips in the same tour are skipped, since the truck would realistically not be able to continue its route without external charging support. This rule ensures the model respects physical battery constraints and mimics operational infeasibility in real-life logistics scenarios.

After running this model, it is known for every trip what the battery level is upon arrival at the destination zone. This results in a list of tours that are all able to be covered by an O-BET with a battery capacity of 150 kWh, representing the *tour-adoption potential.*

In Figure 15, two examples are provided of trips from the final tour adoption potential. It demonstrates the variety in tours that could adopt ERS without having their battery depleted at a certain moment during the tour. The green route represents the distance covered over the ERS network, the purple and pink routes represent distance from origin/destination to the network and the red routes represent the trips in the tour without ERS.

(a) Complex tour with multiple trips

(b) Simple tour with one trip

Figure 15: Examples of different tour structures in the dataset

3.4 Energy Demand

Now that the tours included in the final tour adoption potential are known, the temporal and spatial energy demand can be analyzed. In this subsection, the energy demand is calculated and high-intensity locations along the corridor are highlighted.

3.4.1 Corridor Segmentation

To gain insight into the spatial and temporal energy demand, the location of the trucks at specific times must be known. By knowing the location of the trucks at certain moments, it is possible to identify where the density along the corridor is high and, consequently, where a high power supply is needed to meet the energy demand of the trucks. For example, if it is known that many trucks are located on a segment of the corridor at 8 AM, the ERS infrastructure in that area must be able to provide sufficient power. Future policy can anticipate on this. To determine the truck density along the corridor, the corridor is divided into segments. This allows for an easy assessment of the number of trucks on segment X at, for instance, 8 AM. The corridor is divided into segments of 2 km each. Following the assumptions of Movares [34], connection stations are assumed to be placed every 2 kilometers along an ERS corridor, with each station having a grid connection of 3.6 MVA [28]. It is assumed that every segment is supplied with energy by a single connection station. The segmented corridor is visualized in Figure 16, where every segment has a different color. In total, 98 segments are included, each with a unique ID.

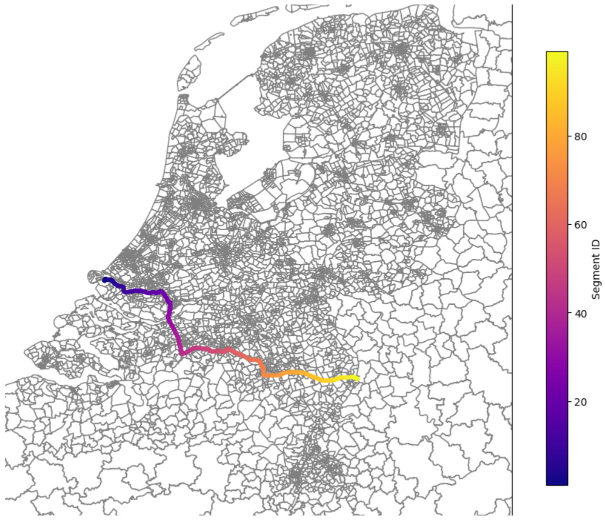
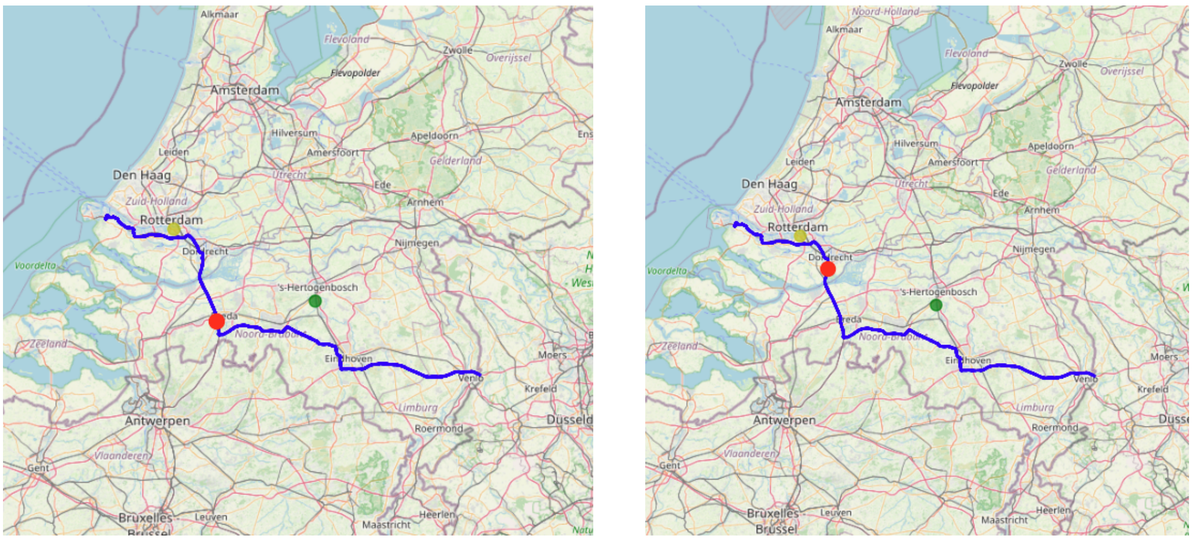


Figure 16: Segmented corridor

3.4.2 Truck Location on Corridor

The next step after dividing the corridor into segments is determining the locations of the trucks at specific timestamps. To accurately estimate the energy demand of the trucks on a segment, it is first necessary to know how many trucks are present on every corridor segment at a given moment in time. A model was developed that tracks the locations of trucks on the ERS infrastructure. The core goal of this model is to determine how many trucks are present on each segment of the ERS corridor at every timestamp. This information is essential for understanding when and where electricity demand is highest. To ensure this model uses the correct routing and departure times for the tours, the tour was first modeled for an individual trip, see Figure 17.



(a) Location of a tour on the corridor at 04:00 PM

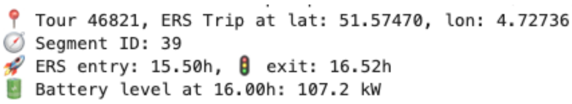
(b) Location of a tour on the corridor 04:30 PM

Figure 17: Visualizations of a truck's position on the ERS corridor at 4.00 PM compared to 4.30 PM

In Figure 17, the truck's location on the corridor is given for a trip within a tour. The origin and destination zones are marked with green dots and the location on the corridor with a red dot. The model keeps track of the time and location accurately, see Figure 18. It also tracks the battery level at the given location. The model determines the location on the corridor based on the time of the day, the departure time at the origin zone and the speed of the truck. The distance from the origin zone to the network is known and can be withdrawn from the distance-to-network matrix. The time it takes to get from the zone to the network is computed by dividing the speed of the truck by the distance to the network. Because the departure time for every trip is already known (given in the dataset), the time it takes to get to the network can simply be added to the departure time to determine the time of entrance at the network.

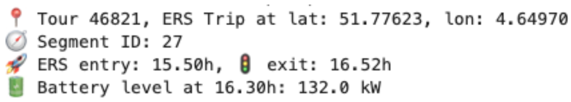
By knowing the time of entrance at the corridor, the location on the corridor at any point in time can be calculated using the constant speed $v_{constant}$ of the truck.

If the location of the truck is known, the model automatically connects it to the belonging segment ID. The battery level simulation from Section 3.3.4 is used to compute the battery level at every point in time, using the battery SoC at the origin zone and the time-on-corridor matrix.



```
Tour 46821, ERS Trip at lat: 51.57470, lon: 4.72736
Segment ID: 39
ERS entry: 15.50h, exit: 16.52h
Battery level at 16.00h: 107.2 kW
```

(a) Tour location data at 4.00 PM



```
Tour 46821, ERS Trip at lat: 51.77623, lon: 4.64970
Segment ID: 27
ERS entry: 15.50h, exit: 16.52h
Battery level at 16.30h: 132.0 kW
```

(b) Tour location data at 4.30 PM

Figure 18: Overview of tour location data and battery level

Now that it can be determined whar the location of a single truck on the ERS corridor is, it is necessary to loop for all the tours in our tour adoption potential. The final set of tours, that belong to the adoption potential, consist of tours that in their place consist of trips. Only the trips within these tours that were part of the trip adoption potential are considered, since determining locations of trucks that do not use the corridor falls outside the scope of this research. Only the trips that use the corridor are considered to determine the spatial and temporal energy demand. For each of these trips, the model determines the closest entry and exit points on the ERS based on the origin and destination locations. It calculates: (1) when the truck reaches the ERS (arrival time); (2) how long it remains on the ERS (based on speed and route length); (3) when it exits the ERS.

3.4.3 15-minute Simulation

To determine the locations of the trucks, a time interval needs to be chosen that shows where the trucks are at the start of each interval. The location is determined by simulating how far the truck has traveled along the route by that time, assuming a constant speed (80 km/h) and using the time the truck entered the network. In this study, a 15-minute interval was chosen for tracking truck presence on ERS segments. This choice is based on the fact that since October 2025, energy is traded per 15 minutes (instead of per hour) [35]. Because forecast tour data for 2040 is used here, it makes more sense to adopt this new rule in the energy market for this research. Besides, traffic patterns, especially for freight transport, often fluctuate over short periods. Peak demand during the morning and afternoon rush hours may occur within a span of minutes. A 15-minute interval provides a granular enough resolution to capture these fluctuations, enabling identification of short-term demand peaks that would be missed with broader intervals (e.g., hourly). Lastly, electricity demand from ERS usage depends on how many trucks are charging simultaneously on a given segment. By updating the truck positions every 15 minutes, the simulation more accurately reflects overlapping usage, rather than averaging usage over too long a period. This leads to a more realistic estimate of momentary power demand, which is critical for energy grid and substation planning.

3.4.4 Counting Trucks per Segment

For every segment the number of trucks that are present at a given moment in time at that segment are counted by the model. The aim of this simulation is to estimate how many trucks are physically present on each segment of the ERS corridor at every 15-minute interval throughout the day. This means that the model counts the number of trucks per segment on 00:00, 00:15, 00:30, ..., 05:15, 05:30, etc. This gives 96 intervals of 15 minutes throughout the whole day. At each of these timestamps, the model from Section 3.4.2 checks for a single truck whether it is currently traveling on the ERS. If the timestamp falls within the truck's ERS usage window, the truck is assumed to be somewhere on the corridor at that moment. To find out which specific segment the truck is on at a given time, the model computes how far the truck has traveled since it entered the ERS, using the formula:

$$\text{Time on ERS (hours)} = \frac{D_{ij}^{\text{ERS}}}{v_{\text{constant}}} \tag{10}$$

It then walks through the list of ERS segments and accumulates segment distances until the cumulative distance exceeds the traveled distance. The current segment at that point is where the truck is counted. For each segment and 15-minute time point combination, a counter is incremented. For example, if a truck is found on segment 42 at 08:15, the record (segmentID=42, time=08:15) receives a count of 1. If another truck is also present on that same segment and time interval, the count becomes 2, and so on. Moreover, the model checks the battery SoC at the timestamp, and gives it a binary value: 0 when the truck has a fully charged battery; 1 when the truck's battery is not full, meaning it will use additional energy from the ERS to charge its battery, besides using the energy for traction. In reality, trucks do not charge from 0 to 100% with constant power, but for the sake of simplicity, for this research it is assumed it does. This process is repeated for every tour in the dataset that uses the ERS. The final output of this phase is a table for every segment, containing: (1) a time series with the 15-minute timestamps; (2) the number of trucks present on that segment at each timestamp; (3) the number of trucks without a full battery. An example of a piece of the output is given in Table 10. For every timestamp, the number of trucks on that segment is given, together with the number of trucks that are not fully charged.

This output serves as a direct input for calculating the momentary energy demand per segment, as each truck contributes to electricity usage when present on the ERS.

segment_id	time	truck_count	not_full_count
15	07:00	64	12
15	07:15	55	12
15	07:30	61	8
15	07:45	56	9
15	08:00	58	14

Table 10: Sample dataset of truck counts and "not-full-counts" for segment 15 over time

3.4.5 Energy Demand per Segment

Now that it is known for every segment how many trucks are located on the segment at every timestamp, it is possible to calculate the energy demand of that piece of corridor throughout the day. The output of the previous phase, containing the truck-count tables of all the 98 segments with the truck intensity throughout the day, is used as input for determining the energy demand per segment (Table 10). The instantaneous power demand on an ERS segment at any given minute is obtained by summing two components: the power required to move the vehicles (traction) and the power used to recharge their batteries while they remain below full state of charge. The underlying assumption is that each truck on the ERS simultaneously draws a constant power of 150 kW for traction, which represents the energy needed to propel the vehicle along the segment. This is inline with the energy consumption rate c of 1.875 kWh/km. In addition, trucks that are not fully charged draw an additional 150 kW for battery charging, reflecting the charging capability provided by the ERS infrastructure. This value is varied for in other scenarios.

If at time t there are $N_{\text{truck}}(t)$ trucks on the segment, each drawing 150 kW ($P_{traction-ERS}$) for propulsion, then the traction demand is:

$$P_{\text{traction},segmentID}(t) = N_{\text{truck}}(t) \times P_{ERS-traction} \tag{11}$$

Likewise, if $N_{not\_full}(t)$ of these trucks have space to charge their battery, each receiving $P_{ERS-charge}$ kW from the ERS infrastructure, the charging demand is:

$$P_{\text{charging},segmentID}(t) = N_{not\_full}(t) \times P_{ERS-charge} \tag{12}$$

Because charging and traction occur simultaneously, the total instantaneous power draw is simply the sum:

$$P_{\text{total},segmentID}(t) = P_{\text{traction},segmentID}(t) + P_{\text{charging},segmentID}(t) \tag{13}$$

These power values are then plotted over time to visualize how the demand fluctuates throughout the day, providing insight into the real-time electrical load that the ERS segment would impose on the power grid. This approach assumes a constant truck power draw and linear charging behavior, allowing for a simplified but informative estimate of segment-level ERS energy demands.

	Tight	Moderate	Flexible
c	2.175 kWh/km	1.875 kWh/km	1.575 kWh/km
$P_{ERS\text{-}charge}$	120 kW	150 kW	180 kW

Table 11: Tour parameters overview

3.5 Scenario Analysis

In the scenario analysis, it is examined how energy demand differs between the various scenarios outlined in Table 11. The values of the two parameters, c and $P_{ERS-charge}$, are varied to observe how energy demand develops under stricter or more favorable conditions. The different values of the parameters are chosen by analyzing literature. It was mentioned in Section 3.2.6 that there is no consensus among literature about the true energy consumption rate of an O-BET. Many different values are assumed or suggested in many different articles. Earlier, it was highlighted that a value of 150 kW is used for traction provided by the ERS. To guarantee coherence throughout this research, the same energy consumption rate c is used on the network and off the network. This means a truck on the network uses $150/80 = 1.875$ kWh/km, assuming a constant speed of 80 km/hour. This value is used for the Moderate scenario. The same value is used for trucks not connected to ERS. Based on c values found in literature ([18], [20], [21]), a range of ± 0.300 kWh/km was chosen for the Tight and Flexible scenario.

Furthermore, the impact of variation in the power delivered by the ERS infrastructure to charge the battery while driving is also examined. As mentioned in Section 3.2.6, it was assumed that a traction power supply of 150 kW by the ERS. The Fraunhofer Institute in Germany is currently actively involved in research and development related to ERS [36]. They are conducting research on the feasibility of ERS and perform real life tests with different O-BETs. They provided actual data from their real-life tests for this research, published this year [31]. One of the trucks they researched was a catenary truck from Scania of the newest generation with 150 kW DC/DC Converter. They have found that the truck could use 150 kW for battery charging. This is in line with the assumptions by De Saxe et al. [8], were they assume the same values for traction and battery charging. Consequently, a value of 150 kW for battery charging is used in a Moderate scenario ($P_{ERS-charge}$). For the Tight and Flexible scenario, 120 kW and 180 kW are used respectively.

These scenarios simulate possible futures, ranging from optimistic technological developments (Flexible) to situations where progress is slower than is expected now (Tight). This affects the expected energy demand along the corridor and provides insight into the potential range within which the actual demand may fall.

It must be said that the total energy demand of a truck on the corridor in the Tight and Flexible scenario differ slightly from the moderate scenario. The parameter values for the Tight and Flexible scenarios were chosen to be evenly spaced around the Moderate scenario in terms of both energy consumption rate and charging power. Although both parameters were offset by the same magnitude, the effect of increasing charging power by 30 kW does not exactly offset the decrease in energy consumption, due to the multiplicative nature of energy consumption. This has meant that the resulting net hourly energy demand while cruising at 80 km/h is not symmetric across scenarios (Tight: $2.175 \times 80 + 120$ kWh $= 294$ kWh; Moderate: $1.875 \times 80 + 150 = 300$ kWh; Flexible: $1.575 \times 80 + 180 = 306$ kWh). The small asymmetry in total hourly energy demand between the Tight and Flexible scenarios does not undermine the validity of the comparison with the Moderate scenario. In reality, a perfectly symmetric manner around the Moderate scenario would not be logical. The current parameter values were deliberately chosen based on literature to reflect plausible future developments under optimistic and pessimistic conditions, rather than to satisfy an artificial mathematical balance.

To obtain comparable results, the results from the moderate trip adoption potential will be used for this analysis. This means that the impact on the energy demand is examined by changing the parameters in the Tight and Flexible scenario (apart from the Moderate scenario that will be mainly focus on in the Results section), using only the tours that are included in the adoption potential in the Moderate scenario (obtained by using the parameters for tour inclusion for the moderate scenario). So, the number of tours used for determining the energy demand will be constant, and only the parameters will be changed.

3.6 Sensitivity Analysis

Besides the scenario analysis, a sensitivity analysis is also performed to identify which parameters have the most influence on the results. Again, the parameters from Table 11 are used: the energy consumption rate of an O-BET (c) and the power a truck can use to charge its battery ($P_{ERS-charge}$). For the two parameters, the individual impact is also assessed by varying each one between a high and low value while keeping the other variables fixed. By doing this, the impact they individually have on the energy demand outcomes can be easily observed.

The sensitivity of the parameters from Table 9 that determine the trips in the adoption potential is not examined. In previous research by Bakker et al. [16], the sensitivity of those parameters has already been analyzed. For this research, the focus is on the impact of the energy consumption parameters, so only the impact of changing the parameter values from Table 11 is examined with a constant number of tours. First, the daily energy demand patterns are plotted with different c values, while keeping the $P_{ERS-charge}$ constant. Subsequently, the analysis is repeated the other way around..

3.7 Assumptions

In this study, several important assumptions must be made that influence the outcomes of the research. These assumptions will be described and explained below.

- **Constant travel speed**
  It is assumed that the trucks have a constant speed of 80 km/h. This is the speed they use at every moment during their tour. This also means that is assumed that no acceleration takes place, which uses additional power.
- **Constant charging power**
  It is assumed that a truck charges its battery from 0% to 100% with constant power.
- **No traffic congestion**
  It is assumed that trucks do not experience any traffic congestion on their routes from origin to destination. Trucks are assumed to drive at a constant speed without delays due to traffic, roadworks, or accidents. At no point does a truck lose speed.
- **Battery capacity of 150 kWh**
  In addition, it is assumed that the capacity of a O-BET battery is 150 kWh. This is based on the used value in the report by [28], where the same value was used.
- **Driveline efficiency of 100%**
  Another assumption is that trucks operate with 100% driveline efficiency. No energy losses are considered from the battery, the drivetrain, or auxiliary systems such as air conditioning or heating.
- **Uniform truck characteristics**
  Furthermore, all trucks are assumed to have the same characteristics. No distinction is made between battery capacity, vehicle mass, payload, or energy consumption. Variation among vehicle types is not taken into account.
- **No battery degradation**
  Battery degradation is also not considered in this study. Battery performance remains consistent over time and does not suffer from capacity fade or efficiency loss due to aging.
- **Truck starts tour with full battery**
  A critical assumption is that each truck starts its tour with a full battery. This means that every

first trip of a tour begins with a battery state of charge of 100% (150 kWh). This implies that each truck has been able to charge overnight at a depot or warehouse from which it departs.

- **No en-route charging**
  Finally, it is assumed that no en-route charging takes place apart from ERS. All additional energy obtained during the route is provided through dynamic ERS charging. No interim stops are made at rest areas or charging hubs along the way. Dynamic charging is particularly attractive for logistics operators because it removes the need for static charging at customer locations or roadside stations, and allows charging while driving—potentially reducing the required battery size. For this reason, there is a focus solely on dynamic charging during the truck's active service.

- **Identical transport every day**
  As described in Section 3.2.1, the dataset that is used in this research simulates freight flow in 2040 for one workweek (five days). Since there is no data available on daily freight flow (only weekly), it is assumed that traffic is identical on every day. To find daily freight flow, weekly freight data needs to be divided by 5.

4 Results

In this section the results of the applied method are presented. First, the results of the trip adoption potential are presented. Next, the results of the tour adoption potential will be discussed. Subsequently, the results of the energy demand, spatially and temporally, are presented, outlining the peak power demand and the truck intensive areas. Finally, the results of the scenario analysis and sensitivity analysis are discussed.

4.1 Trip Adoption Potential

After testing all the trips in the dataset against the criteria from Table 9, a set of trips that would hypothetically make use of the ERS network remains, as they comply with the defined conditions. The results of the selection of trips in the trip adoption potential are presented here.

4.1.1 Overview of Results

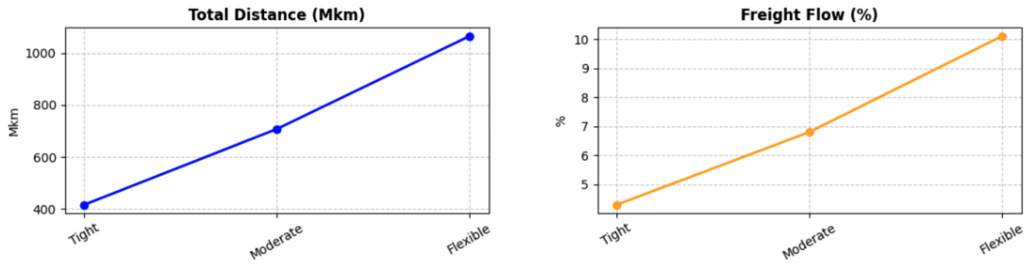
Table 12 presents the findings for the trip adoption potential from Section 3.2. For three different scenarios, the total number of trips are given that would make use of the ERS corridor according to the criteria in our model. In addition to ERS-adopting trips, four other performance indicators are given: (1) total distance traveled over the ERS network; (2) percentage of total freight flow; (3) average distance over the ERS network; and (4) total connections between zones. The table shows the different values for the different scenarios, making it easy to compare them. These values are based on the values of the parameters that were used for the different scenarios in Table 9.

Performance indicator	**Tight**	**Moderate**	**Flexible**
Total distance traveled over ERS network (Mkm)	415.9	707.8	1065.7
Percentage of total freight flow (%)	4.3	6.8	10.1
Average distance over ERS network (km/trip)	101.2	106.8	106.4
Trips in Adoption Potential (#/year)	6,028,646	9,528,422	14,143,334
Total connections between zones (#)	1,636,204	3,703,794	7,189,280

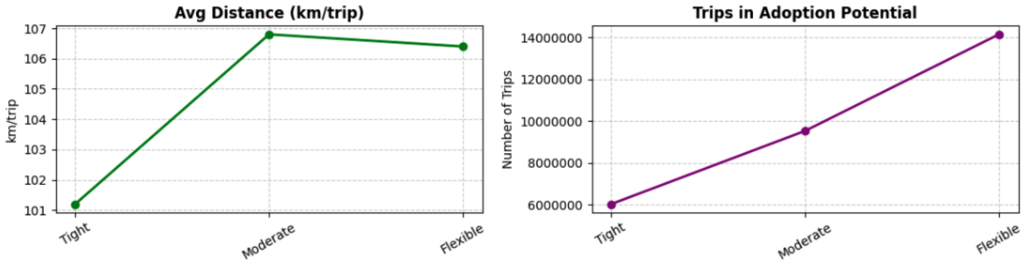
Table 12: Performance indicators for different scenarios

4.1.2 Analysis of Performance Indicator Values

The analysis of performance indicators across the Tight, Moderate, and Flexible scenarios reveals a consistent pattern of increasing values with greater flexibility. This is visualized in the graphs in Figure 19. For instance, the total distance traveled over the ERS network (Mkm) increases significantly from 415.9 Mkm in the Tight scenario to 707.8 Mkm in the Moderate scenario, representing a substantial 70.2% increase. This growth continues to the Flexible scenario, reaching 1065.7 Mkm, an additional 50% increase from the Moderate level. Similarly, the percentage of total freight flow (%) expands from 4.3% (Tight) to 6.8% (Moderate), a 58% rise, and further to 10.1% (Flexible), marking a 49% increase. These patterns were to be expected, as the parameters used in Table 3.2.5 differ between the scenarios in equal intervals. The values used for the Tight and Flexible scenarios were both equally distant from those used in the Moderate scenario.



(a) Total distance over ERS network & Freight flow percentage



(b) Average distance over ERS network & Number of trips in adoption potential

Figure 19: Performance indicator graphs

The average distance over the ERS network (km/trip) shows a different trend. It increases from 101.2 km/trip in the Tight scenario to 106.8 km/trip in the Moderate scenario, a 5.5% increase, but then slightly decreases to 106.4 km/trip in the Flexible scenario, representing a 0.4% decrease. The marginal increases between the scenarios are visualized in graphs in Figure 19. The slight decrease in average ERS distance from 106.8 km to 106.4 km may seem counterintuitive at first, since a more flexible scenario allows more trips to use the ERS. However, it can be logically explained by the nature of the trips that become eligible due to the relaxed parameters. The small drop in average ERS distance between the moderate and flexible scenario results from the inclusion of additional trips with shorter ERS usage, made possible by the more relaxed criteria. Trips only have to use 40% of the ERS network to become eligible for the adoption potential (if they also comply with the other two criteria). This results in the inclusion of more short trips.

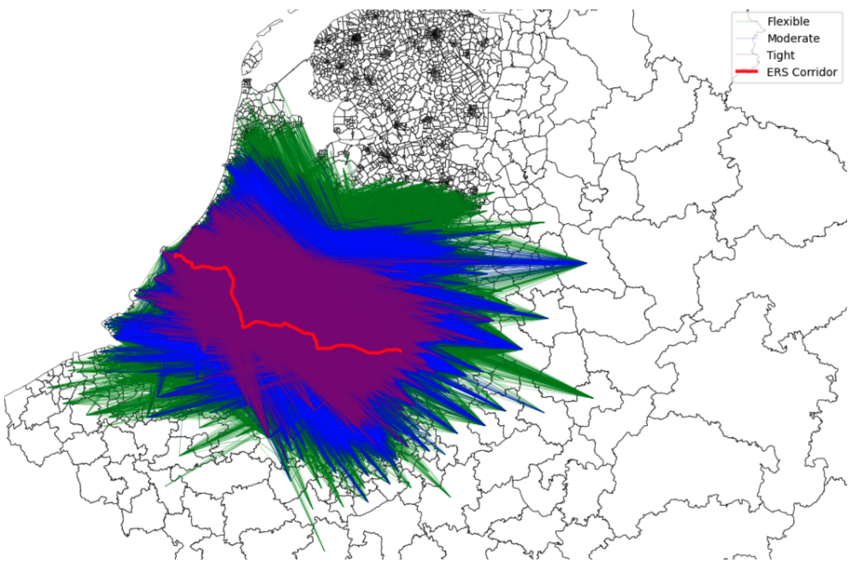


Figure 20: ERS adopting trips between zones for all scenarios: Flexible (green); Moderate (blue); Tight (purple)

4.1.3 Total Trips in Adoption Potential

Eventually, the total number of trips that are included in the adoption potential is what needs to be looked at, which will later be used for finding the tour adoption potential. The adopted trips between zones for all the scenarios are visualized in Figure 20. The red line represents the ERS corridor and the purple, blue and green lines represent the ERS-adopting trips between origin and destination zones in the Tight, Moderate and Flexible scenarios respectively. Figure 20 shows how the ERS-adopting trips gradually increase and how the adoption criteria impact the reach of the trips that use the ERS corridor. In terms of activity volume, trips in the adoption potential (#/year) demonstrate a robust escalation, growing from 6.0 million in the Tight scenario to 9.5 million in the Moderate scenario. This trend persists into the Flexible scenario, with trips reaching 14.1 million. In Figure 21, the number of trips originating from each zone are visualized, with the color intensity of each zone representing the number of trips originating in that zone as part of the adoption potential. The Moderate scenario is used for this figure. What cannot be seen clearly (due to the overlapping red line representing the ERS network), is the fact that zones around the Port of Rotterdam have a dark blue color, meaning many trips originate from there.

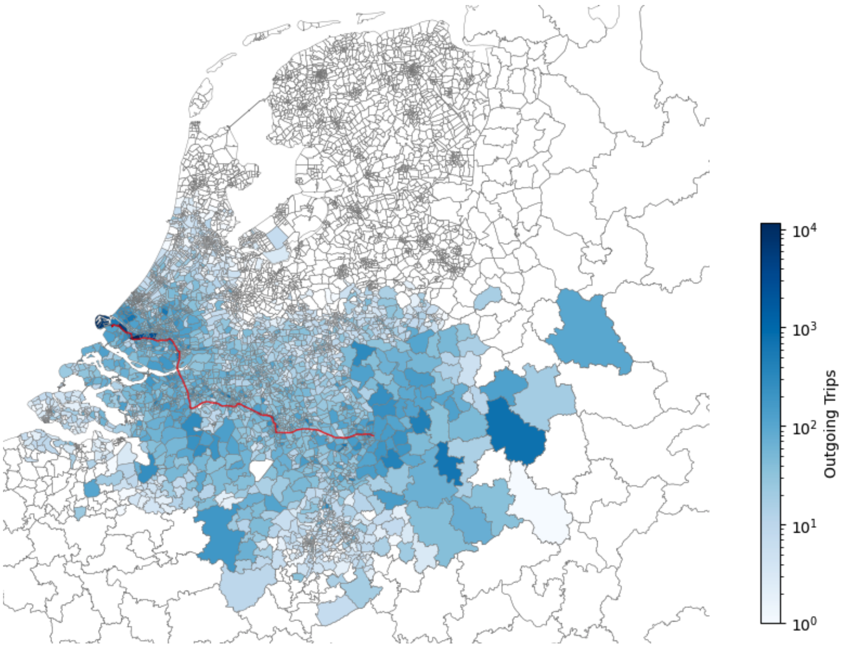


Figure 21: Trip origins by zone: color intensity reflects outgoing trips (Moderate scenario)

4.2 Tour Adoption Potential

After testing for the trip adoption criteria, a set of 6 million, 9.5 million and 14.1 million ERS adopting trips remained in the three respective scenarios. However, as indicated in Section 3.2.1, all trips are part of a larger overarching tour. Ultimately, the full tours that will adopt ERS is what is looked for, not the individual trips. This subsection presents the results of selecting the tours that fall within the adoption potential for tours: the **tour adoption potential**. The final included tours in the adoption potential under different circumstances are given in Table 13.

	Tight			Moderate			Flexible		
Tours	**Tight**	**Moderate**	**Flexible**	**Tight**	**Moderate**	**Flexible**	**Tight**	**Moderate**	**Flexible**
Tours in trip adoption potential (M/year)		3.00			4.28			5.78	
Final number of tours in tour adoption potential (M/year)	1.88	1.91	1.97	2.63	2.76	2.85	3.29	3.52	3.73
Percentage of total freight flow (%)	3.4	3.5	3.6	4.8	5.0	5.2	6.0	6.4	6.8

Table 13: Tour adoption in all scenarios

4.2.1 ERS Adopting Tours

To fresh up the mind, the different parameter values and the scenarios are given one more time in Figure 22. For finding the trips that would make use of the ERS network and would therefore adopt it, the three parameters on the right side were used (α, β and γ), and for finding the tours that eventually adopt ERS, the parameters on the left side were used. The number of tours that contain at least one ERS-using trip are given in the first row of Table 13. The values in the second row of the table are obtained by changing the parameter values of c and $P_{ERS-charge}$, while using the number of adopted trips for that scenario. So, every scenario has a variant within that scenario, for which the parameter values of c and $P_{ERS-charge}$ were adjusted.

	Tight	Moderate	Flexible
c	2.175 kWh/km	1.875 kWh/km	1.575 kWh/km
$P_{ERS\text{-}charge}$	120 kW	150 kW	180 kW

Tour parameter overview

	Tight	Moderate	Flexible
α	50 km	80 km	110 km
β	70%	60%	50%
γ	1.3	1.4	1.5

Trip parameter overview

Figure 22: Overview of parameters used for trip and tour adoption potential for all scenarios

After connecting all ERS-adopting trips to their respective tours, 3.0 million unique ERS-adopting tours remained for the Tight scenario, 4.3 million for the Moderate scenario, and 5.8 million for the Flexible scenario. These values represent the number of tours per year with at least one trip that uses the ERS network. Because these values are much lower than the number of trips in the trip adoption potential, it is known that many tours contain several ERS-adopting trips within the tour. The results in Table 13 illustrate how the inclusion of tours in the tour adoption potential increases across all scenarios and variants within each scenario. As the scenarios become more flexible, reflecting optimistic technological development, the total number of tours that qualify for ERS usage increases significantly. For example, in the Tight scenario, the number of qualifying tours increases from 1.88 million (Tight variant) to 1.97 million (Flexible variant). This trend continues more clearly in the Moderate and Flexible scenarios, where the final adoption potential reaches 2.85 million and 3.73 million tours respectively in the Flexible variant.

The pattern shows that both the scenario conditions and the parameter settings within each scenario (variants) impact the number of tours that can be electrified using the ERS. The scenario analysis in Section 4.4 gets into this in more detail.

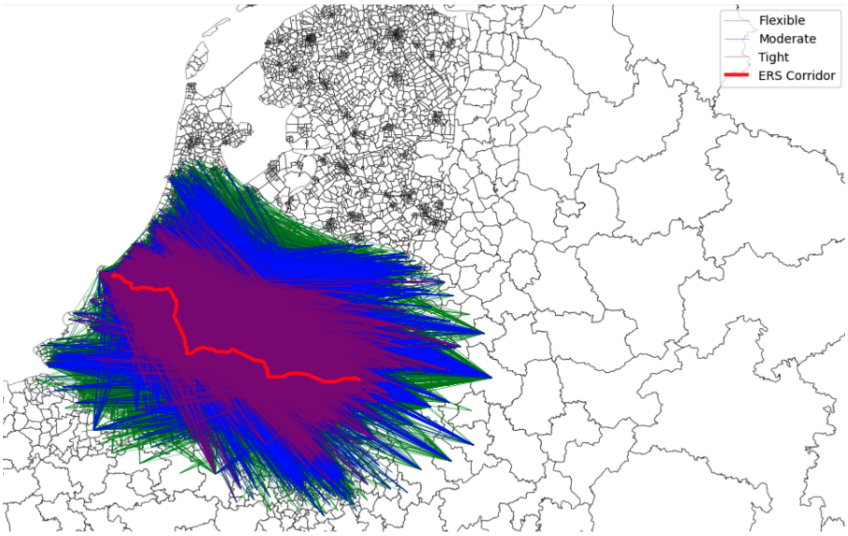


Figure 23: ERS-using trips from tours in the tour adoption potential (Flexible (green); Moderate (blue); Tight (purple))

In Figure 23, the ERS-using trips that are part of a tour in the final tour adoption potential are visualized for all three scenarios. All the trips within these tours that use the corridor are displayed on the Dutch map for all scenarios. It shows how the number of adopting tours increases when the parameters are more flexible. The map in Figure 23 is similar to the one in Figure 20, but one can clearly see that some distant trips have been excluded and that especially the green pattern (from the Flexible scenario) has shrunk properly, as many tours have been removed due to insufficient battery range. This will be discussed in the next subsection.

Figure 24 shows once more the intensity of originating trips per zone. When one compares this figure with Figure 21, the differences are obvious. The colors of the zones are lighter, proving that many trips that were part of the trip adoption potential, have not been included in the tour adoption potential.

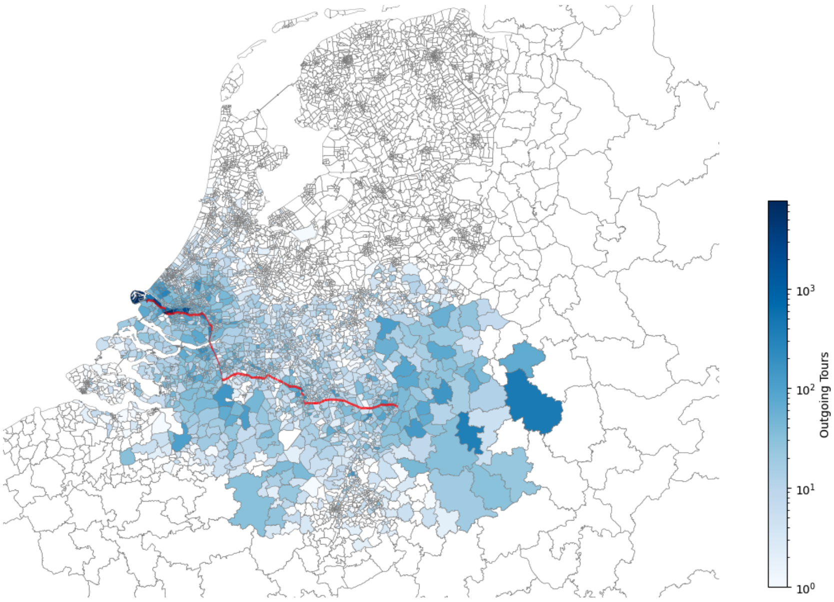


Figure 24: Tour origins by zone: Color intensity reflects outgoing trips (Moderate scenario)

4.2.2 Battery Level

The difference between the figures before and after removing the non-ERS-adopting tours, relates to the exclusion of tours in which the battery runs empty. Many tours that include an ERS-using trip cannot complete the full tour without eventually running out of energy. These tours are excluded from the tour adoption potential. For every scenario and variant combination, it is visualized how many tours were excluded and how many tours were ultimately included in Figure 25. The values in the figure therefore correspond to those in the second row of Table 13. The red part of the bar represents the excluded tours that were unable to complete the full tour due to battery constraints. The tours that were finally adopted in the tour adoption potential are represented by the blue part of the bar. The following results were found for each scenario.

For the Tight variants (bars on the left), the energy consumption rate was highest (2.175 kWh/km), while the charging power was lowest (120 kW). As a result, trucks required more energy to complete their trips but were constrained in their ability to replenish this energy during ERS usage. This imbalance contributed to relatively high exclusion rates due to battery depletion, with approximately 37–43% of all tours excluded depending on the number of tours in the adoption potential used for the battery simulation.

For the Moderate variants (middle bars), both energy consumption and charging power were set to intermediate levels (c = 1.875 kWh/km and $P_{ERS-charge}$ = 150 kW). The exclusion percentages are lower here than for the Tight variants: 35-39%. The lower energy consumption compared to the Tight scenario allowed more trucks to reach their destinations without running out of battery, while the moderate charging power enabled better recovery of battery levels during ERS operation.

The Flexible variants (bars on the right) featured the most favorable energy parameters: the lowest consumption rate (1.575 kWh/km) and the highest charging power (180 kW). These improvements enhanced trucks' ability to maintain sufficient battery charge. The exclusion rates in this scenario are therefore lower than for the other variants: 33-35%. This can be attributed to the fact that the Flexible scenario's relaxed adoption conditions allowed significantly more tours to qualify. The trucks consume less energy, so their battery depletes more slowly meaning more trucks can reach their destination without getting depleted. This leads to more tours being included in the adoption potential. Also, the ERS charging power is higher so trucks will leave the corridor with a fuller battery.

Overall, the results show that battery performance parameters strongly influence the number of successfully completed tours, a gradual increase in the excluded tours is observed when the parameters get more strict.

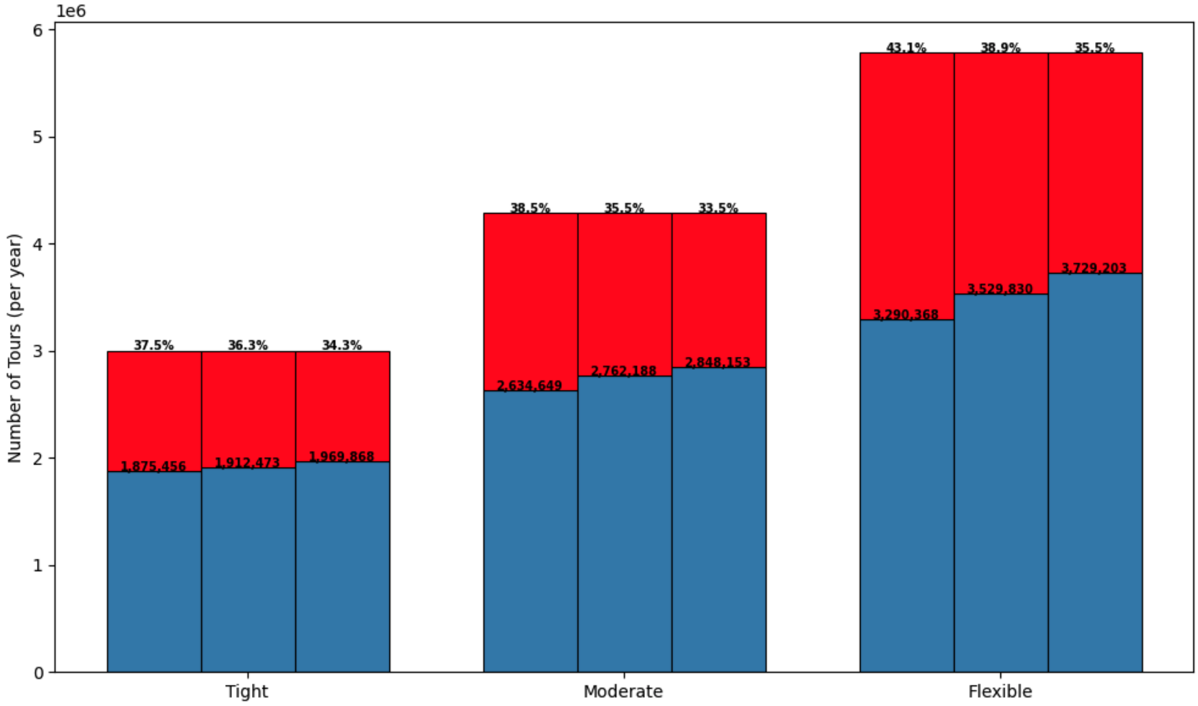


Figure 25: Impact of battery constraints on included tours (red = excluded tours; blue = included tours)

4.3 Energy Demand

In this section the number of tours in the tour adoption potential from the Moderate scenario (2.76 million) are used to determine the energy demand with various c and $P_{ERS-charge}$ values.

After identifying, for all different scenarios and their internal variants, how many tours are ultimately included in the tour adoption potential, a final list of tours that would make use of the corridor without having their battery depleted at some point during the route remains. In addition, the battery level of the truck upon entrance at the ERS network is known for every tour, as the battery level was tracked during pre-ERS travel. The next (and final) step is calculating the energy demand. The energy demand can be presented in several ways:

1. **Spatial energy demand**: Where does the peak demand occur, and how high does this peak demand get?
2. **Temporal energy demand**: When is the energy demand high? What are demand intensive hours?

By combining these two perspectives, the results can provide insight into how energy demand moves across the corridor and where peak demand occurs during the morning and evening rush hours.

4.3.1 Spatial Energy Demand

First, the spatial energy demand. Figure 26 shows where the total energy demand on the corridor is highest throughout the day, for the Moderate scenario and Moderate variant. The figure shows the total daily energy demand per segment. The x-axis displays the segment IDs, ranging from 0 to 98. As a reminder: segment 0 is located at the beginning of the corridor, at the far end of Rotterdam on the North Sea coast, while segment 98 lies at the German border in Venlo. The energy values on the y-axis represent the total energy demand on a segment of the corridor over a 24-hour period. The highest total energy demand is observed at segment 15, reaching up to over 35 MWh per day. The lowest energy demand comes from segment 98: 3.03 MWh per day

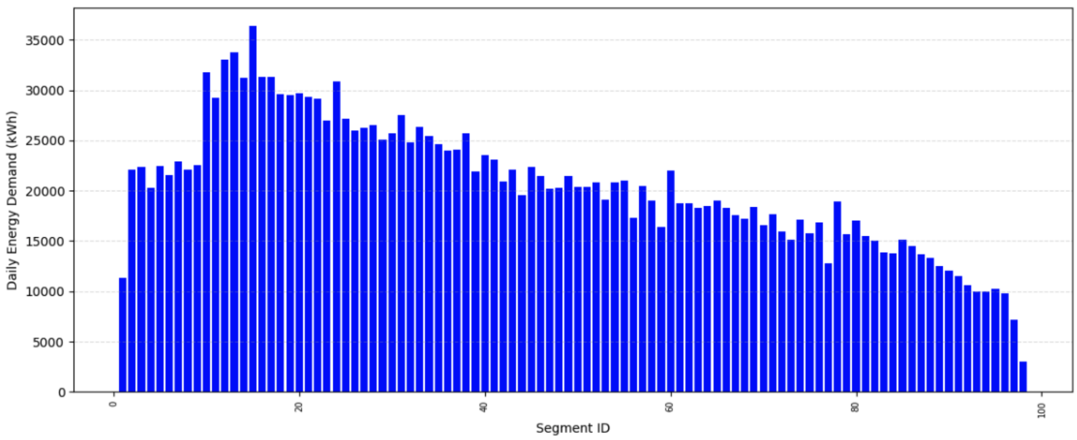


Figure 26: Bar chart of total daily energy demand per segment (Moderate scenario & Moderate variant)

If one looks at the ten highest demanding segments of the corridor, it stands out that almost all of these segments are between the 10th and the 20th segment (Table 14)

Segment ID	Daily Energy Demand (kWh)
15	36375.0
13	33765.0
12	33030.0
10	31777.5
16	31357.5
17	31335.0
14	31245.0
24	30847.5
20	29737.5
18	29625.0

Table 14: Top 10 segments with highest daily energy demand.

When a color is assigned to each segment based on the total daily energy demand, the demand intensity per segment over the whole corridor can be visualized, clearly showing where demand is highest. This is shown in Figure 27. Here, high-demand areas can be easily identified: in and around Rotterdam. As also illustrated by the bar chart in Figure 26, the colors gradually become lighter, indicating that demand decreases from west to east. At the end of the corridor, near Venlo, the total demand per segment per day is barely 5 MWh — almost seven times lower than for the highest-demand segment (segment 15).

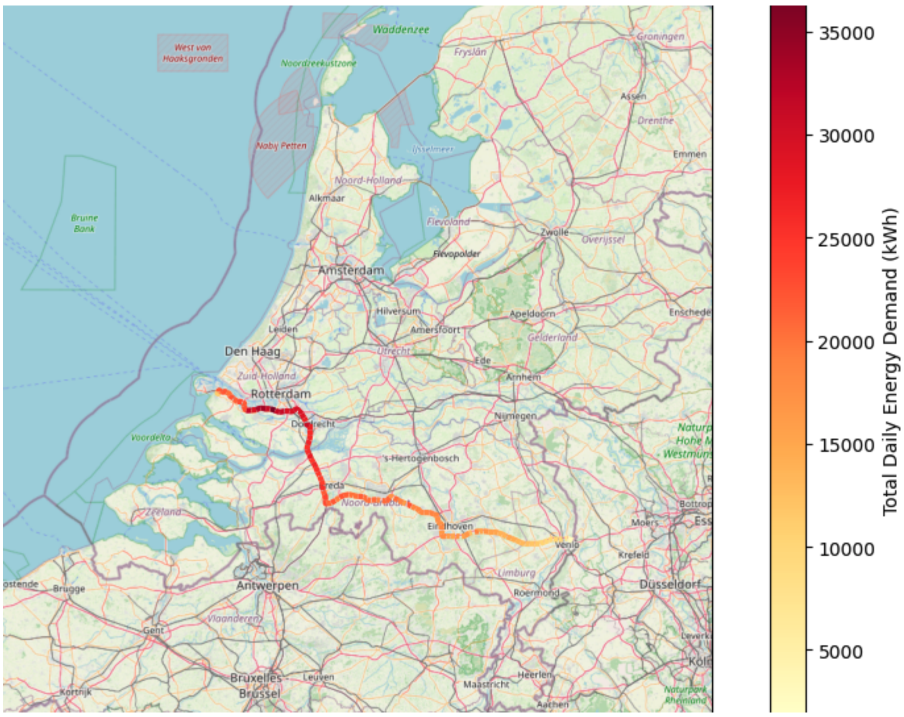


Figure 27: Total energy demand on corridor (Moderate scenario & Moderate variant)

4.3.2 Peak Power Demand

Figure 28 presents the daily peak power demand per segment along the corridor. For every segment, it shows how high the demand maximally gets during the day. The times when peak demand occurs for every segment might differ. The peak values are derived by averaging the weekly peak demand over 5 working days, under the assumption that transport activity is evenly distributed throughout the week. The highest peak demands are concentrated in and around the Rotterdam port area, where segments reach values exceeding 3.4 MW. Segment 12 has the highest peak demand value with 3.42 MW. It is closely followed by segments 10, 15 and 20 with 3.09, 2.91 and 2.85 MW respectively. As the corridor moves toward the southeast — through Breda, Eindhoven, and finally Venlo — segment colors transition to orange and yellow, indicating lower peak demands between 0.5 and 1.5 MW.

To give an impression of the volume of the highest peak demand: a 3 MW peak on a single segment is equivalent to the combined draw of about 10 ERS trucks with depleted batteries.

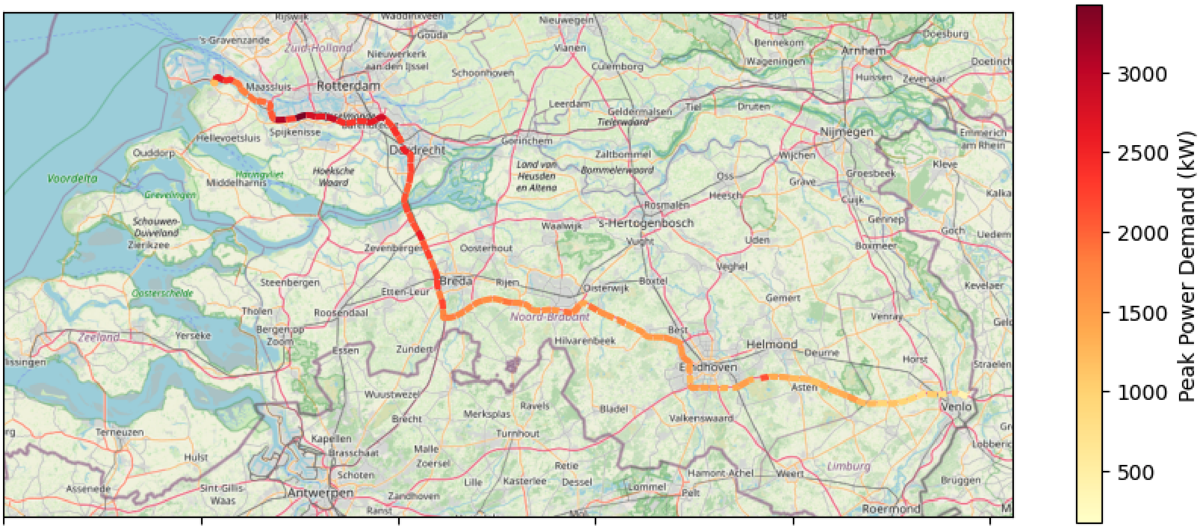


Figure 28: Peak power demand per segment

4.3.3 Temporal Energy Demand

Now that it is known where on the corridor the energy demand is highest, it is crucial to examine the distribution of energy demand throughout the day. There will be significant fluctuations in demand over a 24-hour period, with clear rush hours or peak periods where demand spikes sharply. The total energy demand per quarter are visualized in Figure 29. This graph shows for every quarter how much energy is demanded by the whole corridor during that timestamp. This gives an idea of when the rush hours take place and how the temporal demand is distributed. This temporal demand can be combined with the spatial demand, using a heatmap, which includes all time intervals and the full length of the corridor, and displays the energy demand for each combination (Figure 30). This provides a clear visual representation of where and especially when demand is high throughout the day.

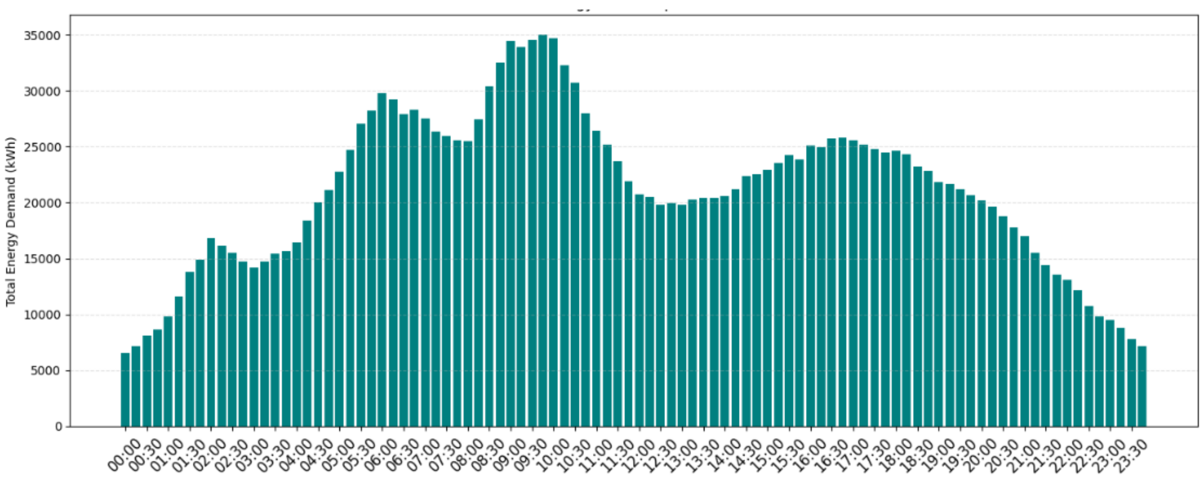


Figure 29: Total daily corridor energy demand per 15-minute interval

The y-axis represents the length of the corridor in kilometers. What immediately stands out is the dark area between 7 AM and 11 AM for kilometer 20 and 50. Demand appears to spread eastward, gradually fading up to about kilometer 82, suggesting trucks moving east across the corridor. One can also observe a smaller dark region, again between kilometer 20 and 50, occurring earlier in the day, between 4 AM and 6 AM in the morning. Additionally, there is a third dark zone, which is more spread out. Once again for segments between 10 and 25, but the temporal span of the demand runs from approximately 2.30 PM to 7.30 PM. After this, from 9 PM to 4 AM almost entirely pale yellow — indicating very low energy demand during these hours. Lastly, a fairly dark red cell can be seen around 10:15 at kilometer 156. This suggests a singular high-demand event.

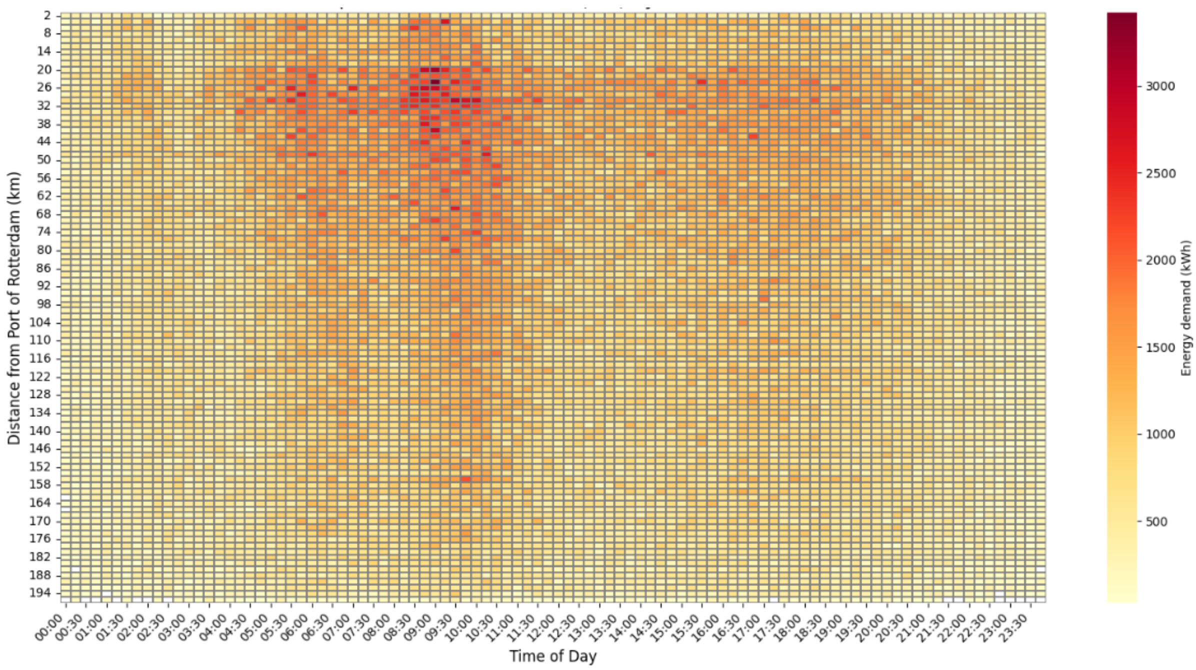


Figure 30: Heatmap of ERS energy demand by segment and time (Moderate scenario)

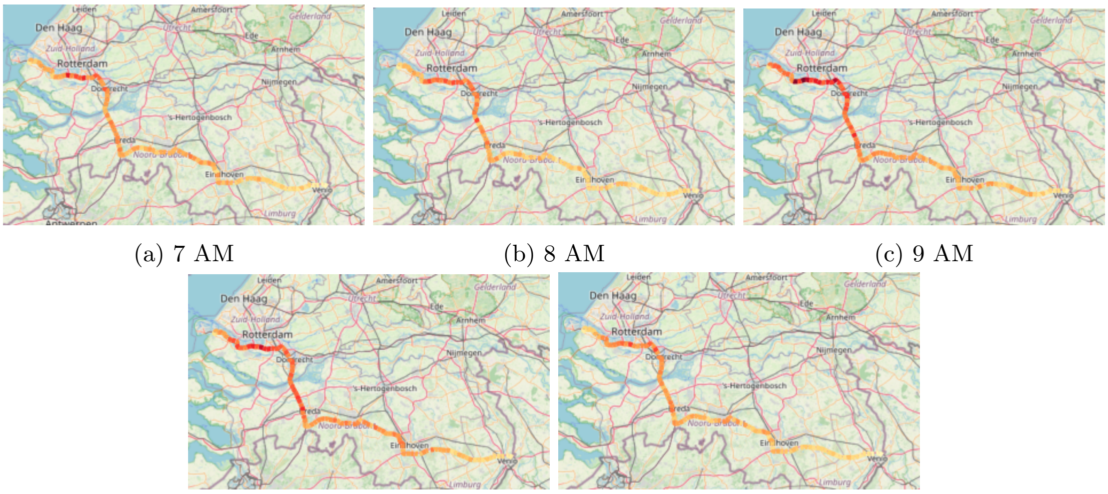
To see how the identified morning rush between 7 AM and 11 AM on the heatmap impacts the corridor, Figure 31 can be analyzed. In Figure 31, the truck density on the corridor is displayed during the morning rush hour with 5 moments in time. Dark red/black areas represent high density and thus high energy demand, while light yellow areas indicate low ERS usage. The following results are observed:

- **7 AM — Initial buildup around Rotterdam**
  High density is already present in and around Rotterdam, indicated by dark tones. Most of the corridor toward the southeast is still light, indicating low truck presence. This is the start of the morning rush hour.

- **8 AM - 9 AM — Peak traffic on west corridor**
  The density is intensifying significantly along the Rotterdam-Dordrecht-Breda stretch. The dark red area gets longer, meaning it gets really busy on the corridor with the energy demand peaking around 9 AM. One can also see high activity stretches further east, suggesting that many trucks are moving along the corridor.

- **10 AM — Dissipation begins**
  The demand is still high, especially between Dordrecht and Breda. Many trucks have now left the Port of Rotterdam and are now on their way to their destination. The activity and demand is now really moving eastward.

- **11 AM — Peak is clearly declining**
  The dark zones begin to shrink. Rush hour is over and only a few short, high-density stretches remain. The demand on the corridor east of Eindhoven and toward Venlo is still quite low, indicating most of the trucks have fully charged.



(a) 7 AM (b) 8 AM (c) 9 AM

(d) 10 AM (e) 11 AM

Figure 31: Spatial distribution of ERS power demand during the morning peak (7 AM – 11 AM)

Indicated by Table 14, the segments with the highest demand are segment 15, 13 and 12. The individual graphs of these segments provide a detailed view of the distribution of energy demand for traction and for battery charging (Figure 32, 33, 34). It can be observed that the traction demand graphs are much more volatile than those for battery charging. The energy demand for battery charging remains relatively constant throughout the day, whereas there are significant fluctuations in traction demand over the course of the day. Notably, the battery charging demand barely follows the morning peak seen in traction demand. Furthermore, the difference in battery charging demand between daytime and nighttime is only minimal.

All three segments exhibit similar overall patterns, but segment 12 reaches the highest peak of over 3400 kWh which is almost entirely driven by traction demand, which closely follows the total demand curve. After the morning peak, demand gradually declines and minimally rises again 3 PM. By 8 PM, demand stabilizes at a much lower level and stays low through the night.

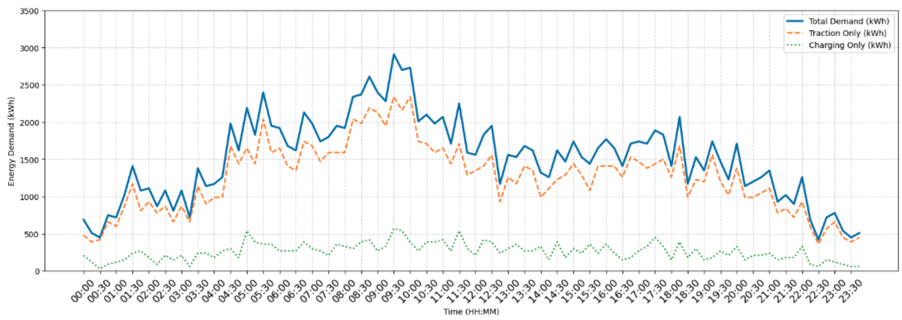


Figure 32: Energy demand graph segment 15

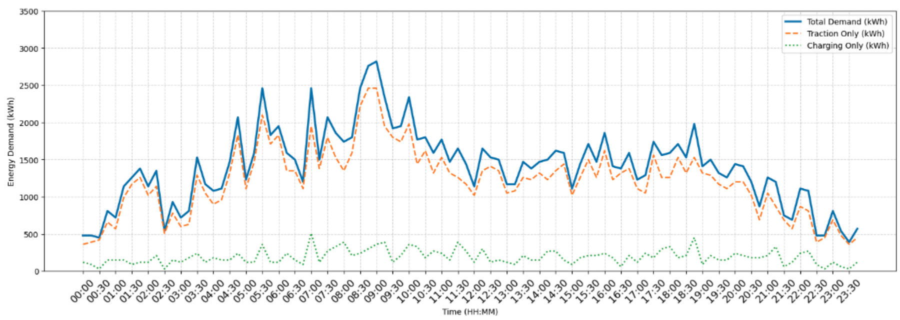


Figure 33: Energy demand graph segment 13

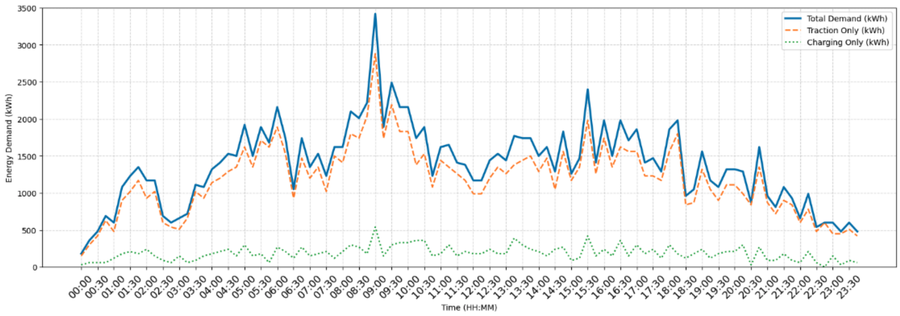


Figure 34: Energy demand graph segment 12

In Figure 35, the three segments are combined into one graph. All three segments show a clear and sharp increase in energy demand starting from around 6 AM, peaking between 8.30 AM and 10.30 AM. This is in line with what was observed on the heatmap and the truck density on the corridor. Peak values reach way above 3000 kWh, which indicates a heavy concentration of truck traffic during this time window. One can observe that segment 15 has the most peaks, particularly between 8.30 AM and 1 PM and stays reasonably constant during the day. This aligns with earlier findings that segment 15 has the highest total daily demand, reinforcing its role as a hotspot. After the peak, demand drops off, but doesn't collapse — it enters a relatively stable plateau phase, indicating continued ERS usage, but at lower intensity. One can also observe another peak in the graph of segment 12 at 3.30 PM. By 7 PM, demand in all segments steadily drops toward baseline. The early morning and late-night hours show low and stable demand across all segments, typical of reduced logistics activity during these times.

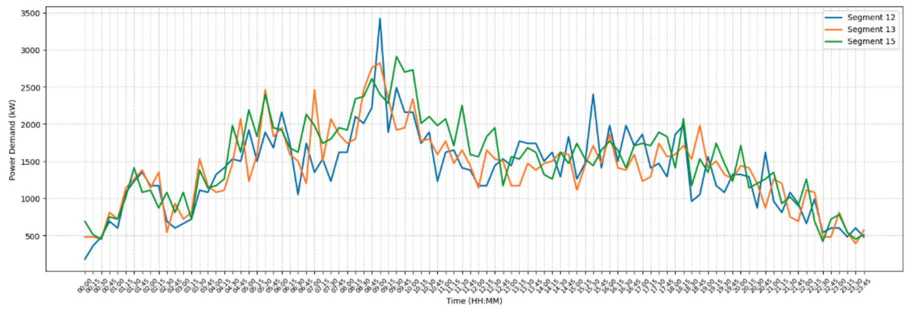


Figure 35: Combined energy demand graphs segments 15, 12, 13

4.4 Scenario Analysis

When the values of the parameters c and $P_{ERS-charge}$ are changed, scenarios are created that represent possible future developments. The values of c and $P_{ERS-charge}$ are given in Table 11. A Tight scenario, with a high energy consumption rate and low ERS power supply for battery charging, reflects low technological development, while a Flexible scenario represents a more favorable or accelerated development. The results of the energy demand under both scenarios, compared to the energy demand in the baseline Moderate scenario, are shown in Figure 36. This figure illustrates the daily energy demand per corridor segment and the extent of the differences between scenarios when the values of c and $P_{ERS-charge}$ are adjusted.

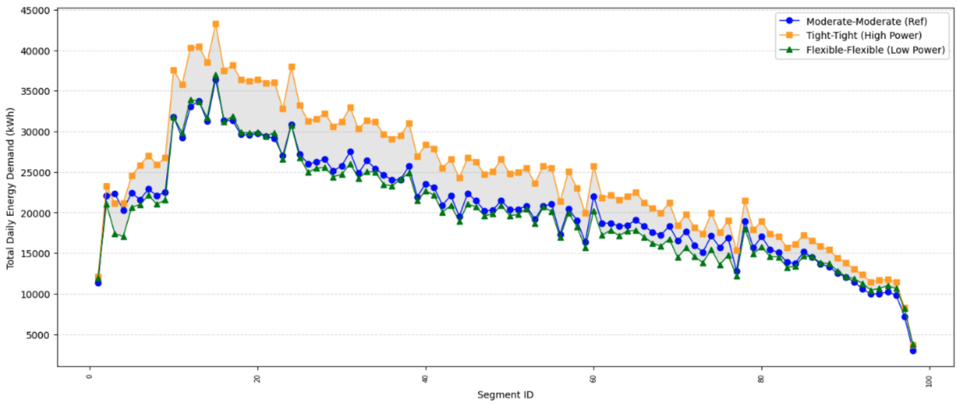


Figure 36: Scenario analysis: Flexible (green) vs. Moderate (blue) vs. Tight (yellow)

For all the three scenarios, the number of ERS-adopting trips from the Moderate scenario were used. These different c and $P_{ERS-charge}$ values were then used to determine the ERS-adopting tours and subsequently the energy demand.

All three graphs follow the same overall pattern, indicating that the spatial distribution of ERS usage remains structurally stable across scenarios. One can see that the graph from the Tight scenario has the highest energy demand at almost all of the segments. The differences between the Flexible and the Moderate scenario however, are small and in some cases, the energy demand in the Moderate scenario is lower than in the Flexible scenario. The difference in energy demand between the Tight and Flexible scenarios shows that technical parameters have major implications for ERS infrastructure design. The Tight scenario requires more energy to be delivered by the ERS, placing greater demands on the system, especially in high-traffic segments. It can also be observed that the differences between the scenarios are larger when the total demand increases.

With the parameter values that were used, the energy demand in the Tight scenario was expected to be consistently higher. For this scenario the energy consumption is highest and the power for battery charging the lowest. On the other hand, in the Tight scenario, fewer tours are included in the adoption potential, which decreases the total energy demand. However, it appears that the parameter values have more impact on the energy demand than the included tours in the adoption potential.

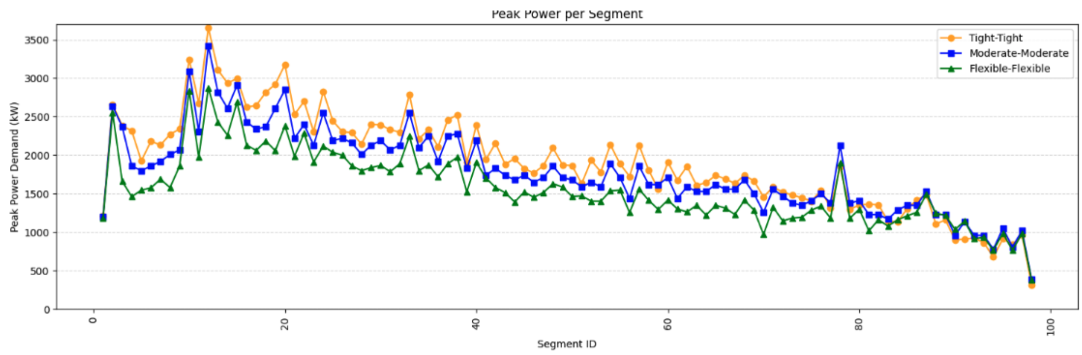


Figure 37: Peak power demand of all three scenarios (green = Flexible; blue = Moderate; yellow = Tight

In Figure 37, the peak power demands for all the corridor segments are visualized for all three scenarios. It can once again be observed that there are similar patterns among the three. Notably, the highest peak occurs in the Tight scenario, reaching 3.7 MW at 09:00 AM. Apart from this, the patterns across scenarios are largely similar, with the peaks gradually flattening as the parameter values become increasingly flexible. This clearly shows that in the Flexible scenario, the average values are lower and the peaks fade away. This observation is consistent with the graph shown in Figure 36.

4.5 Sensitivity Analysis

To test the impact of the parameters from Table 11, a sensitivity analysis was performed, in which the value of one parameter is changed while keeping the other one constant. This allows us to clearly observe the effect of that specific parameter on the results produced by the model. The results from this analysis are presented in Figure 38 and 39. The energy demand in a Moderate scenario, with moderate c and $P_{ERS-charge}$ values are represented by the dotted line.

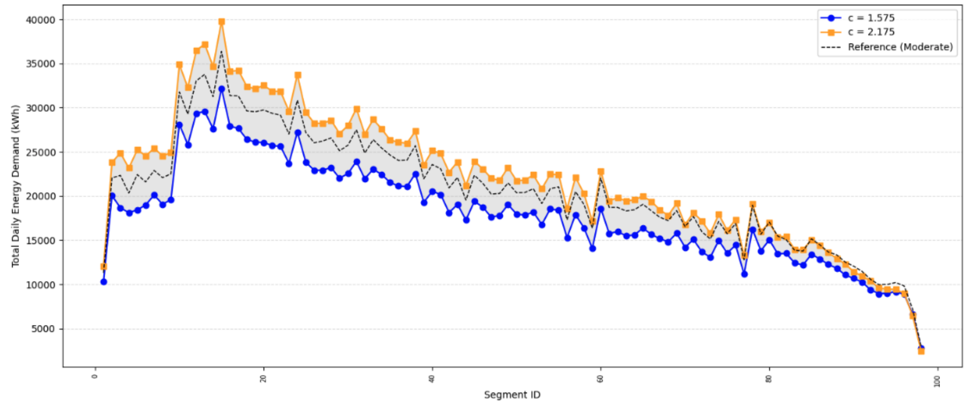


Figure 38: Sensitivity analysis: $c = 1.575$ kWh/km (blue) vs. $c = 2.175$ kWh/km (yellow)

Figure 38 shows the differences in daily energy demand when varying c values are applied. While the differences are not huge, it is still quite obvious that a high c value leads to higher demand, but even more that a low c values leads to less demand. The yellow line, representing a high c value is closer to the reference line than the blue line, representing the low c value. Even though, the adoption potential in a scenario with a low c value contains more tours, the scenario with a high c value is still causing much more demand, with peak demand reaching up to 40 MWh per day for segment 15. This is caused by the fact that due to the higher energy consumption, the truck consumes more energy for traction, which apparently leads to great demand peaks. Even more than the number of tours included in the adoption potential. This shows us that the energy consumption rate for O-BETs will determine strongly how high the energy demand of an ERS corridor will actually be.

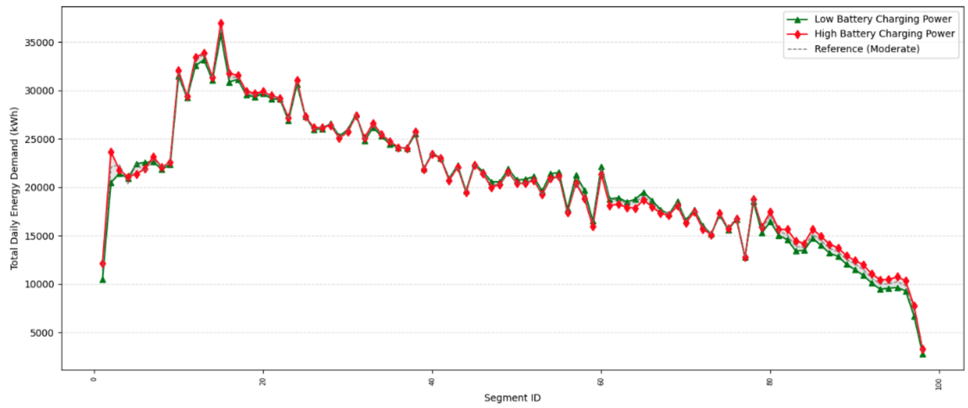


Figure 39: Sensitivity analysis: $P_{ERS-charge} = 120$ kW (green) vs. $P_{ERS-charge} = 180$ kW (red)

Figure 39 shows the sensitivity of the energy demand to the power provided by the ERS for battery charging. The differences of both graphs with the reference graph are minimal. This suggests that the total energy demand of an ERS corridor is not sensitive to the power provided by an ERS for battery charging. Much more influential is the energy consumption rate.

5 Discussion

In this section, the results obtained in Section 4 are interpreted and discussed. First, the novelty of the study will be highlighted. Then, the battery constraints, spatial and temporal energy demand are considered separately comparing their results with findings from other literature. The impact of using an extensive ERS network on energy demand will also be discussed. Next, the limitations of the research are discussed. Finally, the implications for Elaad are formulated after which the contributions of the study are explained.

5.1 Discussion of Results

5.1.1 Novelty of the Study

The novelty of this study stems from the use of tour data instead of the traditional trip data. Looking at how much a truck charges during a single trip or whether it uses ERS says very little about the feasibility of ERS. To be in line with reality, it is crucial to use realistic truck driving patterns, to considering the entire tour, assessing when a truck needs to charge (by modeling and tracking the battery's state of charge), how much energy it needs to complete the tour, whether additional static charging is required, and whether any charging is needed during the ride at all. This is what will actually add value and what leads to realistic results that can actually be used for future policy. Trip data provides only a limited picture of a truck's driving patterns and is therefore not sufficient to draw definitive conclusions.

In other literature, similar researches have been done that examine the energy demand of an ERS corridor, but none have used tour data, making this study so valuable. As described before in this research, Bakker et al. [16] only used trip-level data to determine the adoption potential for ERS. Jelica et al. [20] used data from the Swedish Transport Administration that includes average daily traffic pattern per day and per road segment based on measurement points. The authors do not determine an adoption potential, do not account for battery constraints, and assume a 100% adoption of ERS by trucks, making the results unrealistic for current traffic patterns. Taljegard et al. [21] use hourly freight volume averages for 70 locations on a Norwegian highway, based on traffic data from 2014. The authors also assume a total adoption of ERS for heavy vehicles and do not account for battery constraints and tour-level data, reducing the value of the study.

Although several studies have investigated the energy demand of an ERS network in a similar way, none have accounted for the tour structure of the routes that trucks complete on a daily basis. Not only do these studies refrain from using tour-level data to determine the adoption potential, but they also ignore the impact of tour structure on trucks' battery levels upon arrival at the corridor. This is the first study that, across all aspects, fully considers the fact that trucks operate full tours rather than isolated trips. That is what makes this research so unique and why its results are closely aligned with real-world conditions.

5.1.2 Battery Constraints

Because this study uses tour-level data rather than individual trips, a significant portion of trips initially deemed eligible for ERS use were excluded after applying battery constraints to the full tour. In the Moderate scenario, over 35% of tours from the trip adoption potential were excluded due to insufficient battery range (Figure 25). This emphasizes the importance of accounting for full tour structure, not just individual trip feasibility. While 6.8% of the total freight flow initially qualified for ERS use, only 5% remained eligible when full tour feasibility was assessed (Table 12). These findings show that trip-level analysis can overestimate ERS viability if battery limitations across the entire tour are not considered.

Mostly it shows the dependence on the battery size for the ERS to be a successful investment. The battery size and range is a critical factor in determining the success of an ERS corridor, as illutrated in other literature [28]. In addition, as highlighted by Van Ommeren et al. [37], Bakker et al. [16], and SRE [38], the decision of truck operators to opt for O-BETs with smaller batteries is not solely a technical one, it is also highly dependent on the geographical overlap between ERS infrastructure and the operators' logistical networks. Logistic operators may be reluctant to choose vehicles with reduced battery capacities, as they would become highly dependent on the reliability and accessibility of a single ERS route. Therefore, the fact that a significant portion of the initially eligible trips were excluded once battery range limitations at the tour level were applied, is consistent with these concerns.

5.1.3 Spatial Energy Demand

The energy demand was found to be by far the highest between kilometer 20 and 40 (segment 10 - 20). These segments correspond to the stretch from the Botlek area in Rotterdam to the A16 highway near Ridderkerk (see Figure 40). This outcome is not surprising and can be logically explained by several factors. First, this area is a major logistical hotspot. The Botlek and Maasvlakte regions are part of the Port of Rotterdam, one of Europe's largest freight hubs. A substantial share of national and international freight flows originate from this area. As a result, a major part of the adopting tours that use the ERS corridor either start or pass through these segments. This result aligns with findings from previous studies indicating that early ERS deployment is most viable near dense logistical centers due to the high volume of electrifiable heavy-duty traffic. In a report by Hacker et al. [39] on expansion strategies for ERS in Europe, the authors state that at early stages of ERS network development, in addition to the high volume of traffic, the structure of the traffic plays an important role. Especially in the case of a high proportion of journeys that end and begin not far from the electrified corridor, routes are particularly suitable, the authors claim. Proximity to logistical transfer points (such as ports or other hubs of commerce and industry) can be of advantage and create a base load of suitable traffic. The aligns with the high energy demand around the Port of Rotterdam that was found in this research.

Figure 40: High demanding trace of corridor: kilometer 20 - 40

Secondly, the ERS network in this area is highly accessible. Because the segments are located near major industrial zones and well-connected highways (A15, A16), they are easily reached by trucks without requiring significant detours. This makes it more likely that a larger number of adopted tours include these segments in their route.

Third, these segments are passed through not just by originating tours, but also by through-traffic heading towards the south or east of the country. Tours originating from The Hague for example, are likely to use a large part of this section en-route to their destination in the south or east. For such trips, segment 10-25 are the first parts of the corridor they use after traveling to the corridor from their origin zone first. As a result, many trucks use this initial part of the ERS not only for propulsion but also to actively recharge their battery, leveraging the dynamic charging capability of the system. This dual demand (energy for movement and energy for recharging) leads to high energy consumption in these early segments of the corridor. As the corridor progresses, more trucks have their battery fully charged again, reducing the demand for battery charging in later segments.

These explanations all align with the forecast by ElaadNL [30], where they estimate the number of battery electric trucks in 2050 for every area in the Netherlands (Figure 41). One can clearly see the dark areas around Rotterdam and around Oosterhout. These dark areas align with the dark red areas in Figure 27 and Figure 28, where the dark areas represent high demand.

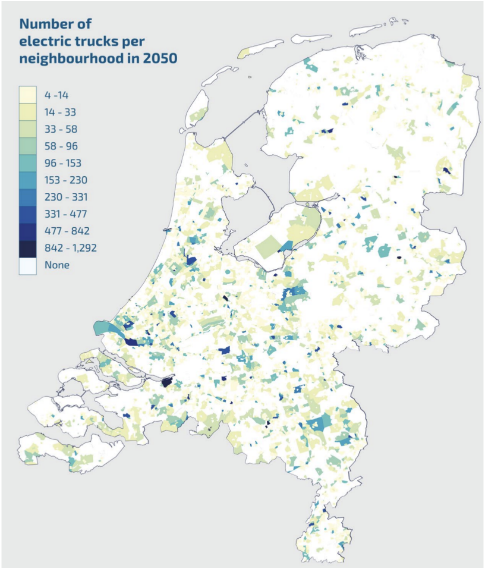


Figure 41: Number of BETs per zone in 2050, predicted by ElaadNL ([5])

In the results from this research, it was also seen that as the corridor progresses eastward from Rotterdam to Venlo, the total energy demand per segment gradually decreases. The number of trucks using the ERS corridor is highest near Rotterdam, where most tours originate or pass through early in their route. As trucks continue along the corridor, many of them leave the ERS before reaching Venlo, leading to lower vehicle density and thus reduced total energy demand in the eastern segments. In addition, trucks that remain on the corridor benefit from continuous dynamic charging. As their battery level increases during the journey, the need for further energy input decreases. In later segments, most of the energy demand comes only from traction, not from battery replenishment.

Also, it becomes clear that most of the trips on the corridor are eastbound. The segments near Rotterdam consistently show the highest energy demand. This suggests not only a high number of trucks but also that many of them start their tours in the west, using the ERS early in their routes. Return trips from the east may either take different routes or occur outside peak ERS hours. This is explained by Figure 30, that shows the widely distributed peak between 1:00 PM and 5:00 PM. If there were just as many trucks driving east to west, more symmetric energy demand patterns would be expected, with peaks near both ends or a more balanced distribution. It is no surprise that this asymmetric distribution was observed, as it makes practical sense. Goods often leave from Rotterdam and are transported inland toward Germany and the southeast of the Netherlands, including Venlo.

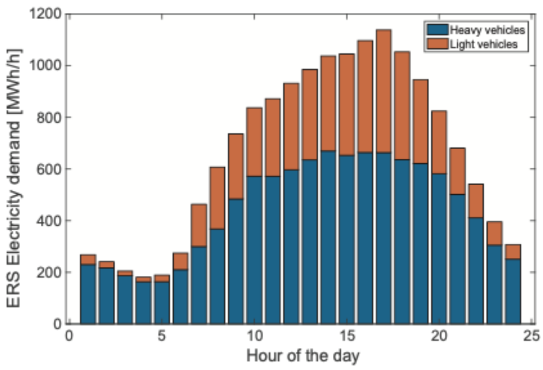
But what do these results actually mean? Of what use are they? All together the spatial demand analysis provides an indication of the power that the electricity grid must be able to supply in order to meet the energy needs of trucks. For example, it is now known that the grid must be able to deliver up to 3.42 MW of power between kilometer 22 and 24 (segment 12). Substations installed to supply electricity to the ERS must therefore be capable of delivering such power levels in high-intensity segments. Besides, as a result of the peak power demand analysis, peak shaving strategies could be implemented to limit the peak power demand. This can be achieved through smart charging systems that delay or reduce charging rates when the grid is under high stress. When demand is too high the ERS could potentially limit the power it supplies to the trucks to reduce stress on the grid.

As a result of this analysis, it is now clear how much power substations along the corridor need to be able to provide. In low-intensity segments, such as at the end of the corridor, fewer substations may be needed due to lower demand. This could lead to potential savings on infrastructure investments.

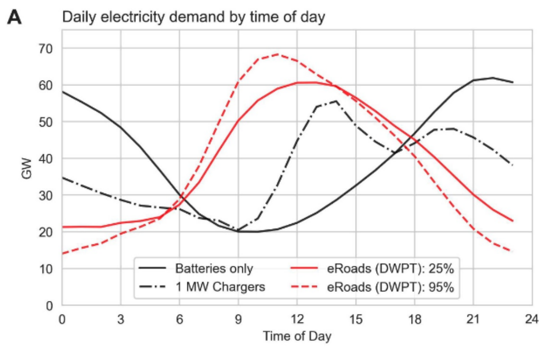
5.1.4 Temporal Energy Demand

The heatmap in Figure 30 reveals clear daily temporal patterns in energy demand across the entire corridor. The morning peak between 8 AM and 11.30 AM is by far the most prominent peak in the heatmap, visible as a dense red band across kilometer 20-50, indicating peak energy demands in the range of 2.5 to 3.4 MWh in some cells. This demand peak is of course in line with the start of the logistics workday, when trucks depart from origin zones. The stretch of this peak, from early morning till early afternoon, has to do with trips coming from further origin zones that arrive at the corridor late in the morning. Also, some tours might have an ERS trip late in their schedule. After the morning peak, a midday plateau can be observed, showing a moderate but sustained level of demand during that period, particularly across segments 20–40. This can be explained by the fact that many trucks that used these segments during the morning rush hour and originated from the Rotterdam area are now already on their way to their destination and are no longer on these segments. They are either further along the corridor or have already exited the corridor on their way to their final destination or an intermediate stop. Moreover, many trucks have a full battery around this time, after having entered the ERS corridor in the morning with a partially depleted battery.

The patterns that were identified are validated by the energy demand timeline in Figure 31. The high demand is already visible at 7 AM around segment 10-15, near the Botlek industry area in the Port of Rotterdam. The energy demand is moderate due to charging needs after a short pre-ERS trip from origin zone to the corridor. Especially between 9 AM and 10 AM, the demand around Eindhoven can be seen intensifying. This can partly be explained by the energy demand from the trucks that have left Rotterdam between 7 and 8 AM, as they will have reached Eindhoven between 9 and 10. This results in a temporal concentration of trucks on the ERS in this segment during mid-morning. In addition, one of the reference points from Figure 12 that were used to indicate important junctions on the corridor in Section 3 is located in Eindhoven. This means that trips originating from zones closes to this reference point/junction, are obliged to use that reference point while driving from east to west or the other way around. This because of the way the distance-over-network trips were modeled to travel from zone to zone.



(a) ERS energy demand pattern in Sweden [20]



(b) ERS energy demand pattern in the US [18]

Figure 42: Comparison of daily ERS energy demand patterns in Sweden and the US

One can observe the pattern of the total temporal energy demand in Figure 29. The rush hours are clearly visible here as well. When one compares this with the daily demand patterns found in other literature, there are some interesting differences. In the article by Jelica et al. [20], the demand peak on the ERS occurs between 3 PM and 5 PM, given in Figure 42a. It shows a smooth, bell-shaped curve. Demand gradually increases throughout the morning, peaks in mid-afternoon, and then tapers off (for heavy vehicles). The pattern that was found in this research (Figure 29) shows a more jagged curve with sharper rises and falls. Some differences can be observed in the hours of peak demand and compared to the results from this research, Figure 42a shows no volatility during day hours. In the demand pattern for an ERS corridor in the United States, Yeow et al. [18] found the pattern given in Figure 42b. Even though the time of the peaks are not perfectly aligned, the typical shape of an ERS network is similar to what was found in the results from this research, but also to the demand pattern in Figure 42a: the energy demand pattern peaks during the day and gradually decreases to a minimum at night.

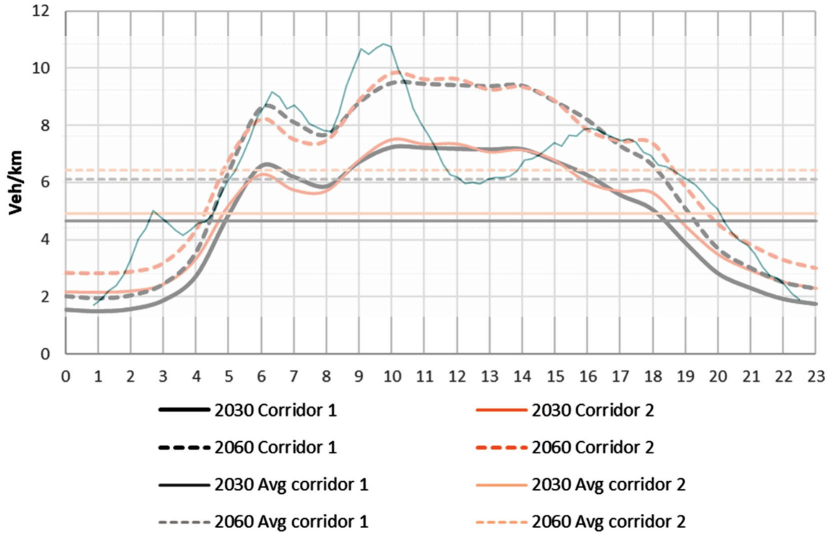


Figure 43: Projected Heavy Goods Vehicles averaged over the length of the corridor (corridor 1) [28] combined with temporal energy demand from results (Figure 29)

In Figure 43, the projected number of HGV (Heavy Goods Vehicles) on the Rotterdam-Venlo corridor are visualized predicted by TNO [28] (black line for 2030 and black dotted line for 2060) and layered together with the graph from the temporal energy demand results (green line) (Figure 29). The bar chart was changed into a line graph in order to compare the two. Even though the two graphs have a slightly different pattern during the day, the figure also shows similarities in the shapes of the graphs. There is a clear resemblance in the time of the morning peak and the decline at the end of the day. This graph tells a couple of things. First of all, it underscores the importance of the freight activity in determining the shape of the energy demand curve. One can see similar temporal patterns, which shows that the freight activity patterns on the corridor are a driving factor for the energy demand distribution. This validates the modeling approach that links ERS demand to actual freight activity, even when using independent datasets. Since the energy demand output mirrors the flow input trends seen in external data, it suggests the model effectively captures key real-world dynamics. But, most importantly, this figure suggests that energy demand patterns will be similar, no matter the number of included tours in the adoption potential. The projected vehicles per kilometer from the study by TNO [28] show similar patterns as our results, even though their graph represents all the HGVs and ours just the ERS-adopting tours. This suggests that if the included tours in the adoption potential would increase or decrease, the energy demand graph would look similar percentage-wise.

Beyond validating the modeling approach, the similarity in temporal patterns between the energy demand and projected truck density curves suggests that the model is robust for scenario testing. Specifically, it indicates that even if the number of ERS-adopting trucks increases or decreases (due to higher or lower adoption rates or technological developments) the timing of energy demand peaks remains largely stable. In other words, while the total energy demand of a single ERS corridor may vary under different adoption scenarios, the model provides reliable insights into when that demand will occur throughout the day.

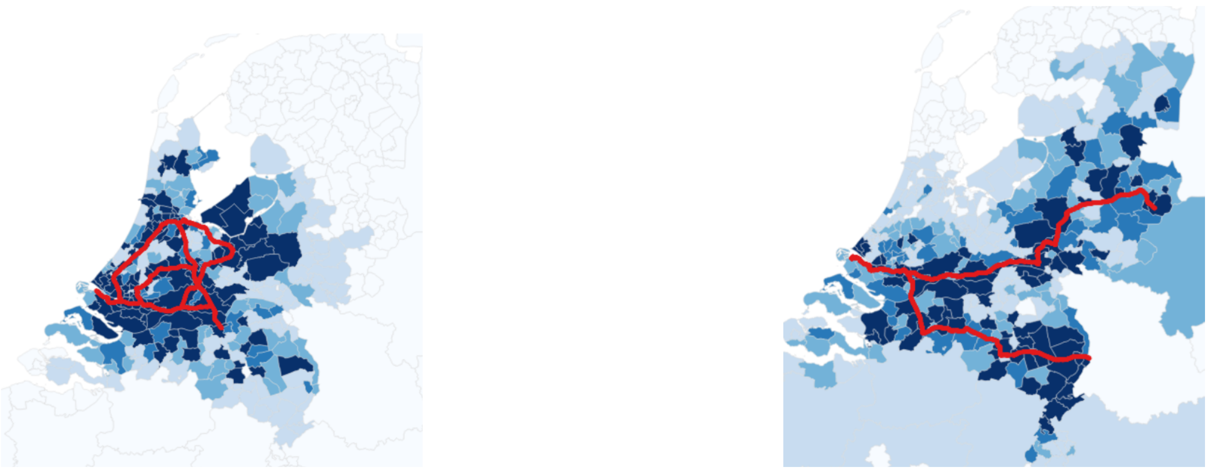
All together, the results of the temporal energy demand analysis can be used for the following. First of all they show when demand will be at its highest. This is valuable information because it enables actions to be taken to reduce these peaks and relieve stress on the power grid. In order to implement such measures, it is first essential to identify when grid stress occurs, and that is exactly what this analysis has mapped out.

In addition, through peak shaving strategies, the high peak around 9 AM can be lowered, and energy demand can be spread over a longer period of time. One possible solution could be working with time slices for truck operators, regulating when they may depart from the depot. In any case, it is crucial to have insight into when pressure on the grid occurs, so that it can be anticipated and mitigated.

5.1.5 Impact of an Extensive ERS Network on Demand

In this case of this study, using a single corridor, looking at complete tours instead of individual trips has a limiting effect on the number of trucks that make use of the ERS. This can be seen by comparing the tour adoption potential with the trip adoption potential: the trip adoption potential contains many more trips. But in the case of a network of ERS corridors, the ERS-adopting tours would likely increase exponentially. Literature by Liao et al. [24] and Bakker et al. [16] clearly illustrates the power of an extensive ERS network. For example, Liao et al. [24] shows that the energy demand of an ERS network continues to grow steadily as the network expands, up to around 20,000 km of ERS infrastructure. This indicates that a more extensive network leads to higher energy demand. Similarly, in the article by Bakker et al. [16], the authors demonstrate the advantages of having a network of multiple ERS corridors. Figure 44 visualizes how the reach of an extensive network increases the adoption potential massively. Compare this to Figure 21 and 24 and the differences are obvious. The battery constraints would diminish very fast. The chance that a trip in a tour overlaps significantly with the ERS network increases and gives the tour the option to charge dynamically. Such an extensive ERS network would reduce the need for static/depot charging. In other literature by De Saxe et al. [8], it was found that the average battery size reduction of an O-BET versus a normal battery-electric truck in a scenario with a highly extensive ERS network (8500 km) reached up to 75%. In a limited extensive ERS network scenario (2750 km), this value was 41%. This emphasizes the impact of the implementation of multiple ERS corridors on the need for battery power outside the network. With respect to our research question, in such a scenario, considering an extensive ERS network throughout the country/Europe, the energy demand for trucks would switch completely to daytime, as charging would be done solely on the corridor and depot charging would not be necessary anymore. The demand would be more evenly distributed during the day and along the corridors. Instead of being dispersed across depots, charging stations, and logistics hubs, all truck charging would occur directly on the corridor segments. This would create dense, localized demand clusters at high-traffic ERS segments, like the Port of Rotterdam. During the day, trucks are likely to keep their battery fully charged, as they spend much more time on ERS segments.

In addition, in the case of a dynamic/static charging combination, the included tours would increase massively as well. Battery constraints become more flexible. A tour that includes one or two non-ERS segments may still be feasible if static charging is available between trips. So, as the ERS infrastructure becomes more extensive, the bottlenecks that limit tour adoption are reduced more significantly than those affecting individual trips.



(a) Concentrated ERS Network [16]

(b) Double Corridor [16]

Figure 44: Comparison of ERS network configurations from [16]

5.2 Limitations

Despite the effort taken to conduct this research as thoroughly as possible and to ensure the reliability of the results, several limitations must be acknowledged that have likely affected the accuracy of the outcomes.

First, when calculating the battery level upon arrival at the corridor, at intermediate stops, or at the final destination zone, the straight-line distance ("as the crow flies") between points was used. Only the distance traveled on the ERS corridor itself was calculated using the actual route on the road network. For distances between zones and the corridor, or between two zones not connected via ERS, straight-line distances were applied. This approach underestimates the true travel distance, as straight-line distances are always shorter than real-world routes. As a result, battery consumption is underestimated throughout the tour. This means that some tours that currently fall just within the adoption potential may not, in reality, be feasible without depleting the battery. This would also affect the included tours in the adoption potential.

Second, the dataset used, provided by Rijkswaterstaat, is simulated for the year 2040 and is based on data from 2018. Furthermore, the data represent a simulated five-day workweek, assuming each week is identical in terms of tour patterns. To make annual estimates, a simple factor of 51.2 (256 workdays divided by 5 weekdays) was applied to scale the data to yearly. For daily energy demand, weekly data was divided by 5 to derive daily patterns. Weekends were not included. Naturally, this is far removed from reality, where more variability in tour patterns and energy demand across days and weeks is expected. This affects the reliability of the results, as it is likely that actual energy demand will be significantly influenced by tour dynamics not captured in the current model. Besides, the data lacks granular information on specific vehicle routes. Only origin and destination zone are known. This limits the understanding of how truck operators actually adopt and use ERS in practice. In previous studies, it can be seen that vehicle routing added clear value ([8], [40], [41]).

Besides, this study assumes that trucks have a constant speed during the entirety of their tour. This automatically means that this study does not account for traffic congestion, as the speed is constant. In reality, however, trucks will encounter traffic congestion on the road, which will affect the energy demand along the corridor. In such situations, trucks will accumulate closely behind one another in larger numbers. This will lead to variations in both the temporal and spatial distribution of energy demand. The trucks will spend longer on the network and due to the clustering of the trucks in time and space, the peak power demand could increase at certain segments. Especially at segments like segment 15, where the peak demand is already high, this could cause major peaks that would require robust grid capacity.

Additionally, the model assumes that all tours falling within the adoption potential will actually make use of the ERS. For logistics operators, this would mean partially adapting their fleet to trucks equipped with a pantograph capable of using ERS infrastructure. These operators would be taking a risk by transitioning to dynamic charging for some trucks with smaller batteries, without knowing whether the ERS corridor will gain traction in the logistics sector. In reality, it is likely that some logistics companies will not make the switch to O-BETs, even if their tour technically fits within the adoption potential. Other factors come into play, such as investment costs and trust in this unfamiliar technology. As a result, the actual number of tours using the ERS is likely overestimated, which in turn means the energy demand has also been overestimated. If fewer tours make use of the corridor, the overall energy demand will be lower. Moreover, the model does not account for interactions with key external factors such as traffic volume, electricity prices, or battery prices. In practice, these elements can significantly influence route choice, charging behavior, and fleet investment decisions. By not including these dynamics, the analysis may oversimplify the decision-making processes of operators and underestimate the variability in actual ERS usage.

5.3 Implications for ElaadNL and other actors

With the results obtained from this research, it is now important to highlight implications derived from the findings. These implications translate the results and insights into practical and theoretical consequences for ElaadNL and other actors.

First of all, the results obtained by this research provide ELaadNL with valuable data that they can use for forecasts regarding the future charging mix. With the data generated by this research, ElaadNL can effectively inform grid operators about the impact of an ERS corridor on the grid. However, ERS is currently still under-investigated and acts as one of the options to reduce grid congestion and make the transport sector more sustainable. However, there are no plans yet for the construction of an actual electric road system in the Netherlands. Therefore, the results found in this research can be used as data for future scenarios in which ERS might actually be constructed. In such a case ElaadNL will be a step ahead and is already provided with necessary data for energy forecasts. This will help them set out the future charging mix including ERS-charging.

The results of this research also have implications for other actors from three different sectors: policy makers, grid operators and market actors. First of all, the policy makers. This study forecasts the percentage of total freight flow projected to use ERS (in the Moderate scenario): 5%. What does this mean for the likelihood that an actual Electric Road System will be constructed between Rotterdam and Venlo? How does this compare to the use of fast chargers along the highway or logistics charging hubs as alternatives? Is this percentage worth the investment for policy makers compared to other charging alternatives?

These are critical questions that can be explored by the Ministry of Infrastructure and Water Management or other policy makers to draw conclusions about the viability and justification of investing in ERS infrastructure. If only a small share of freight traffic is expected to benefit, the cost-effectiveness of such a system may be challenged, especially when compared to more flexible, potentially cheaper alternatives like public fast-charging stations or depot-based charging.

Secondly, the implications for grid operators. It is valuable to understand what the future implementation of an Electric Road System would mean for charging demand and its impact on the energy grid. The obtained results reveal how energy demand from ERS use is distributed across both time and location along the corridor. For grid operators, this is essential information. It helps identify where and when the electricity network will face the greatest load due to ERS activity. This allows for more accurate grid reinforcement planning, targeted infrastructure investments, and smarter load balancing strategies. The results show clear patterns in peak power demand per segment and time of day. Knowing the maximum power required in specific locations supports grid operators in determining whether existing infrastructure can cope or whether additional measures are needed.

Lastly, market actors like logistic operators can use the results found in this research to assess whether they would invest in a truck fleet with smaller batteries that can use the ERS infrastructure. Understanding the temporal patterns allows operators to plan departures or adjust driving schedules to maximize ERS usage and minimize ERS need during peak demand. By comparing their typical routes and schedules with the high-demand ERS segments and peak hours, they can determine whether their trucks would consistently have access to ERS charging during transport.

5.4 Contributions

This study introduces a novel methodology for estimating energy demand based on tour-level data and a high-resolution zoning system. A custom-built model was developed to assess the adoption potential of an ERS corridor based on user-defined criteria. The model tracks the battery state-of-charge of trucks to determine whether an entire tour can be completed using ERS charging, monitors the truck's location along the corridor, and automatically calculates the energy demand per corridor segment. As such, this research provides the first spatial-temporal analysis of ERS corridor energy demand based on tour-level data. The study demonstrates the significant impact of using tour data, as opposed to trip data, on the estimated adoption potential of a single ERS corridor. The model and methodology developed in this research can be applied to future studies assessing the energy demand of other corridors or larger-scale ERS networks.

6 Conclusion & Recommendations

This section presents the conclusions that can be drawn from this research and the recommendations for future research. First a short summary of the research is presented before the conclusions are given.

6.1 Conclusion

In this research, the temporal and spatial energy demand of an Electric Road System corridor between Rotterdam and Venlo was analyzed. The research question that was aimed to answer was:

What is the expected temporal and spatial distribution of energy demand of an Electric Road System along the Rotterdam-Venlo corridor?

This research presents a novel methodology, incorporating complete tour data instead of using individual trips, and applying it to a tailor-made model that calculates energy demand patterns per quarter. The following results were found.

In a Moderate scenario, it was found that approximately 6.8% of all the trips would be performed using the ERS network. All these trips are part of a tour and after implementing battery constraints to these tours, a total of 5% of the total freight flow that would adopt ERS remained, corresponding to around 2.8 million tours per year. 35.5% of the tours in the *trip adoption potential* could not be completed due to battery constraints, leading to 2.8 million tours finally included in the *tour adoption potential*. Using these tours, the resulting energy demand on the corridor was calculated and it was found that a substantial share of this demand occurs between kilometer 20 and 40 of the corridor (segment 10-20), around the Port of Rotterdam. The maximum daily energy demand is observed between kilometer 28 and 30 (segment 15), exceeding 36 MWh per day. Other energy-intensive segments are kilometer 24-26 (34 MWh/day) and kilometer 22-24 (33 MWh/day). The peak power demand occurs at 9:00 AM between kilometer 22 and 24 of the corridor (segment 12), reaching a value of 3.4 MW. Notably, all peak values are concentrated around the Rotterdam port area, with demand gradually decreasing moving eastward along the corridor.

Over the course of the day, three distinct demand peaks are observed. The first occurs between 4:00 and 6:00 AM, followed by a morning peak during the 8:00–10:00 AM window, which shows the highest segment-level demand (up to 3.4 MWh per 15 minutes). A clear pattern emerges of truck movement during the morning: energy demand increases first near the port and then shifts eastward toward Eindhoven, as trucks proceed along their routes. Finally, a broad afternoon peak appears between 3:00 and 5:00 PM, after which the demand steadily declines to its lowest point during the night.

Additionally, in the scenario analysis, it was found that the Tight scenario has the highest energy demand, with values up to over 40 MWh per segment per day and peak demand values up to 3.6 MWh at 09:00 AM between kilometer 22 and 24 of the corridor. The Flexible scenario was responsible for the lowest daily energy demand, as expected, but the marginal differences compared to the Moderate scenario were smaller. The sensitivity analysis showed us that the energy consumption rate c has strong influences on the total energy demand of the trucks on the corridor. Notable differences in total demand were observed in the results after changing its values. The power provided for battery charging had negligible impact on the total energy demand of the corridor.

For the first time, complete tours were used to determine energy demand of an electric road system between Rotterdam and Venlo. This provides valuable insights for various stakeholders regarding the potential implementation of an ERS corridor in the Netherlands. For ElaadNL, the results offer essential input for forecasting future charging mixes and informing grid operators about the potential grid impact of ERS. Policy makers, like the Ministery, can use the findings—such as the estimated 5% ERS adoption in the Moderate scenario—to assess the viability and cost-effectiveness of ERS compared to alternatives. For grid operators, the analysis highlights where and when peak power demand will occur, supporting targeted infrastructure planning. Finally, logistic operators can use the temporal and spatial demand data to evaluate whether investing in ERS-compatible fleets aligns with their operational patterns.

6.2 Recommendations

For ElaadNL, it is recommended to investigate the spatial and temporal energy demand of other corridors in the Netherlands, but also in other countries. Previous studies (Johrens et al. [42], Olovsson et al.

[43]) have already researched the impact on the energy grid of an ERS between Sweden and Germany, but no research has been done yet on the energy demand of a transnational corridor connected with the Dutch highway network. Together with information of energy demand of other corridors within the Netherlands, this would be valuable information for ElaadNL, as they could forecast the impact of ERS on the charging mix more realistically. The more information ElaadNL has on energy demand of other potential ERS corridors, the better they can estimate the impact on the charging mix.

Future research could also focus on the implementation of precise routing information to better determine the adoption potential. In previous literature ([8], [40], [41]), it was found that this added clear value. If data is available on the actual routes truck drivers choose to access the ERS corridor, more accurate estimates can be made as it allows for an even better assessment of both the distance traveled before entering the corridor and the feasibility of detours required to access it. Without exact routes, models rely on straight-line distances, which systematically underestimate energy consumption. As a result, some tours may be incorrectly classified as feasible for ERS use.

Also, future research could estimate the adoption potential and eventually the energy demand if depot charging is slowly eliminated. This means trucks can only charge dynamically on the corridor. The model in this research assumes that every tour starts with a fully charged battery (100%). In reality, not all trucks will begin their tour with a full battery, especially in the case of O-BETs. Logistics operators may view ERS as a substitute for depot charging, and O-BETs may not be recharged outside of operation hours at depots or charging hubs. It would be interesting to see how the adoption potential and the energy demand would develop in such a scenario with no charging overnight. If no depot charging is needed, logistic operators would not have to invest in large on-site charging facilities, making ERS only more appealing and valuable. The more extensive the ERS network, the less depot charging needed. How the equilibrium would switch from depot charging to ERS charging in scenarios with increasingly more ERS corridors would be highly interesting to see.

Moreover, it is recommended that future work includes traffic congestion in its model to determine even more realistically the energy demand of an ERS corridor, accounting for static trucks during high traffic intensity instead of using a constant speed at all times. Currently, no research exists that accounts for traffic congestion in determining the energy demand, even though this would add great value to the results.

Besides, future research could also focus on incorporating freight flow data for weekends, rather than only weekdays. The data used in this study considers freight movements during the workweek, but the potential adoption of ERS for weekend tours has not been examined. Other studies ([20], [21]) have shown that traffic patterns differ significantly on weekends, which led to a completely different distribution of energy demand. This means that the data used in this research cannot be generalized to weekends, as different patterns are likely to emerge. Adding weekend data would make the energy demand estimates more reliable and realistic.

Finally, future research and planning efforts should incorporate tour-level data as a standard for modeling ERS energy demand. As explained in Section 5.1.1, tour data provides a more accurate reflection of reality and reveals the actual driving patterns of trucks. By using this, the true charging demand becomes visible, allowing for a better assessment of en-route charging requirements.

7 Academic Reflection

Looking back on the process of building the model, doing this research and writing this report, it gives me a sense of pride. After a difficult start, during which I struggled to formulate a definitive research question that aligned with ElaadNL's interests, the process actually progressed smoothly towards the end of the project. It proved challenging to identify a research goal that matched both the knowledge I acquired during my master's program and what was realistically achievable within six months. Once an agreement was reached between ElaadNL and my TU Delft supervisors regarding the research question, it quickly became clear to me how to approach the problem.

Developing the model to estimate energy demand—while accounting for the tour structure in the data—went without major issues. By working iteratively and debugging along the way, I had plenty of time left to document the model and write up the results. As a result, I was never pressed for time and look back on the process as both stress-free and productive.

During the project I massively improved my programming skills. I spent the majority of my time designing the model, which involved a significant amount of programming. Over the course of the project, I became increasingly skilled in this area, and compared to the programming skills I had at the start, I have improved tremendously. This technical growth not only supported the quality of this research but also aligns with my broader academic and professional goals: pursuing data-driven work at the intersection of sustainability, mobility, and infrastructure.

One key lesson I take away from this period is that debugging someone else's model can be very time-consuming and should be factored into the project timeline. The model developed by Bakker et al., which served as a starting point for this research, had to be completely deconstructed to make it functional for my analysis. This required significantly more time than I had initially anticipated. Fortunately, by allocating extra time early on, I was able to stick to the overall schedule without delays.

Additionally, I'm very positive about the guidance I received from both TU Delft and ElaadNL. I was given full freedom and responsibility to manage my own schedule and set internal deadlines. As a result, the final outcome truly feels like my own work, and I'm proud to have accomplished it so independently.

AI Statement

While preparing this work, I used ChatGPT and Grammarly to improve sentence structures, readability and academic word use. After using this tool/service, I reviewed and edited the content as needed and I take full responsibility for the content of my report. ChatGPT was also used to find bugs in pieces of code.

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