# BUILDING THE CHARGING DEMAND CURVE AT A HEAVY DUTY ELECTRIC VEHICLE CHARGING STATION

**by**

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# Preface

This thesis marks the conclusion of my Master's in Sustainable Energy Technology at the TU Delft, within the EEMCS faculty. The work contributed to the broader PhD research of Leila Shams Ashkezari and explores the planning and optimization of charging infrastructure for electric trucks in the Netherlands. I am grateful to have been involved in a project that addresses such a relevant and urgent challenge in the transition to sustainable transport and energy systems.

I've always been interested in electric vehicles and the transition to cleaner transport. This topic gave me a unique opportunity to dive into real world challenges and learn how energy systems and infrastructure come together in practice.

I'd like to sincerely thank my thesis supervisor, Dr. Gautham Ram Chandra Mouli for his valuable guidance during the monthly meetings. I am especially grateful to my daily supervisor Leila Shams Ashkezari, for her consistent support, insightful feedback, and constructive advice throughout this project. I also appreciate the input from Dr. Neil Yorke-Smith, whose feedback helped shape the direction of this work.

Finally, I am deeply grateful to my parents, Wim Lagae and Annick van den Bossche, for their support and giving me the opportunity to study at this university.

I hope this thesis can contribute to the ongoing research in electric vehicle infrastructure and serve as a small step toward a more sustainable and electrified future.

Bart Lagae

Delft, June 10, 2025

# Abstract

The electrification of the heavy-duty freight sector requires a robust charging infrastructure that balances operational needs with grid and cost constraints. This thesis develops an integrated modeling framework to simulate charging demand and optimize the placement and configuration of high power charging stations for HDEVs.

The first phase involves modeling charging demand by simulating energy depletion across real world truck trips. Using detailed vehicle specifications and regulatory driving limits, State of Charge (SoC) calculations identify when and where trucks are likely to require charging. These simulated charging events reflect realistic operational behavior across Dutch and cross border freight routes.

The second phase applies a Mixed-Integer Linear Programming (MILP) model to determine optimal station locations and configurations. The optimization selects candidate stations, either generated trough regulatory rules (AFIR) or traffic clustering, and minimizes system wide costs while accounting for wait times, charger availability, and grid connection limits. Events are assigned to specific stations and time slots to ensure feasible, cost effective infrastructure deployment.

Two station placements strategies are evaluated for the year 2025 and 2030: (1) AFIR based regulatory , and (2) demand driven locations based on clustering from simulated charging events. The simulated electrification rates are 0.75% for 2025 and 7.5% for 2030. The optimization model provides the number of chargers, where to place them, and how charging events are assigned. From these results, demand curves at the station are created. The findings show that demand based placement can reduce wait times and overall installation cost, while better handling growing charging needs compared to AFIR compliant layouts. Note that the AFIR layout station locations are fixed to the regulatory minimum requirements, and only the number of chargers is adjusted to meet future demand.

This thesis presents a practical method for planning charging networks using real truck data. It shows how simulated charging demand can help design better infrastructure, taking into account operational limits and policy goals to support the shift to electric freight transport in Europe.

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# Abbreviations

| | |
|---|---|
| **AFIR** | Alternative Fuels Infrastructure Regulation |
| **API** | Application Programming Interface |
| **BasGoed** | Dutch national freight transport model |
| **CBS** | Centraal Bureau voor de Statistiek (Dutch Statistics Agency) |
| **CCS** | Combined Charging System |
| **CO2** | Carbon Dioxide |
| **DBSCAN** | Density-Based Spatial Clustering of Applications with Noise |
| **DFS** | Depth-First Search |
| **EVIPro** | Electric Vehicle Infrastructure Projection tool |
| **ETCA** | Energy Transition Campus Amsterdam |
| **EU** | European Union |
| **EV** | Electric Vehicle |
| **FCFS** | First-Come-First-Serve |
| **FLD** | Fair Load Distribution |
| **HDV** | Heavy-Duty Vehicle |
| **HDEV** | Heavy-Duty Electric Vehicle |
| **ICCT** | International Council on Clean Transportation |
| **IEA** | International Energy Agency |
| **JDK** | Java Development Kit |
| **kW** | Kilowatt |
| **kWh** | Kilowatt-hour |
| **LP** | Linear Program |
| **MCS** | Megawatt Charging System |
| **MILP** | Mixed-Integer Linear Program |

| | |
|---|---|
| **MW** | Megawatt |
| **MWh** | Megawatt-hour |
| **NREL** | National Renewable Energy Laboratory |
| **pbf** | Protocolbuffer Binary Format (used in OpenStreetMap) |
| **RWS** | Rijkswaterstaat (Dutch highway authority) |
| **SoC** | State of Charge |
| **STEP** | Stated Energy Policies Scenario |
| **TCO** | Total Cost of Ownership |
| **TEN-T** | Trans-European Transport Network |
| **TOU** | Time-Of-Use |

# 1 Introduction

The transportation sector significantly contributes to global carbon emissions, with heavy duty-vehicles accounting for a substation portion. As global policies and market forces increasingly favor electrification, understanding and optimizing the infrastructure necessary to support this shift becomes crucial.

Current EU initiatives provide foundational regulatory guidelines for charging infrastructure along key transport corridors. One of the main challenges in the widespread adoption of HDEVs is the lack of a well established charging network along major transport routes. Additionally, the demand at these future charging stations is uncertain, which makes effective planning and deployment even more difficult. Regulations like AFIR prescribe where stations should be, but now how much charging capacity is needed, nor do they account for traffic patterns, grid limitations, or wait times during peak periods.

This research aims to address this research gap by developing a methodology for charging infrastructure planning and constructing detailed charging demand curves at HDEV charging stations. This approach integrates real world route specific data, state-of-charge (SOC) simulations, and a robust optimization algorithm. The goal is to optimize charging station allocations keeping variables like maximum wait times and grid limitation in mind.

To achieve this goal, the study is structured around the following research questions:

- Primary research Question
  - How can station locations and configurations be optimized based on simulated HDEV charging demand, considering reasonable wait times and grid limitations?
- Secondary Research Questions
  - How can real world truck trip data be used to simulate charging demand through SoC modeling?
  - What optimization method can be used to assign charging events to stations and time slots, while balancing cost, grid limits, and wait times?
  - How do regulatory stations compare to demand driven station layouts in terms of infrastructure cost, wait time, and scalability under different electrification scenarios?

The following chapter provides a thorough literature review highlighting prior approaches to HDEV infrastructure planning. Chapter 3 presents the methodology. It starts with the routing problem, then the SoC calculations followed by the charging station candidates generation and lastly the charging station allocation optimization. Chapter 4 defines the model configuration, including all scenario inputs and cost parameters. Chapter 5 analyzes results across several deployed scenarios. Chapter 6 discusses the implications and trade offs of different planning strategies, and Chapter 7 concludes with recommendations for future research.

# 2 Literature Review

## 2.1 Context of HDEV Adoption

The transportation sector plays a vital role in the reaching global climate objectives, as heavy-duty vehicles (HDVs) account for approximately 25% of $CO_2$ from road transport [Link and Plötz, 2022, Cieslik and Antczak, 2023]. With the ongoing acceleration towards decarbonization, heavy-duty electric vehicles (HDEVs) have surfaced as a compelling solution for mitigating emissions and enhancing sustainability within freight and logistics operations. This section investigates the historical and anticipated adoption rates of HDEVs, analyzes regional disparities with particular emphasis on EU policies, and addresses the unique challenges associated with fleet electrification.

### 2.1.1 Electrification Rates of HDEVs

**Historical Adoption Trends.** The electrification of HDVs has gained momentum over the past decade, driven by global climate commitments and technological advancements. Figure 1 discusses the historical electric truck sales by market share by region from 2015 to 2023. It shows that in 2023, electric trucks represented about 3% of new truck sales in China and 1.5% in Europe [(IEA), 2024]. While Chine has led in both market share and sales, there is a clear upward trend visible in the adoption rates across Europe and the United States since 2018.

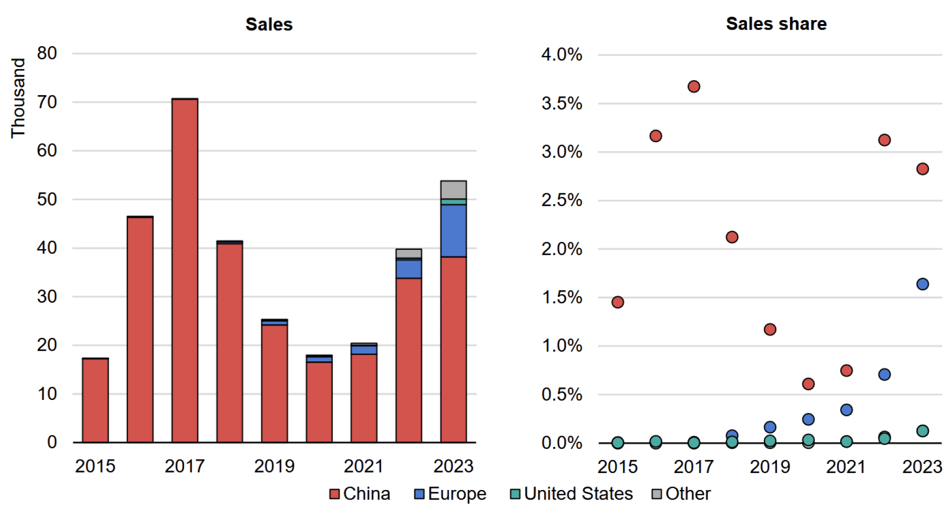


Figure 1: Historical electric truck sales and market share by region (2015–2023) [(IEA), 2024].

**Projected Growth.** The adoption of HDEVs is projected to grow significantly in the coming decade. Forecast very depending on the level of regulatory ambition and market readiness. For instance, [Link and Plötz, 2022, Cieslik and Antczak, 2023] suggest that HDEVs could account for 10 to 15% of new truck sales by 2030. This is what they call an optimistic but realistic scenario. Figure 2 presents future projections for electric truck adoption rates under different policy scenarios for 2030 and 2035 from the IEA. It shows that adoption rates vary significantly under the different scenarios, ranging from 7% under current policy settings (STEP) to over 30% of all new vehicle sales under a Net Zero Emmisions (NZE) Scenario. The most optimistic scenario, NZE, aims to accomplish net zero by 2050.

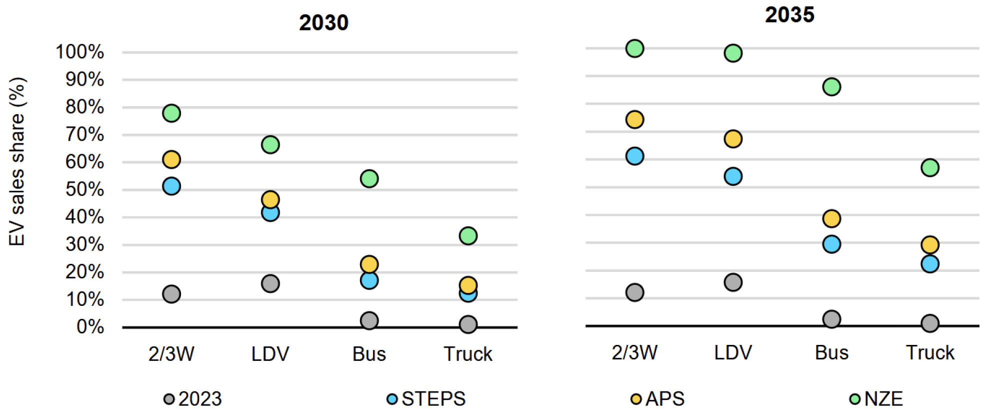


Figure 2: Projected EV sales share by transport mode and scenario for 2030 and 2035 [(IEA), 2024].

**Regional Variations and Influencing Factors.** The EU stands at the forefront of HDEV adoption, supported by policies such as the Alternative Fuels Infrastructure Regulation (AFIR) and financial incentives for fleet electrification [Agenda, 2022]. Countries like the Netherlands have set ambitious national targets, including the electrification of 250,000 delivery vans and 16,000 trucks by 2030. These will be supported by the deployment of charging infrastructure and the creation of zero-emission urban logistics zones [Agenda, 2022]. In contrast, adoption in emerging markets is hindered by affordability issues and infrastructure gaps. Globally, regulatory incentives like purchase subsidies and tax exemptions have proven effective in stimulating market growth [Cieslik and Antczak, 2023].

China in particular is advancing rapidly, with strong government incentives, investments in local manufacturing, and deployment of megawatt charging systems (MCS) positioning it as a global leader in HDEV adoption [(IEA), 2024]. Its well-established EV supply chain and policy-driven market provide a strong foundation for sustained growth. Meanwhile, adoption rates in regions such as North America and parts of Asia remain slower, hindered by infrastructure challenges and the high upfront costs of electric trucks. However, corporate commitments and pilot programs for zero-emission freight corridors suggest the potential for accelerated growth in these regions over the coming years [Link and Plötz, 2022, Cieslik and Antczak, 2023].

**Electrification Challenges.**

- **Range Limitations:** A critical challenge for HDEVs is the limited range compared to internal combustion engine vehicles. Current battery technologies typically support ranges of 200–600 km, sufficient for urban and regional logistics but inadequate for long-haul operations [Link and Plötz, 2022] . The development of MCS aims to address this gap, enabling quicker recharging and greater range suitability.
- **Payload Constraints:** Battery weight significantly impacts payload capacity, especially for trucks designed for high-volume transport. Studies indicate that larger battery systems, while extending range, reduce the truck's usable payload, affecting economic efficiency [Link and Plötz, 2022, Cieslik and Antczak, 2023]. Solutions such as lightweight materials and optimized battery designs are being explored to mitigate this issue.
- **Cost Barriers:** The high upfront costs of electric trucks and their infrastructure remain a significant barrier to adoption. Although total cost of ownership (TCO) parity is expected by 2030 in regions with high fuel costs, the initial investment required for fleet operators remains a deterrent [Link and Plötz, 2022, Cieslik and Antczak, 2023]. Incentives and innovative financing models, such as leasing options, are critical to overcoming this challenge.
- **Infrastructure Barriers:** Charging stations, especially for HDEV's, require substantial amounts of power. The use of MCS, compared lower power fast chargers, could further increase the demand. These high loads can lead to lower quality power and supply-demand imbalances, resulting in major local grid congestion problems [(IEA), 2024]. One proposed solution to mitigate these challenges is to implement Energy Management solutions. Large amount of batteries or hydrogen based storage could solve the required demand challenge but will drive up the capital investment requirements, posing a potential financial barrier to investors.

## 2.2 Charging Infrastructure for HDEVs

As HDEVs enter broader commercial use, the deployment of adequate charging infrastructure has become a major operational and planning challenge. Infrastructure must accommodate diverse logistics patterns, vehicle configurations, and power requirements. This section summarizes findings on on-route charging, depot charging, and existing public charging networks, incorporating insights from recent studies.

### 2.2.1 Depot Charging

Depot charging forms the backbone of fleet electrification, particularly for vehicles returning to a centralized base. According to ElaadNL, 88% of trucks and 61% of vans have their base locations on industrial sites[ElaadNL, 2025a]. Depot charging typically occurs during long dwell periods allowing the trucks to charge at a lower rate and make use of optimized charging schedules and smart charging systems. However, depot charging faces significant technical and economic barriers.

**Challenges:**

- **Grid Congestion:** Urban depots often face grid capacity limitations, which may require the integration of stationary batteries and energy hubs to manage peak loads [van Cappellen et al., 2022].
- **High Costs:** Infrastructure investments per charger can range between €44,700 and €615,800, depending on power levels and the complexity of grid connections [Bernard et al., 2022].

### 2.2.2 On Route Charging and public infrastructure

The on route charging network plays an important role in enabling long haul electrification for HDEVs. While depot charging will serve the majority of the charging needs, some routes require mid-trip charging. A study done by Elaad concluded that around 12% of the trips would require on-route charging [ElaadNL, 2025a]. Although this seems a small number, the infrastructure required is substantial due to the fast charging requirements. Strategic placement of these stations is essential to serve all on route demand.

Public charging infrastructure represents the real world implementation of this on route charging need. These stations are designed to complement depot-based charging by providing access to high-power chargers along key transport corridors. Charging capacities typically range from 300kW fast chargers to ultra-fast systems exceeding 1 MW [Bernard et al., 2022, Borlaug et al., 2022]. With the growing adoption of MCS, future charging stations will be able to deliver even higher power levels to minimize downtime for freight operators.

As of 2025, the rollout of public charging infrastructure for HDEV's across the EU is still in its initial phase. While the current number of charging locations is limited, substantial expansion is anticipated in the near future.

Several initiatives are underway to boost the HDEV charging network:

Milence, a joint venture by Volvo group, Daimler Truck, and TRATON Group has set a target of building 1700 public charging points by 2027 [Milence, 2025a]. Its network currently includes Combined Charging System (CCS) stations which support up to 400 kW, along with initial installations of MCS units rated at 1440 kW (1500A at 1000V). As of February 2025, Milence has brought one of the first operational MCS equipped charging hubs online at the Port of Antwerp Bruges. It offers 22 charging bays with a total capacity of 6.8 MW [Milence, 2025b].

Shell is also contributing to HDEV infrastructure by piloting several charging concepts. These include hybrid energy stations that combine EV fast charging with renewable diesel and Bio LNG supply. One notable project is the development of of Shell's own MCS prototype, located at the Energy Transition Campus Amsterdam. This unit delivers up to 1 MW of power and is meant to support both electric trucks and vessels, promoting shared infrastructure standards [Morris, 2024, Plaza, 2023].

Integrating depot and public charging solutions is crucial for the widespread adoption of HDEVs. Addressing infrastructure costs, grid constraints, and charging technology advancements will enable the transition to sustainable freight operations. Coordination among stakeholders and regulatory support will play a pivotal role in scaling charging networks effectively.

## 2.3 Infrastructure Planning Methods

Planning and deploying charging infrastructure for HDEVs is a critical factor in enabling the electrification of the freight sector. Infrastructure placement must balance competing objectives, including minimizing cost, ensuring accessibility, reducing grid impact, and meeting future demand. Optimization methods and charging algorithms are central to achieving these goals, providing systematic approaches to determine the optimal locations for charging stations and manage energy distribution effectively. This chapter explores infrastructure planning methods and optimization techniques, highlighting their applicability and limitations in addressing the challenges of HDEV infrastructure deployment.

### 2.3.1 Optimization Methods for charging network planning

Several studies have addressed the problem of optimal charging station placement for HDEV's, most common in the context of highway corridors and urban freight networks. Most approaches fall into one of the following categories:

**Linear and Mixed-Integer Programming.** Linear Programming and MILP are are commonly used in charging infrastructure planning because they can efficiently minimize costs and maximize network coverage while respecting various constraints. LP deals with continuous variables, while MILP extends this by incorporating binary variables to model decisions like whether to install a charging station at a specific location. These techniques have proven effective in optimizing station placement along highway networks to meet accessibility regulations, such as maximum spacing requirements between stations.[Hall and Lutsey, 2019, Bernard et al., 2022]. The example of Hall and Lutsey provides cost-optimal placement of charging infrastructure along the TEN-T network to meet regulatory spacing requirements and projected demand. Bernard et al extended this with constraints for land use and multi vehicle compatibility.

**Clustering-Based Approaches.** Clustering methods are particularly suitable for urban and regional contexts where charging demand is spatially concentrated. Borlaug et al used K-Means Clustering groups to identify high-demand locations identifying optimal placement for charging hubs. Density-Based Spatial Clustering (DBSCAN) was also used and is well-suited for dynamic demand patterns, such as varying traffic flows or seasonal variations. These methods facilitate the prioritization of infrastructure investment by targeting areas with the highest potential usage [Borlaug et al., 2022].

**Multi-Objective Optimization.** Multi-objective optimization models address the trade-offs inherent in infrastructure placement by simultaneously optimizing criteria such as cost, environmental impact, travel time, etc. Solutions are typically presented as a Pareto front, allowing decision-makers to evaluate trade-offs between competing objectives. For example, optimizing the spatial placement of charging stations while minimizing associated grid reinforcement costs represents a typical application of multi-objective approaches [Borlaug et al., 2022].

**Simulation Based Optimization** Simulation-based approaches combine traffic simulations with optimization techniques, enabling the evaluation of charging infrastructure under various scenarios. These methods allow for a better understanding of infrastructure performance under different conditions as demonstrated in CE Delft's urban logistics simulation [van Cappellen et al., 2022].

### 2.3.2 Charging Algorithms

Static algorithms assign charging slots based on known, preplanned demand. This makes them well suited for depot environments. These algorithms rely on assumptions that vehicle energy needs and arrivals are predictable, which aligns perfectly with logistics operations involving fleet that regularly return to a central depot. [van Cappellen et al., 2022].

Dynamic algorithms adapt to real-time variations in vehicle arrival patterns, state-of-charge levels, and grid conditions. For instance, First-Come-First-Serve (FCFS) and Greedy Algorithms prioritize immediate charging needs but may not account for future demand fluctuations. These algorithms are particularly useful in public charging scenarios where user behavior is less predictable [Borlaug et al., 2022].

Smart charging algorithms integrate predictive models to optimize charging schedules and power levels. Time-of-Use (TOU) Optimization adjusts charging times to align with off-peak electricity rates, thereby reducing operational costs and grid strain.

Priority-Based Charging assigns higher priority to vehicles with urgent schedules or critical battery levels, ensuring efficient resource allocation [van Cappellen et al., 2022].

Load balancing algorithms manage power distribution across multiple chargers to prevent local grid congestion. Techniques such as Fair Load Distribution (FLD) and Adaptive Power Sharing dynamically allocate power based on charger utilization, ensuring equitable and efficient energy distribution [Hall and Lutsey, 2019].

### 2.3.3 Applications and Case Studies

A wide range of studies have explored public charging network planning, particularly for light-duty electric vehicles (LDEVs) in urban settings and, more recently for HDEVs along highway corridors. For LDEVs, studies often use mobility data, population density, and perking patterns to estimate charging demand. For example, EVI-Pro [Wood et al., 2017], developed by NREL, simulates daily driving patterns and EV characteristics to predict how much public charging is needed. The tool estimates the number and type of chargers based on regional travel behavior and vehicle usage.

While EVI-pro and similar tools focus on LDEVs, this thesis models demand for HDEVs using real truck routes and vehicle specific parameters. Unlike EVI-Pro, it includes detailed scheduling, grid constraints, and charger level optimization. Charging demand is simulated from route based energy depletion, and a MILP model is used to decide where and when trucks charge, and how station capacity is allocated over time.

There is less research on HDEVs, but interest is growing. Hall and Lutsey [Hall and Lutsey, 2019] focus on planning chargers along major corridors to meet minimum coverage rules, like those in the AFIR regulations. Studies such as Borlaug et al. (2022) have used telematics data to simulate charging demand along major freight corridors. Clustering algorithms and multi-objective optimization methods were employed to identify optimal station locations, prioritizing rural interstates for fast-charging infrastructure [Borlaug et al., 2022]. Their model minimizes cost, but does not include wait times, grid constraints, or time based scheduling. CE Delft [van Cappellen et al., 2022] looks at urban energy hubs and uses MILP for planning, but focuses mostly on depot charging in cities.

This thesis builds on these studies but adds several important features. It uses real truck trips and vehicle data to simulate charging demand through SoC calculations. It includes a MILP model that selects station locations, and assigns charging events to time slots. The model considers cost, grid limits, and wait times.

## 2.4 Regulatory and Policy Considerations

**EU Directives and Goals** The EU has established a comprehensive regulatory framework to promote the adoption of HDEVs and the development of corresponding infrastructure. This framework is integral to the EU's broader climate objectives, including achieving climate neutrality by 2050 as outlined in the European Green Deal [contributors, 2025]

**CO Emission Standards for Heavy-Duty Vehicles** To address emissions from the transport sector, the EU has introduced strict CO reduction targets for HDEVs. These regulations require emissions to decease 45% by 2030, 65% by 2035, and 90% by 2040 relative to baseline levels. [of the European Union, 2024]. These progressive targets are designed to accelerate the transition to zero-emission technologies within the heavy-duty vehicle segment.

**Alternative Fuels Infrastructure Regulation** The AFIR sets binding targets for the rollout of recharging and refueling infrastructure across the EU's TEN-T transport corridors. By 2025, member states are required to deploy truck charging stations with a minimum installed capacity of 350kW at intervals of maximum 60 km on the core TEN-T core network. For the comprehensive network, intervals of maximum 100 km are mandated [Observatory, 2023]. AFIR also mandates the availability of hydrogen refueling stations in all urban nodes and at least every 200 km along the core network by the end of the decade [CleanTechnica, 2023]. These measures are set in place to make sure the availability of reliable infrastructure to support the transition to HDEVs.

**Clean Vehicles Directive** The revised Clean Vehicles Directive promotes the procurement of clean and energy-efficient vehicles in public tenders. The directive includes a definition of clean vehicles and sets member states to meet minimum procurement targets, thereby stimulating market demand and encouraging the deployment of low- and zero-emission vehicles [Commission, 2025a].

## 2.5 Charging Demand Estimation Studies

Estimating the future charging demand for HDEVs is critical for aligning infrastructure with expected fleet electrification levels. Recent studies have proposed a range of electrification scenarios, often based on assumptions about fleet turnover, technological advancements, and regulatory targets. Table 1 provides an overview of the suggested electrification rates per scenarios for HDEVs.

Table 1: Suggested Electrification Rates for HDEVs by Scenario

| Year | Scenario | Electrification Rate | Sources |
|---|---|---|---|
| 2025 | **Current** | 0.5% – 1% | Statista (2023) |
| 2030 | **Policy Push** | 5% – 10% | Global Drive to Zero / CALSTART (2022), EVBoosters (2022) |
| 2040 | **Future Shift** | 20% – 35% | Global Drive to Zero / CALSTART (2022), The ICCT (2023) |
| 2050 | **Near Full Adoption** | 65% – 90% | EU Green Deal, ICCT (2023) |
| 2060 | **Full Transition** | ≥90% – 100% | Extrapolated from policy targets |

Electrification rates are usually scenario based and vary by timeframe. For this thesis, two key scenarios are used. The first represents the current situation in 2025. It has an estimated adoption rate of 0.75% baed on recent market figures and vehicle registration data [Statista, 2023]. The second scenario represents a future policy-driven outlook in 2030. 7.5% of the HDEV fleet is expected to be electric. This aligns with projections from EVBoosters and CALSART's Global Roadmap [to Zero and CALSTART, 2022, EVBoosters, 2022]. Both studies highlight the importance of accelerating infrastructure deployment to support growing demand.

By 2040, electrification is expected to reach up to 35%. This will mainly be driven by the EU's zero-emission vehicles sales mandates [on Clean Transportation, 2023, to Zero and CALSTART, 2022]. Long term projections foresee near-complete adoption by 2050 and 2060 depending on the fleet turnover rates and policy enforcement [to Zero and CALSTART, 2022]

A notable example of a regional demand estimation tool is the ElaadNL Load Generator [ElaadNL, 2025b]. It is an online platform developed to support regional charging infrastructure planning for electric vehicles, including both freight and delivery transport. The tool uses aggregated freight trip data from CBS and RWS to estimate annual transport volumes per region. These volumes are then converted into energy demand using average consumption values and assumptions about trip length and vehicle types.

The resulting demand is distributed across the year to produce monthly, daily, and hourly load profiles. Users can select between vehicle based or charger based profile types, choose charge power levels, vehicle classes, and apply smart charging strategies. The tool outputs region level load curves, which are useful for identifying where and when energy demand peaks may occur.

While the ElaadNL tool provides valuable high level insights into regional charging needs, it does not model individual truck behavior or vehicle routing. It also lacks temporal assignment at the vehicle level, and does not include grid constraints, station capacity, or optimization of station locations. In contrast, this thesis uses real truck GPS data, simulates vehicle specific energy depletion through SoC calculations, and applies a MILP model to optimize station locations, charger allocation, and event scheduling. The objective is to minimize the installation cost, while also considering wait time, and grid limits.

Therefore, while tools like ElaadNL are useful for strategic planning and grid forecasting, this thesis addresses more detailed operational questions by modeling charging demand and infrastructure use at a much finer resolution.

# 3 Methodology

Figure 3 summarizes the overall workflow used in this thesis. The process begins with truck trip data and vehicle specifications. These are used to simulate energy consumption and charging behavior across realistic routes. Based on the resulting demand, candidate station locations are generated for the traffic flow configuration. The AFIR layout candidate stations are the result of an optimization based on the regulations. Either the AFIR based stations or the demand-based stations are used, not both at the same time. These candidate stations form the input to a MILP optimization model, which determines the optimal station configuration and assignment of trucks events to charging stations. After solving the optimization problem, additional post processing steps are applied to calculate performance such as average wait times, early charging penalties, and total system cost. The final output consists of quantitative results (the costs and penalties) and visualizations (maps and Pareto fronts).

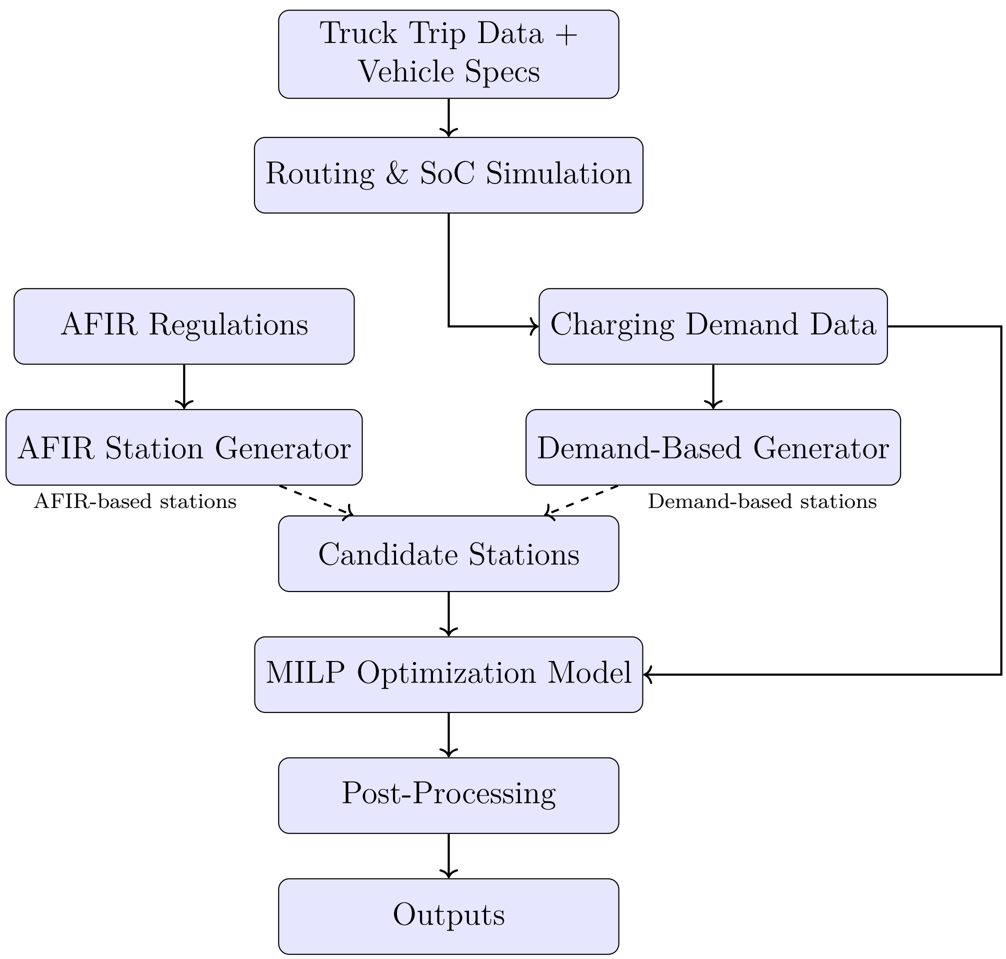


Figure 3: Overview of the charging infrastructure optimization process.

## 3.1 Routing Problem

To accurately estimate the energy consumption of HDEVs, each trip in the dataset must be translated into a real driving trajectory. This requires determining the actual route that the vehicle would take along the route network.

### 3.1.1 Considered API's

Various tools were considered, including **OSMnx**, **Google Maps**, and **GraphHopper**. After evaluating these options, **GraphHopper** was chosen for its balance of performance, accuracy, and flexibility.

- **OSMnx**: Offered unlimited free usage but proved inefficient for large-scale routing tasks, taking several minutes to calculate even a small number of routes. Additionally, it generated routes that occasionally used unconventional streets.
- **Google Maps API**: would provide high-quality results but incurred significant costs for frequent use, making it unsuitable for this project.
- **GraphHopper**: Emerged as the optimal choice. Its routing algorithm was extremely fast, producing routes comparable to those provided by Google Maps or Apple Maps, with response times measured in milliseconds. While the hosted version of GraphHopper imposes limitations on the number of API calls, the locally hosted API did not.

### 3.1.2 Setting Up the Local GraphHopper Server

To bypass the API call limitations, two local instance of GraphHopper were hosted. One for the domestic routing and the other one to compute surface level data for routes starting or ending outside of the Netherlands. The following steps were undertaken to set up the server:

1. **Java Installation**: The Java Development Kit 8 (JDK8) was installed as a prerequisite.
2. **GraphHopper Files**: The `.JAR` file from the GraphHopper GitHub repository was downloaded. Alternatively, the entire repository could be cloned.
3. **Road Network Data**: A `.pbf` file containing road network data for the relevant region was downloaded from Geofabrik.
4. **Server Setup**: Using the downloaded files, the server was initiated in Java. Once running, the API endpoint became accessible locally at `http://192.168.0.001:8989/route`.

This configuration enabled unlimited API calls while maintaining high-speed routing computations.

### 3.1.3 Challenges

One particular challenge arises when trip start or end points outside the Dutch border. Because the primary routing engine is configured only for the Netherlands, coordinates beyond this may cause errors and return empty results. To resolve this, a fallback mechanism was implemented to snap the destination point to the nearest border crossing on a major highway.

If either the origin or destination lies outside the national borders, the routing process is split into segments. An external (non-Dutch) segment and an internal (Dutch) segment. The external segment goes right up to the border crossing where the internal segment takes over. To reduce the data volume and because we maintain focus on the domestic charging infrastructure, only the total travel distance and time are recorded for the external portion.

Detailed node-level data is collected only for the Dutch segment of the route. This refers to the sequence of geographic coordinates (nodes) along the route, along with the added information such as cumulative distance, travel time, and bearing at each point. Node-level data is essential for accurately simulating SoC depletion, identifying charging opportunities along the route, and applying spatial filters to find candidate charging stations.

## 3.2 SoC calculations

Its essential to simulate battery behavior for each trip in order to evaluate the feasibility of electric trucks across various routes and estimate charging demand. This chapter describes the methodology used to model the SOC along vehicle routes including the driving time, energy consumption, charging needs, and regulatory breaks requirements. This will provide an overview on when and where charging stations are needed and how they will be used.

### 3.2.1 Overview

The route nodes obtained in the previous step are used to simulate energy depletion and charging events along the roads. Each trip's SOC is tracked from the departure point to arrival. It accounts for

- **Energy consumption:** Each vehicle is assigned a specific vehicle class in the Bass-Goed dataset based on the type of vehicle. Each class has their own set of parameters (see Table 2).
- **Driver break regulations:** Drivers require a 45-minute break after 4.5 hours of continuous driving.
- **Charging events:** A charging event is necessary if the SOC falls below 20% and it would not reach its destination without a 15% safety buffer.

This ensures that the trip simulations are not only technically feasible, but also represent real world driving conditions.

### 3.2.2 Vehicle parameters

Every tour (vehicle) has a predefined class for which the Battery capacity, consumption and charging power are defined.

Table 2: Vehicle class parameters: battery capacity, energy consumption, and charging power

| ID | Vehicle Type | Battery Capacity (kWh) | Consumption (kWh/km) | Charger Power (kW) |
|---|---|---|---|---|
| 0 | Truck (small) | 400 | 0.88 | 1000 |
| 1 | Truck (medium) | 500 | 0.88 | 1000 |
| 2 | Truck (large) | 600 | 0.88 | 1000 |
| 3 | Truck + Trailer (small) | 400 | 1.2 | 1000 |
| 4 | Truck + Trailer (large) | 600 | 1.2 | 1000 |
| 5 | Tractor + Trailer | 600 | 1.2 | 1000 |

*Note:* Parameters are based on publicly available sources, including Volvo Trucks datasheets [Volvo, ], Mercedes-Benz configurator [Mercedes-Benz, ], the NREL guide [Laboratory, 2025], and related studies on LEVVs and micromobility [Federation, 2025, Forum, 2025].

To account for real-world vehicle variability, battery capacity and consumption rates are from a normal distribution with a standard deviation for 10% around the base value. The sampled values are clipped within ±10% to avoid unrealistic outliers.

### 3.2.3 SoC Calculations

The SOC tracks the remaining energy in the vehicle's battery as a percentage. The SOC is kept between 15 and 80% to prolong the battery life.

The calculations are as follows

Energy depletion is calculated based on the distance traveled:

$$\text{Depletion (\%)} = \left( \frac{\text{Distance (km)} \times \text{Consumption (kWh/km)}}{\text{Battery Capacity (kWh)}} \right) \times 100$$

SOC is reduced by the depletion:

$$\text{SOC} = \text{SOC}_{\text{previous}} - \text{Depletion}$$

A charging event is triggered when the SOC drops below 20% and the remaining SOC is insufficient to complete the trip with a SOC left of 15%. The location of these charging events is logged and will function as the input of the optimizations. The charge session decides how much energy is necessary based on the remaining distance, including international travel and will decide on a maximum of 80%.

For trips that exit the Netherlands, the model assumes that trucks must carry enough energy to reach the nearest EU charging station. To account for this, a fixed post-border driving buffer of 60 km is added to the remaining trip distance to the border when calculating the required SoC.

For trips entering the Netherlands, a similar approach is taken. If the vehicle starts close to the border, energy depletion is calculated from the actual departure location. For longer trips originating deeper within the EU, it is assumed that the vehicle has charged at a station approximately 60 km from the Dutch border before entering the country.

This ensures that vehicles departing the country can reach charging infrastructure assumed to exist in neighboring EU regions. The 60 km assumption reflects AFIR regulations requiring stations stations within that distance on core corridors, and aligns with the thesis focus on planning the network only for the Netherlands.

Required SoC to complete the remaining distance is:

$$\mathrm{SOC}_{\mathrm{required}} = \left( \frac{D_{\mathrm{remaining}} \times \mathrm{Consumption}}{\mathrm{Battery\ Capacity}} \right) \times 100 + 15$$

The energy added during the charging event is calculated as follows:

$$\mathrm{SOC}_{\mathrm{target}} = \begin{cases} 80\% & \text{if } \mathrm{SOC}_{\mathrm{required}} > 80\% \\ \mathrm{SOC}_{\mathrm{required}} & \text{if } \mathrm{SOC}_{\mathrm{required}} \leq 80\% \end{cases}$$

$$E_{\mathrm{added}} = \frac{(\mathrm{SOC}_{\mathrm{target}} - \mathrm{SOC}_{\mathrm{current}}) \cdot C_{\mathrm{battery}}}{100}$$

The charging time is calculated as:

$$\text{Charge Time (min)} = \frac{\text{Energy Added (kWh)}}{\text{Charger Power (kW)}} \times 60$$

After charging, both SOC and the departure time are updated.

## 3.3 Generating Charging Station Candidates

### 3.3.1 AFIR Regulation-Based Generation

This section outlines the method used to distribute charging stations along the TEN-T network in accordance with AFIR regulations. The directive sets minimum infrastructure requirements. It requires that stations must be available within a maximum distance of 60 km in any direction. These stations must be equipped with at least 350 kW of charging power. [TNO, 2021].

The TEN-T network is an EU initiative focused on creating a unified and well connected system of roads, railways, airports, and waterways across the EU. Its objective is to build a sustainable, efficient, and multi modal transport infrastructure that maintains connectivity across the continent [Commission, 2025b].

**Road network:**
The road network is represented as a weighted unidrected graph. The nodes correspond to intersections and the edges represent the road segments with each its own distance. Each edge is defined in the format (node 1, node 2, distance). NetworkX is used to model the network. It is a graph processing library that represents the transport network. The graph is bidirectional, meaning the vehicles can travel across each edge in both directions.

**Preprocessing:**
This phase consists of two main steps: road segment subdivision and path exploration.

- **1. Road Segment Subdivision:**
  To create a finer road network, each road segment is subdivided into 2 km sections. At every subdivision point, a new node is introduced, representing a potential charging station location. The 2 km subdivision length is specifically chosen to ensure a high density of potential station locations while keeping the optimization computationally efficient.

- **2. Path Exploration:**
  Once the road network is structured, paths are explored using a Depth First Search (DFS) algorithm to identify every viable truck route and determine strategic charging station locations. This is done by analyzing all paths originating from each node within a maximum range of 60 km, in accordance with EU regulations. Some fine tuning is done after computing all the possible routes. Paths that end in short leaf nodes are removed from the list.

- **Depth-first search:**
  DFS is a method for traversing graphs or trees that begins at a root node and explores each branch as far as possible before going back. When it then encounters a node with no unexplored neighbors, it returns to the previous node with remaining unexplored paths and resumes the search. This process repeats until every node has been visited [Brilliant.org contributors, 2024].

This creates a paths list that will be used in the constraints element of the optimization.

**LP model formulation**

To determine the optimal locations for charging stations, we formulate a LP model that minimizes the number of stations while ensuring all routes are covered.

- **Decision Variables**
  - Let $x_i$ be a binary decision variable where:

$$x_i = \begin{cases} 1, & \text{if a charging station is placed at node } i \\ 0, & \text{otherwise} \end{cases}$$

- **Objective Function**

  The objective is to minimize the total number of charging stations:

$$\min \sum_{i \in \text{Nodes}} x_i$$

- **Constraints**
  - **Coverage Constraint:** Every node must be within 60 km of at least one charging station:

$$\sum_{j \in R_i} x_j \geq 1, \quad \forall i \in \text{Nodes}$$

    where $R_i$ is the set of nodes reachable from node $i$ within a 60 km range. This constraint ensures every point of the network is covered.
  - **Path Coverage Constraint:** Each truck route must have at least one charging station on every path calculated in the pre processing:

$$\sum_{i \in P_k} x_i \geq 1, \quad \forall k \in \text{Truck Routes}$$

    where $P_k$ represents the set of nodes along truck route $k$.

The result of this optimization provides a list of nodes where charging stations should be placed, ensuring complete coverage with the minimal number of stations.

### 3.3.2 Demand-Driven Station Generation

Candidate charging station locations are generated using clustering or come from a predefined list of TEN-T network intersections. The generated station will be directional while the stations at intersections will be able to serve demand from all directions.

- **Clustering:** Charging events are clustered using K-means. Each cluster center will be considered a possible charging station. If most vehicles in the cluster travel in the same direction, the station faces that dominant direction. Otherwise, the station faces the average direction of all the vehicles of the events in that location. Adding the bearing to the stations allows the optimization to place charging stations on either side of the road.

- **Bearing Computation:** Each events bearing is calculated using the last pair of coordinates before the charging event and the coordinates of the charging event itself.
- **Feasible Pairs:** Each charging event is generated based on vehicle specific energy needs and arrival times. These events are specially matched to candidate charging stations. To ensure realism in charger placement, candidate stations are filtered by the following constraints:
  - **Route proximity:** Stations must lie within a 5 km buffer of the trucks matched route.
  - **SoC constraints:** Stations must be reachable within 20% of the trucks battery percentage behind and 5% ahead of the event.
  - **Directional alignment:** The bearing difference between the truck's route and the stations must be less then a predetermined angle for the spatially determined stations.

## 3.4 Charging Station Allocation Optimization

This section introduces the MILP model used to allocate charging stations based on simulated charging demand. The model selects optimal locations from a predefined list determined through an optimization process of possible sites and determines how many chargers to install at each station. It also considers variable wait time constraints, grid capacity limits and installation costs. The goal is to create a cost effective charging network that meets operational requirements while minimizing early charging penalties.

**MILP model formulation:**
The MILP model is formulated to decide which station is build, how many chargers to install at each station and which event is assigned to which station and time slot.

- **Decision Variables**
  - $x_j$: Binary variable, 1 if a charging station is built at location $j$, 0 otherwise.
  - $c_{j,k}$: Integer variable representing the number of chargers of type $k$ installed at station $j$. Each type $k$ has its own power rating (e.g., 350 kW, 1 MW).
  - $a_{e,t,j,k}$: Binary variable, 1 if event $e$ is assigned to station $j$ at time slot $t$ using charger type $k$, 0 otherwise.
  - $y_e$: Binary variable, 1 if event $e$ is successfully assigned to a station and time slot, 0 otherwise.
  - $p_e$: Binary variable, 1 if event $e$ triggers a penalty (e.g., early charging or unserved), 0 otherwise.

- **Objective Function:** Minimize total system cost including station installation, chargers, grid capacity, and penalties:

$$\min \sum_{j} \left( C_{\text{station}} \cdot x_j + \sum_{k} C_{\text{charger},k} \cdot c_{j,k} + \sum_{k} C_{\text{grid\_per\_kW}} \cdot P_k \cdot c_{j,k} \right) + \sum_{e} C_{\text{Early Charge Penalty}} \cdot p_e \tag{1}$$

Where: - $P_k$: power rating (in kW) for charger type $k$ - $C_{\text{charger},k}$: purchase/installation cost per charger of type $k$ - $C_{\text{station}}$: cost of building a charging station - $p_e$: early charge penalty indicator for event $e$

- **Constraints:**

1. **Charger Linkage:** A station cannot have chargers installed unless it is built. This is enforced by linking the charger variables to the station variable.

$$c_{j,k} \leq \text{max\_chargers}_k \cdot x_j \quad \forall j, k$$

2. **Grid Capacity:** The total installed capacity can't exceed the the grid capacity for each charging station.

$$P_k \cdot c_{j,k} \leq \text{GridCapacity}_j \cdot x_j \quad \forall j, k$$

3. **Event assignment:** Each event must be assigned to exactly one station and one candidate start time.

$$\sum_{t \in T_e} \sum_{j \in J_e} \sum_{k} a_{e,t,j,k} = y_e \quad \forall e \in \text{Events}$$

Additionally, the assignment variables are connected to the station build decision. This ensures an event can only be assigned to an active station.

$$a_{e,t,j,k} \leq x_j \quad \forall e, t, j, k$$

4. **Capacity:** For each time and station, the number of assigned events should not exceed the number of chargers.

$$\sum_{e \in E_t} a_{e,t,j,k} \leq c_{j,k} \quad \forall j, t, k$$

5. **Coverage Constraint:** At least 90% of the events must be assigned. This will ensure high enough coverage for the network.

$$\sum_{e \in \text{Events}} y_e \geq 0.9 \cdot |\text{Events}|$$

6. **Wait time:** To preserve operational realism across vehicle schedules, each tour accumulated wait time is limited to a maximum threshold. This ensures the allocation does not introduce excessive delays.

$$\sum_{e \in \text{Tour}_r} \sum_{t \in T_e} \sum_{j \in J_e} \sum_{k} (t - t_{e,0}) \cdot a_{e,t,j,k} \leq \text{MaxTourWait} \quad \forall r \in \text{Tours}$$

**Solution Process and Post-Processing**
The MILP is solved using Gurobi with an optimality gap of 2%.

- **Wait-Time Analysis:** The assigned candidate start time for each event is compared to its charging start time to compute the wait time. Overall and per station statistics are then calculated.

- **Export and Visualization:** The selected station locations and number of chargers for the different types are exported and will be used to benchmark the optimization results against the AFIR regulation based stations. An interactive map is generated using the Folium package to visualize and validate the results.

# 4 System Modeling

## 4.1 Dataset

The dataset used in this study is derived from the Dutch national freight transport model BasGoed, which provides a forecast of truck movements throughout the Netherlands [Rijkswaterstaat, 2024]. The file contains trip data that forms the basics for the routing simulations, SoC analysis and the optimizations.

### 4.1.1 Data Structure

Each entry in the dataset corresponds to a truck tour and includes the following key attributes

- **Origin and destination** coordinates (latitude, longitude)

- **Vehicle type** identifier used to determine battery capacity and consumption rates

- **Departure times** expressed in hours since midnight

- **Distance** of the trip in kilometers

The dataset includes several million records representing a typical weekday. The focus is limited to relevant truck categories (light, medium and heavy-duty freight) that are assumed to use the highway charging network.

### 4.1.2 Data Preprocessing:

The raw data, as described in Chapter 3.2 SOC Calculations, undergoes several steps of preprocessing.

- **Data Cleaning:** Events missing critical attributes are removed. This ensures any mistake in the data is removed before continuing.

- **Time Conversion:** All timings are converted to a standardized format. I'm using a combination from HH:MM to minutes after midnight to streamline the following calculations.
- **Candidate Time Slots:** For each event time, a set of candidate charging start times is generated after the arrival time. These are at regular intervals of 5 minutes up to the maximum wait time. This results in a set of candidate time slots used by the optimization.

## 4.2 Model Configuration

Table 3: Key parameters used in the optimization model

| Category | Symbol | Value | Unit | Source |
|---|---|---|---|---|
| Cost | $C_{350\,\mathrm{kW}}$ | €175 000 | /charger | [Company, 2023] |
| | $C_{1\,\mathrm{MW}}$ | €500 000 | /charger | [Company, 2023] |
| | Station Base Cost | €2 000 000 | /station | [Laboratory, 2025] |
| | Grid connection cost | €350 | /kW | [B.V., 2024] |
| | Penalty $C_{\mathrm{pen}}$ | €175 000 | /penalty | §4.3.4 |
| Scenario | Electrification 2025 | 0.75 | % of fleet | Table 1 |
| | Electrification 2030 | 7.50 | % of fleet | Table 1 |

The cost assumptions used in this model represent realistic estimates for large scale truck charging deployments based on industry and institutional sources.

The cost of a 350 kW charger is set at €175 000, inline with McKinsey's 2023 estimates for installed DC fast charging infrastructure [Company, 2023]. The report estimates the total cost of a fast charger cost to be between roughly €85 000 and €250 000 depending on the location, power rating and equipment. This comes down to about €500/kWh, used to determine the price of a MCS. This price includes the hardware and installation cost.

A station level base cost of €2 million is chosen per site. This value is derived from the NREL (2022) estimate of 4.1 million for 3.9 MW truck charging depot, where approximately half the cost is attributed to site development and halve to charging hardware [Laboratory, 2025]. This cost includes all preparations made to the land, excluding the grid connection costs.

The grid connection cost is modeled at €350/kW based on a 10 year total cost structure from Stedin [B.V., 2024]. It contains one time connection fees and fixed annual costs.

Lastly, the penalty value is determined in section 4.3.4 where the methodology and the results are described.

## 4.3 Model Calibration

### 4.3.1 Objective of Calibration

The optimization model minimizes total system installation costs while penalizing early-charging events. These early charging events are characterized by needing another charge to complete its journey rather then charging the minimal amount of times. A monetary value is added to the objective function to discourage such events but not to rule it out completely. This chapter focuses on calibrating the penalty parameter to avoid excessive infrastructure costs and inadequate service quality.

### 4.3.2 Penalty Calibration Methodology

**Penalty Parameter Sweep**
The calibration involves varying the penalty cost from 50,000 to 400,000 euro in increments of 50,000. A special value of 175,000 is also added because it represents the price of exactly one 350 kW charger. The analysis is performed on all the scenarios (both the traffic flow simulations for 350kW and 1MW, and the AFIR simulations for 350kW and 1MW).

**Evaluation Metrics**
Each scenario provided the following metrics:

- Total system cost (sum of the infrastructure, grid connection cost and penalty costs)
- Number of early-charging penalties
- Total number of charging stations and chargers

**Analysis**
An incremental analysis is done by calculating the marginal cost per penalty removed. This identifies the points where the infrastructure investments were most cost-effective, also known as the knee/elbow point.

### 4.3.3 Calibration Results

**Traffic simulations Layout**
Figure 4 shows the total system cost relative to the number of early charging penalties for both 350 kW and 1 MW charger scenarios. The total system cost includes the cost of building stations, installing/purchasing chargers, grid connection costs, and penalties for early charging events. An early charging penalty is applied when a truck chargers significantly earlier than needed, which would result in needing an extra charging event to

get to its destination.

For the 350 kW chargers, the optimal balance, or ”knee point”, occurs at around 55 remaining early charging penalties. Beyond this point, further reducing penalties becomes disproportionately expensive. Table 4 indicates the same results. It highlights that the most cost-effective reductions occurs at the 55 penalties with an early charging penalty value of 200,000€ or at 65 remaining penalties at 100,000€ , which corresponds to about 0.54M Cost per penalty. At 400k the optimizer switches to a different charger mix that happens to remove five extra penalties at relative low incremental cost, but the absolute CAPEX is still higher then the knee-point solution

The scenario for the 1 MW chargers follows a similar pattern, with the clear optimal knee point at 54 penalties, as shown in Figure 4. Table 5 confirms this result. Only two major penalty reductions occur around 54 or 50 penalties each with a marginal cost per penalty reduction of 1.49M and 2.30M euro, corresponding to a penalty cost of 175,000 and 350,000 euro.

These results help identify cost effective trade offs between infrastructure investment and system performance. The selected knee points are marked in the plots and tables to make interpretation easier.

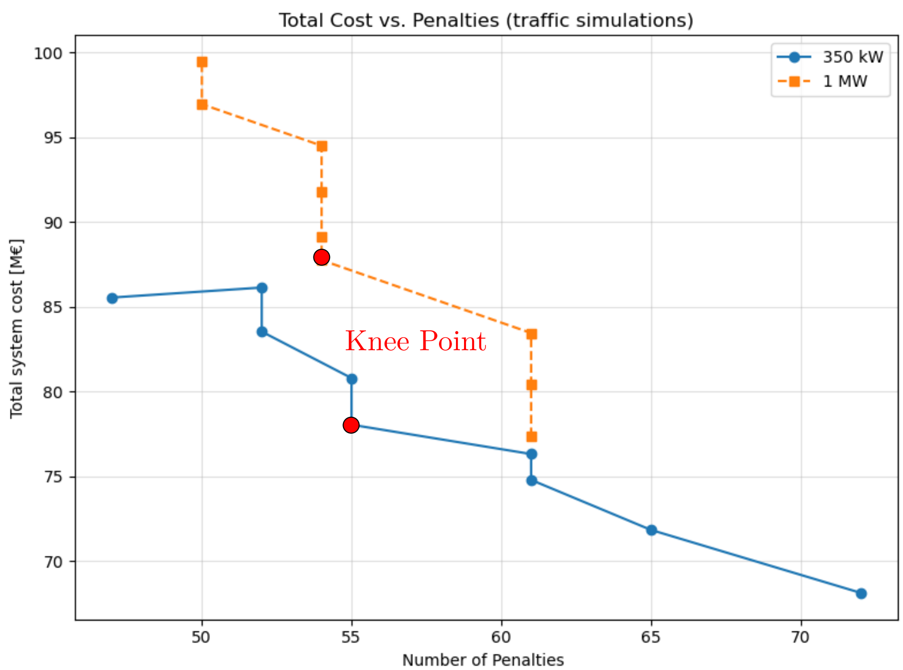


Figure 4: Total Cost vs. Penalties (Traffic flow layout). The red marker indicates the knee point of optimal trade-off.

Table 4: Incremental cost analysis – 350 kW Traffic simulations layout

| Penalty value (€) | Remaining penalties | Total Cost (M€) | ΔTotal cost (M€) | Penalties removed | Cost/penalty (M€) |
|---|---|---|---|---|---|
| 100 000 | 65 | 71.84 | 3.71 | 7 | 0.53 |
| 150 000 | 61 | 74.78 | 2.95 | 4 | 0.74 |
| **200 000** | 55 | **78.04** | **3.25** | 6 | **0.54** |
| 300 000 | 52 | 83.53 | 5.49 | 3 | 1.83 |
| 400 000 | 47 | 85.54 | 2.01 | 5 | 0.4 |

*Note: Only configurations where penalties were eliminated are shown.*

Table 5: Incremental cost analysis – 1 MW Traffic simulations layout

| Penalty value (€) | Remaining penalties | Total cost (M€) | Δ Total cost (M€) | Penalties removed | Cost/penalty (M€) |
|---|---|---|---|---|---|
| 175 000 | 54 | 87.75 | 10.40 | 7 | 1.49 |
| 350 000 | 50 | 96.95 | 9.20 | 4 | 2.30 |

*Note: Only configurations where penalties were eliminated are shown.*

**AFIR layout**

Table 6 and 7 summarize the calibration results for the AFIR layout. Compared to the traffic based station placement, the AFIR configuration is less responsive to changes in early charging penalty values. The first infrastructure adjustments only occur at penalty thresholds of €250,000 for the 350 kW scenario and €150,000 for the 1 MW scenario.

The limited sensitivity is likely due to the fixed nature of the station locations, which are predetermined by regulatory spacing requirements. Because stations cannot be relocated, the model has fewer options to optimize charger allocation in response to penalty increases.

In the 350 kW case, a noticeable change occurs at an early charging penalty of €250,000, where the number of early charging penalties drops from 66 to 60, and the marginal cost per penalty removed is €2.18M. The large delta comes form the comparison with a penalty value of only 50k. In the 1 MW case, changes remain modest, with a reduction of just three penalties at €150,000 and at a marginal cost of €1.87 million per penalty removed and later on at a €400,000 with a marginal cost of 0.75 million er penalty removed.

Table 6: Incremental real-cost analysis – 350 kW AFIR layout

| Penalty value (€) | Remaining penalties | Total cost (M€) | Δ Total cost (M€) | Penalties removed | Cost / penalty (M€) |
|---|---|---|---|---|---|
| **250 000** | **60** | 80.33 | **13.0** | **6** | **2.18** |
| 300 000 | 56 | 83.3 | 3 | 4 | 0.75 |

*Note: Only configurations where penalties were eliminated are shown.*

Table 7: Incremental cost analysis – 1 MW AFIR layout

| Penalty value (€) | Remaining penalties | Total cost (M€) | Δ Total cost (M€) | Penalties removed | Cost / penalty (M€) |
|---|---|---|---|---|---|
| **150 000** | **55** | **91.91** | **5.61** | 3 | **1.87** |
| 400 000 | 52 | 105.65 | 13.69 | 3 | 4.56 |

*Note: Only configurations where penalties were eliminated are shown.*

#### 4.3.4 Recommended Penalty Value

Based on the analysis, a penalty value of €175,000 is selected as the default across all scenarios. This value represents a practical trade-off point that works well in both charger configurations while maintaining consistency in comparison.

The penalty of €175,000 is optimal for the 1 MW traffic flow layout which is likely the most relevant for future high demand conditions. It results in the lowest cost per penalty removed and represents the knee point in the trade off curve. For the 350 kW traffic flow scenario, the best cost per penalty value occurs at €200,000. However, €175,000 is fairly close to this optimum and still falls near the knee of the cost curve.

In the AFIR layouts, station locations are fixed to the minimum to satisfy the regulations, making the optimization less sensitive to penalty value changes. Choosing €175,000 ensures consistency across scenarios while having minimal impact on the AFIR results.

# 5 Results

This section discusses the outcomes of the optimization models, the comparison different results and considerations. More specifically it analyses the balance between total system cost, maximum allowed wait time, and grid connection capacity, using a Pareto front approach.

The Pareto analysis methodology consists of systematically varying maximum grid connection capacities per station and maximum wait times constraints to generate a complete Pareto surface. The surface illustrates the relationships between the total system cost, service quality, and infrastructure requirements. The analysis is performed separately for 350 kW and 1MW charger configurations in the 2025 scenario and for both AFIR and Traffic flow layouts.

## 5.1 Results analysis

Figure 6 displays the Pareto surfaces obtained for the 2025 scenarios for 350 kW chargers. The process for evaluating these results goes as follows:

Through comprehensive data evaluation, the configuration with specific grid capacity and max wait time emerged as the optimal solution based on the following selection process:

### 5.1.1 Maximum Wait time Determination

The maximum wait time parameter was evaluated first as it directly impacts user experience while having a high impact on infrastructure requirements. The critical point was identified by analyzing where additional increases in wait time resulted in only small reductions in total costs. In other words, the selected wait time reflects the point at which cost savings begin to level off, while the user burden (in the form of longer wait time) continues to grow. This approach balances service quality with cost efficiency. Configurations with very short wait times show steep cost increases due to high charger requirements, while longer wait times offer diminishing returns.

### 5.1.2 Grid Capacity Optimization

Similar to the wait time analysis, a point was observed beyond which increasing the maximum allowed grid capacity per station led to only minimal cost improvements. This is due to the way the limit is implemented in the model. It only acts as an upper constraint. The model optimizes each site individually, meaning most stations will have a grid connection significantly below maximum, sized to match total charger demand. This plateau effect, visible in the Pareto surface plots, indicates that the infrastructure becomes saturated in its ability to benefit from additional allowed capacity.

While the grid capacity is included in the model, limiting the maximum installed charging capacity per station, the model assumes a uniform limit across all locations. It does not account for station specific or regional grid availability. As a result, the sensitivity to grid capacity is somewhat lower than that observed for the wait time.

To support the selection of the optimal configuration, nearby solutions on the Pareto surface were examined. This are not alternative optima, but rather configurations with slightly different grid capacities or wait times. The purpose is to confirm that the chosen solution represents the most favorable trade off between cost and system performance.

## 5.2 Results 2025 - 350kw

This section presents the detailed results for the 2025 scenario using 350 kW chargers. Two layouts are compared: one based on traffic flow simulations and the other one on the AFIR-regulated locations. Each evaluation is based on the infrastructure cost, charger deployment, max grid capacity, and user wait times. The purpose is to explore how varying grid capacities and allowing different wait times affects the network and costs.

### 5.2.1 Traffic flow layout

The selected configuration for the traffic flow layout uses a maximum grid capacity per station of **2000 kW** and allows a maximum wait time of **15 minutes** per tour. This setup results in a total system cost of **€72.02M**, with **23 stations** and **51 chargers** installed. The average wait time experienced by users under this configuration is **7.07 minutes**. This point was chose as the optimal trade off between infrastructure cost, grid capacity, and service quality.

Table 8 compares small variations around the selected configuration. The chosen setup of a maximum station grid capacity of 2000 kW and a 15 minute max wait time per tour offers the lowest cost. Slightly lowering the grid capacity increases the the total cost, while increasing it further has no cost benefit.

Table 8: Traffic flow layout - Cost comparison of nearby configurations around the selected point (350 kW)

| Grid Cap. (kW) | Max Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|
| 1500 | 15 | 23 | 52 | +0.30 (+0.42%) |
| **2000** | **15** | **23** | **51** | **72.02** |
| 2500 | 15 | 23 | 51 | +0.00 (+0.00%) |

Figure 5 compares the installed charger capacity at all the selected stations under two maximum installed capacity scenarios: 2000kW and 4000kW. The distribution of installed capacity remains identical between the two runs, with no station exceeding 1400kW. This confirms increasing the grid capacity beyond 2000kW does not impact the results in any significant way for most max capacity and wait time combinations. This helps explaining why the Pareto surface plot tends to flatten for a fixed maximum wait time.

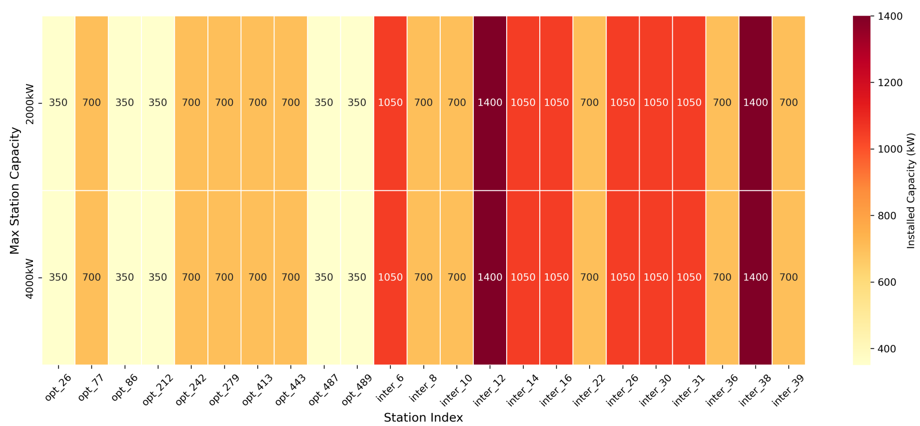


Figure 5: Installed station capacity per site under two maximum grid capacity scenarios (2000 kW and 4000 kW) for the 350 kW traffic flow layout.

Table 9 shows that lowering the wait time to 10 minutes increases to cost by 1.1% while increasing it to 20 minutes reduces the total cost slightly but leads to longer delays. The selected 15 minute setting provides a balanced trade off between service quality and infrastructure cost, making it the most efficient option.

Table 9: traffic flow - Cost comparison of wait time variations (350 kW layout)

| Grid Cap. (kW) | Wait Time (min) | Avg Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|---|
| 2000 | 10 | 4.75 | 23 | 53 | +0.77 (+1.1%) |
| **2000** | **15** | **7.07** | **23** | **51** | **72.02** |
| 2000 | 20 | 9.14 | 23 | 49 | -0.59 (-0.8%) |

### 5.2.2 AFIR layout

The selected configurations uses a maximum grid capacity of **2000 kW** per station and allows a maximum wait time of **20 minutes** per tour. This setup results in a total system cost of **€69.24M**, with **22 stations** and **46 chargers** installed. The average wait time for users is **9.25 minutes**.

Table 10 shows that the selected configuration, using 2000 kW maximum grid capacity per station and a 20 minute maximum wait time per tour has the lowest total cost. Reducing the grid capacity to 1500 kW increases the cost by 1.6% due to infrastructure inefficiencies, while increasing it to 2500 kW provides no cost benefit.

Table 10: AFIR layout - Cost comparison of nearby configurations around the selected point (350 kW layout)

| Grid Cap. (kW) | Max Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|
| 1500 | 20 | 23 | 46 | +1.12 (+1.6%) |
| **2000** | **20** | **22** | **46** | **69.24** |
| 2500 | 20 | 22 | 46 | +0.00 (+0.00%) |

Table 11 shows that reducing the wait time increases total cost by 2.7% due to additional chargers and stations. Increasing to 25 minutes lowers the cost slightly (-0.9%) but also results in longer wait times. The selected 20 minute setting offers a good middle ground between cost and user experience.

Table 11: AFIR - Cost comparison of wait time variations (350 kW layout)

| Grid Cap. (kW) | Wait Time (min) | Avg Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|---|
| 2000 | 15 | 7.09 | 23 | 49 | +1.84 (+2.7%) |
| **2000** | **20** | **9.25** | **22** | **46** | **69.24** |
| 2000 | 25 | 11.10 | 22 | 45 | -0.65 (-0.9%) |

The data supports that the a maximum allowed station grid capacity of 2000 kW and a 20 min wait time per vehicle configuration represents the knee point in the Pareto curve, where meaningful improvements in either grid capacity or wait time require disproportionate cost increases.

Figure 6 and 7 shows the Pareto surface for the 350 kW and 1 MW traffic flow and AFIR layouts. The plot illustrates how the total system cost changes with different combinations of grid capacities and maximum allowed wait time. The selected optimal solution is marked in bright red, while nearby alternative solutions are marked smaller. In both cases, cost reductions level off beyond a certain grid capacity and wait time threshold, forming a ”knee” in the surface. Section 5.4 further explains the interpretation of these fronts and reasoning behind the unconventional shape of the demand Pareto surface front.

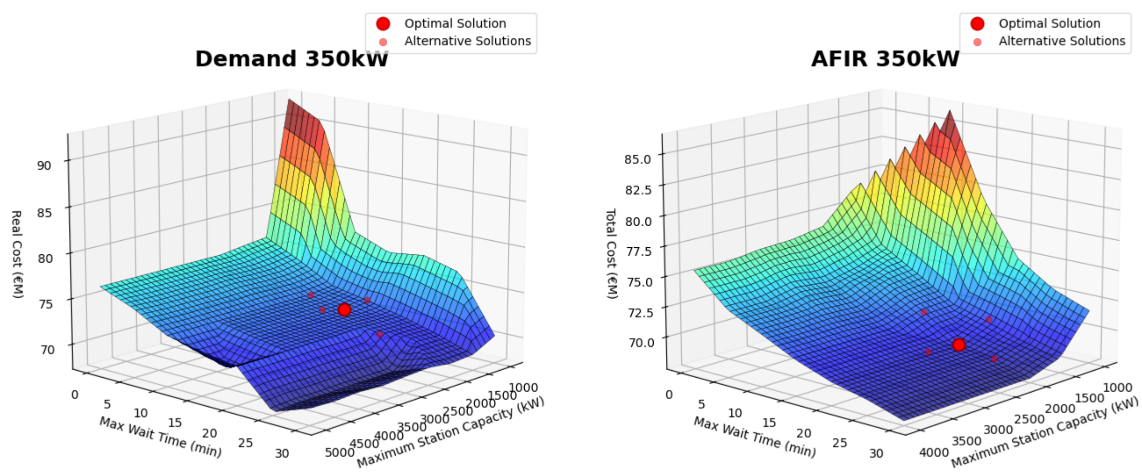


Figure 6: Pareto front 350 kW traffic flow and AFIR charging station layout

### 5.2.3 AFIR vs Traffic flow layout

This sections fucuses on comparing the chosen configurations for the traffic flow layout and the AFIR layout.

Table 12 shows the differences in core parameters configurations. Both layouts have the same 2 MW per station grid capacity limit, the only real change is how much queuing they allow. AFIR accepts a 20 minute ceiling, while the Traffic flow layout only allows 15 minutes. Everything else, the charger count, station count and costs, flow directly from that 5 minute choice.

The difference, as explained in previous sections, is due to the ”knee point” being shifted downwards for the AFIR configuration. The layout experiences a much steeper max wait time, total cost curve pushing the ”knee point” down.

The AFIR's scenario increased wait time allows it to stretch the charging start times, so each charger turns more vehicle hours before a queue forms. When queues form, these will experience a 2.18 minute longer average then the Traffic flow. This also means less chargers will be necessary to provide the same service.

Table 12: Core Configuration Parameters – Traffic flow vs AFIR (350 kW)

| Parameter | Traffic flow | AFIR | Difference |
|---|---:|---:|---:|
| Max Grid Capacity | 2000 kW | 2000 kW | 0% |
| Max Wait Time | 15 min | 20 min | +33% |
| Tour Average Wait | 7.07 min | 9.25 min | +31% |
| Total Cost | €72.02M | €69.24M | –3.9% |

Table 13 compares the infrastructure requirements. The shorter queue limit in the traffic flow layout forces one extra site and 5 more chargers resulting in a 9.8% increase in total installed capacity. With 2.09 chargers per site, the traffic flow layout concentrates more capacity per site, increasing the outage risk if a single hub fails.

Table 13: Infrastructure Requirements – Traffic flow vs AFIR

| Infrastructure | Traffic flow | AFIR | Difference |
|---|---:|---:|---:|
| Number of Stations | 23 | 22 | –4.3% |
| Total Chargers | 51 | 46 | –9.8% |
| Charger-to-Station Ratio | 2.22:1 | 2.09:1 | –5.8% |
| Total Installed Capacity | 17,850 kW | 16,100 kW | –9.8% |

Table 14 reports operational performance. Both layouts achieve similar wait ratios and penalty costs, although the AFIR layout results in slightly more early charging penalties. Even so, the saving in cap-ex outweighs the extra fines.

Table 14: Operational Performance – Traffic flow vs AFIR

| Performance Metric | Traffic flow | AFIR | Difference |
|---|---:|---:|---:|
| Wait Ratio (Avg/Max) | 47.1% | 46.3% | –1.8% |
| SOC Penalties | 62 | 66 | +6.5% |
| Penalty Cost | €10.85M | €11.55M | +6.5% |

**Key Takeaways:** At 350 kW, the regulatory AFIR grid shows its strength in cap-ex efficiently but leaves user with longer dwell times. The demand driven layout pays 4% more to cut the maximum wait time per tour by a fourth. Its a premium that looks modest next to the much steeper price AFIR pays once electrification rises in 2030 (See section 5.5)

## 5.3 Results 2025 - 1MW chargers

This sections examines the 2025 results for the two scenarios deploying 1MW charging infrastructure. The two scenarios are: one based on traffic flow simulations and the other one on the AFIR-regulated locations. The analysis will look at the system cost, station configuration, grid sizing, and operational performance.

### 5.3.1 Traffic flow layout

The selected configuration for the traffic flow layout with 1 MW chargers uses a maximum grid capacity of **1000 kw** per station and a maximum wait time of **15 minutes** per tour. This setup results in a total system cost of **€69.83M**, with 32 stations and 21 chargers installed. The average wait time is **7.35 minutes**.

Table 15 compares configurations with higher grid capacity around the selected point. Increasing the capacity to 2000 kW or 3000 kW leads to a 5.7% cost increase, with no improvement in station count and only three extra chargers. This confirms that the 1000 kW station grid limit is the most cost efficient chose for the 1 MW chargers in the Traffic flow layout.

Table 15: Traffic flow - Cost comparison of nearby configurations around the selected point (1 MW layout)

| Grid Cap. (kW) | Max Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|
| **1000** | **15** | **21** | **21** | **69.83** |
| 2000 | 15 | 21 | 24 | +3.95 (+5.7%) |
| 3000 | 15 | 21 | 24 | +3.95 (+5.7%) |

Table 16 shows that lowering the maximum wait time to 10 minutes increases the cost by 11.7% due to the need for more infrastructure. Extending it to 20 minutes reduces the average wait time impact and only increases the cost by 0.5%. The selected 15 minute configuration offers the best compromise between user waiting time and overall system cost.

Table 16: Traffic flow - Cost comparison of wait time variations (1 MW layout)

| Grid Cap. (kW) | Wait Time (min) | Avg Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|---|
| 1000 | 10 | 4.75 | 24 | 24 | +8.20 (+11.7%) |
| **1000** | **15** | **7.35** | **21** | **21** | **69.83** |
| 1000 | 20 | 9.31 | 21 | 21 | +0.35 (+0.5%) |

### 5.3.2 Afir layout

The selected configuration for the AFIR layout uses a maximum grid capacity of **2000 kW** per station and allows a maximum wait time of **20 minutes**. This results in a total system cost of **€77.40M**, with **23 stations** and **25 chargers**, yielding a charger to station ration of 1.09:1. The average wait time is **9.05 minutes**. This setup was selected as the most balanced option in terms of infrastructure cost and user experience.

Table 17 compares different grid capacity limits around the selected AFIR configuration. Reducing the grid capacity to 1000 kW results in a 7.7% increase in total cost due to the need for more stations. Increasing it to 3000 kW leads to a smaller cost increase of just 0.5%, with minor changes in infrastructure.

Table 17: AFIR - Cost comparison of nearby configurations around the selected point (1 MW layout)

| Grid Cap. (kW) | Max Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|
| 1000 | 20 | 26 | 26 | +5.98 (+7.7%) |
| **2000** | **20** | **23** | **25** | **77.40** |
| 3000 | 20 | 22 | 27 | +0.40 (+0.5%) |

Table 18 shows that reducing the wait time to 15 minutes increases the total cost by 3.2%, due to higher charger and station counts. Increasing the wait time to 25 minutes slightly reduces cost (-1.6%) but also increases average wait time by over 2 minutes.

Table 18: Cost comparison of wait time variations (1 MW AFIR layout)

| Grid Cap. (kW) | Wait Time (min) | Avg Wait (min) | Stations | Chargers | Total Cost (M€) |
|---|---|---|---|---|---|
| 2000 | 15 | 6.94 | 24 | 26 | +2.50 (+3.2%) |
| **2000** | **20** | **9.05** | **23** | **25** | **77.40** |
| 2000 | 25 | 11.71 | 23 | 24 | -1.20 (-1.6%) |

The data clearly shows that the 2000kW, 20min configuration represents the optimal point in the cost benefit curve. Reducing either parameter results in significant cost increases, while increasing them yields diminishing returns.

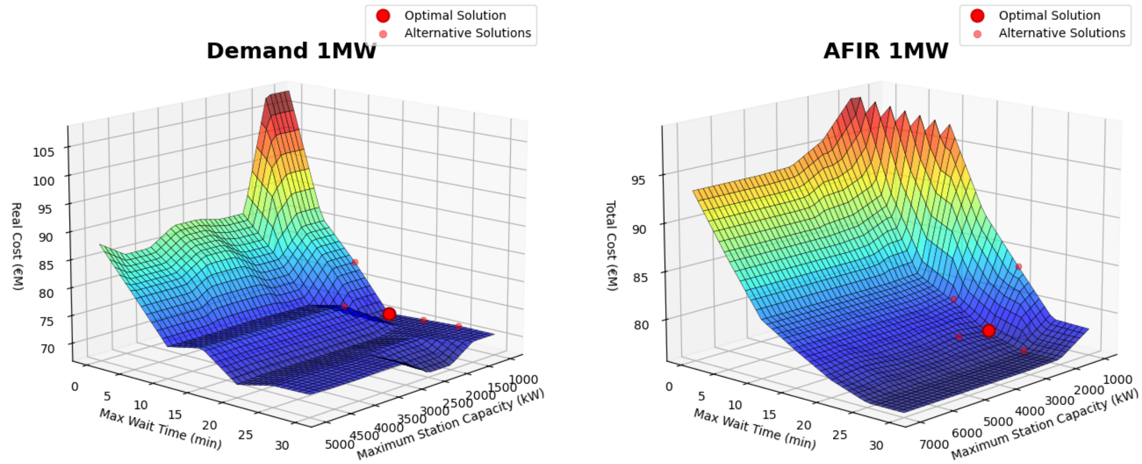


Figure 7: Pareto front 1 MW traffic flow and AFIR charging station layout

#### 5.3.3 AFIR vs Traffic flow layout

This section evaluates the 1 MW charger configurations under the AFIR and traffic flow layouts. While both scenarios achieve similar coverage, they differ in grid capacity limits, infrastructure needs, and resulting system costs.

Table 19 outlines the core setup differences. The AFIR scenario allows twice the grid capacity per station and permits a longer maximum wait time. With 1 MW chargers, this comes down to a maximum of two chargers per station instead of only one. With this added flexibility, it places more chargers and results in a higher total cost. The traffic flow configuration achieves lower cost with tighter constraints, suggesting more efficient station placement through demand-driven optimization.

Table 19: Core Configuration Parameters – Traffic flow vs AFIR (1 MW)

| **Parameter** | **Traffic flow** | **AFIR** | **Difference** |
|---|---|---|---|
| Max Grid Capacity | 1000 kW | 2000 kW | +100% |
| Max Wait Time | 15 min | 20 min | +33% |
| Tour Average Wait | 7.35 min | 9.05 min | +23% |
| Total Cost | €69.83M | €77.40M | +10.8% |

Table 20 compares infrastructure deployment. The AFIR layout uses more stations and chargers overall, leading to a higher total installed capacity. This implies less efficient infrastructure use relative to the traffic flow layout, which achieves similar service levels with fewer assets.

Table 20: Infrastructure Requirements – Traffic flow vs AFIR (1 MW)

| **Infrastructure** | **Traffic flow** | **AFIR** | **Difference** |
|---|---:|---:|---:|
| Number of Stations | 21 | 23 | +9.5% |
| Total Chargers | 21 | 25 | +19.0% |
| Charger-to-Station Ratio | 1.00:1 | 1.09:1 | +9.0% |
| Total Installed Capacity | 21,000 kW | 25,000 kW | +19.0% |

Table 21 presents the operational performance. With the denser charging stations, AFIR delivers a lower wait ration. The early charging penalties are almost identical meaning the total cost difference comes only from the increased chargers and stations.

Table 21: Operational Performance – Traffic flow vs AFIR (1 MW)

| **Performance Metric** | **Traffic flow** | **AFIR** | **Difference** |
|---|---:|---:|---:|
| Wait Ratio (Avg/Max) | 49.0% | 45.3% | –7.6% |
| SOC Penalties | 57 | 58 | +1.8% |
| Penalty Cost | €9.98M | €10.15M | +1.7% |

The 1 MW comparison reaffirms the trade-off between regulatory coverage and demand-optimized layouts. The traffic flow configuration meets performance targets with lower cost and fewer stations and chargers, while the AFIR layout compensates for a more rigid structure by increasing charger density and allowed wait time. This highlights the flexibility and efficiency advantages of traffic-driven planning.

## 5.4 Pareto Front explanation

This section will provide insight into the unconventional shape of the infrastructure cost Pareto surface shown in figure 8. The figure plots two surfaces, the objective function 1 and the infrastructure cost.

The objective function surface plot behaves as expected. It shows higher cost for scenarios with tight queue limits and low max grid capacity per station. These scenarios typically lead the optimization model to place numerous smaller stations, each with relatively few chargers, resulting in significantly increased overall cost. As the grid capacity increases, the total number of stations required diminishes, lowering the objective value until it stabilizes at the optimal capacity. The grid capacity is modeled as an upper constraint. Most stations will have a grid connection far below this to match their installed capacity. So Beyond this point, further increases in maximum allowed grid capacity per station yield minimal changes in total cost. Allowing longer maximum wait time provides greater scheduling flexibility to the optimization, reducing the number of chargers required, and thus steadily decreasing the objective value.

A crucial aspect influencing this behavior is the model's way with omni-directional stations. It is guided towards placing one of such stations only if it can replace 3 or more directional station locations. This is done by increasing the cost of an omni-directional station to 2.5 times that of a direction one.

In contrast, the infrastructure cost surface combines the stations costs (all types at uniform cost), charger cost, grid connection cost, and early charging penalty cost. Unlike the objective function plot, this surface reveals several unexpected bumps and dips. These primarily result from shifts in configuration between omni-directional and directional stations, as well as variations in the total number of penalties incurred. For example, infrastructure costs at the 30 minute maximum wait time are higher compared to those at the 25 minute mark for grid capacities ranging between 2500kW and 5000kW, even though the objective function values are lower at 30 minutes. This occurs because , at the 25 minute configurations, the model opts to place an omni-diretional station. this significantly reduces penalties but inflates the objective cost due to the higher valuation of such station. Contrarily, the infrastructure cost plot, which treats all station types equally, reflects lower cost despite the higher valued omni-directional station.

Therefore, the different cost structures are clearly illustrated by the difference between these plots. The objective function's cost structure is designed to guide the optimization model towards a specific configuration, only placing a omni-directional station when justified. Meanwhile the infrastructure cost surface presents the realistic network cost without such biases.

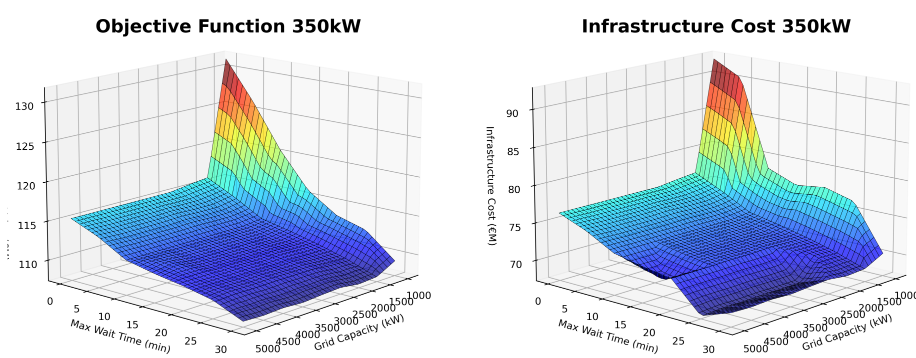


Figure 8: Pareto surface comparison Objective function vs Infrastructure cost - traffic flow simulation 350 kW chargers

## 5.5 2025 vs 2030

This section compares the AFIR and traffic flow configurations for the years 2025 and 2030, analyzing how increased electrification rate impacts the infrastructure, performance and efficiency. The electrification rate increases from 0.75% in 2025 to 7.5% in 2030. While the maximum wait time remains constant, max grid capacity per station is increased to at least 15,000 kW and later revisited after the simulations to check if the results are reasonable.

### 5.5.1 Afir layout - 350 kW Chargers

Table 22 outlines the core setup changes for 350 kW AFIR layout. The maximum wait time remained the same for both scenarios, while the average wait time improved slightly for the 2030 scenario. The total cost increased by 149% to accommodate for the major infrastructure expansion.

Table 22: Core Configuration Parameters – 2025 vs 2030 (AFIR, 350 kW)

| **Parameter** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---:|---:|---:|
| Max Wait Time | 20 min | 20 min | 0% |
| Tour Average Wait | 9.25 min | 8.93 min | –3.5% |
| Total Cost | €69.24M | €172.32M | +148.9% |

Table 23 shows the infrastructure scaling required. It is strongly nonlinear. Charger deployment grows over 4x, while the number of stations increases by 55% to 34. Noticeably, 34 is the minimum required amount of stations to satisfy the AFIR regulations.

Table 23: Infrastructure Requirements – 2025 vs 2030 (AFIR, 350 kW)

| **Infrastructure** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---:|---:|---:|
| Number of Stations | 22 | 34 | +54.5% |
| Total Chargers | 46 | 193 | +319.6% |
| Charger-to-Station Ratio | 2.09:1 | 5.68:1 | +171.5% |
| Total Installed Capacity | 16,100 kW | 67,550 kW | +319.6% |

Table 24 reveals a large increase in applied penalties. This indicates that while service levels are preserved, many more trips needed early charging penalties. The root cause lies by the AFIR model that con only add chargers at the 34 fixed nodes. They might be insufficient around the edges of the network, leading to the massive increase.

Table 24: Operational Performance – 2025 vs 2030 (AFIR, 350 kW)

| Performance Metric | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Coverage | 90.06% | 90.00% | –0.1% |
| Wait Ratio (Avg/Max) | 46.3% | 44.7% | –3.5% |
| Applied Penalties | 66 | 268 | +306.1% |
| Penalty Cost | €11.55M | €46.90M | +306.1% |

The results demonstrate that while the AFIR-based 350kW network scales sufficiently in terms of charger count and meets the regulatory coverage, it begins to show structural limitations under 2030 electrification levels. The sharp increase in early charging penalties suggests that the station placement, although compliant with AFIR spacing rules, may not align optimally with the actual demand patterns.

#### 5.5.2 Afir layout - 1MW Chargers

Table 25 summarizes the primary configuration parameters for 2025 and 2030 using 1 MW chargers for the AFIR layout. While electrification rates rise from 0.75% to 7.5%, the total cost rises by 136% reflecting the network scaling needed to accommodate increased electrification.

Table 25: Core Configuration Parameters – 2025 vs 2030 (AFIR, 1 MW)

| Parameter | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Grid Capacity per station | 2,000 kW | 20,000 kW | +900% |
| Max Wait Time | 20 min | 20 min | 0% |
| Tour Average Wait | 9.05 min | 8.99 min | -0.1% |
| Total Cost | €77.40M | €183.08M | +136.5% |

Table 26 illustrates the scale of infrastructure growth between the two scenarios. Like with the 350 kW chargers, the station count increases to 34, the minimum needed stations to cover the AFIR regulations. The charger count more then triples to cover the increased demand, lifting the average site from a single plug to almost three.

Table 26: Infrastructure Requirements – 2025 vs 2030 (AFIR, 1 MW)

| Infrastructure | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Number of Stations | 23 | 34 | +47.8% |
| Total Chargers | 25 | 80 | +220.0% |
| Charger-to-Station Ratio | 1.09:1 | 2.35:1 | +116.5% |
| Total Installed Capacity | 25,000 kW | 80,000 kW | +220.0% |

Table 27 presents key performance indicators. While the coverage remains the same, there is a dramatic rise in early charging penalties, mirroring trends seen in the 350 kW charger use case. This is likely due to the stations not covering the increased demand at the edges of the network, resulting in early charging penalties.

Table 27: Operational Performance – 2025 vs 2030 (AFIR, 1 MW)

| **Performance Metric** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---|---|---|
| Coverage | 90.06% | 90.00% | –0.1% |
| Wait Ratio (Avg/Max) | 45.3% | 45.0% | -0.9% |
| Applied Penalties | 65 | 269 | +313.8% |
| Penalty Cost | €11.38M | €47.08M | +313.8% |

The 1MW AFIR layout demonstrates better scaling efficiency than the 350kW counterpart, with the lower percentage increase in charger count. Despite the expanded grid capacity, the network still struggles to absorb the increased demand without incurring a massive increase in early charging penalties. These results suggest that while the 1 MW network can deliver on the core demand, optimal station placement will be crucial to controlling the penalties and ensuring service quality in future scenarios.

### 5.5.3 Traffic flow layout - 350kW Chargers

Table 28 presents the core configuration parameters for the 2025 and 2030 traffic flow based layouts using 350 kW chargers. The 10 fold increase in electrification rate almost doubles the total cost. The maximum wait time remains fixed at 15 minutes and the average wait time decreases only slightly in 2030.

Table 28: Core Configuration Parameters – 2025 vs 2030 (350 kW)

| **Parameter** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---|---|---|
| Max Wait Time | 15 min | 15 min | 0% |
| Tour Average Wait | 7.07 min | 6.93 min | -2.0% |
| Total Cost | €72.02M | €134.99M | +87.4% |

Table 29 highlights the scale of infrastructure required to meet the 2030 demand. The number of stations increases by 60%, while the number of chargers quadruples. The increased Charger to Station ratio suggests higher throughput per site compared to 2025.

Table 29: Infrastructure Requirements – 2025 vs 2030 (350 kW)

| Infrastructure | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Number of Stations | 23 | 37 | +60.9% |
| Total Chargers | 51 | 205 | +302.8% |
| Charger-to-Station Ratio | 2.22:1 | 5.54:1 | +149.5% |
| Total Installed Capacity | 17,850 kW | 71,750 kW | +302.0% |

Table 30 shows the most striking performance increase. All penalties are eliminated for the 2030 configuration. Despite the significant increase in electrified trips, the system handles demand more effectively. This suggest that the 37 selected stations cover the whole network perfectly.

Table 30: Operational Performance – 2025 vs 2030 (350 kW)

| Performance Metric | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Coverage | 90.06% | 90.00% | –0.1% |
| Wait Ratio (Avg/Max) | 47.1% | 46.2% | -1.9% |
| Applied Penalties | 62 | 0 | –100% |
| Penalty Cost | €10.85M | €0.00M | –100% |

The 2030 traffic flow layout with 350 kW chargers demonstrates the advantage of demand driven optimization at scale compared to the AFIR layout. Despite the double in station count and fourfold in charger count, the model completely eliminates any early charging events while the minimal AFIR configuration penalty count increased significantly. This reflects that traffic optimized station placement more effectively aligns infrastructure with actual spacial and temporal demand patterns.

#### 5.5.4 Traffic flow layout - 1MW Chargers

Table 31 presents the core configuration parameters for the 1 MW traffic flow based layout in 2025 and 2030. Raising the fleet electrification from 0.75% to 7.5% more then doubles the total cost. The maximum wait time remains fixed while the actual average wait decreases slightly.

Table 31: Core Configuration Parameters – 2025 vs 2030 (1 MW)

| Parameter | 2025 Scenario | 2030 Scenario | Change |
|---|---|---|---|
| Mas Station Capacity | 1000 kW | 15,000 kW | +1400% |
| Max Wait Time | 15 min | 15 min | 0% |
| Tour Average Wait | 7.35 min | 7.17 min | –2.4% |
| Total Cost | €69.83M | €148.85M | +113.2% |

Table 32 highlights the infrastructure growth needed to meet the 2030 electrification goals. The number of station increases by 70% while the total charger count more than quadruples. These changes focus on a higher throughput per station.

Table 32: Infrastructure Requirements – 2025 vs 2030 (1 MW)

| **Infrastructure** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---|---|---|
| Number of Stations | 21 | 37 | +76.2% |
| Total Chargers | 21 | 86 | +309.5% |
| Charger-to-Station Ratio | 1.00:1 | 2.32:1 | +132.0% |
| Total Installed Capacity | 21,000 kW | 86,000 kW | +309.5% |

Table 33 shows strong performance gains. Penalties are nearly eliminated in the 2030 scenario with only ten remaining compared to the 57 in 2025. The reduction highlights the correct station placement and scaling with demand.

Table 33: Operational Performance – 2025 vs 2030 (1 MW)

| **Performance Metric** | **2025 Scenario** | **2030 Scenario** | **Change** |
|---|---|---|---|
| Coverage | 90.06% | 90.00% | –0.1% |
| Wait Ratio (Avg/Max) | 49.0% | 47.9% | –2.2% |
| Applied Penalties | 57 | 10 | –82.5% |
| Penalty Cost | €9.98M | €1.75M | –82.5% |

The 2030 traffic flow layout with 1 MW chargers, just like with the 350 kW chargers, confirms the effectiveness of demand driven planning under highly electrified future conditions. The reduction in penalties confirms the correct placement of these stations. Compared to the AFIR layout, this approach achieves lower wait times and dramatically better penalty outcomes, demonstrating that flexibility in station placement is critical for performance and efficiency at scale.

## 5.6 Energy Demand Curves

Figure 9 illustrates the power demand profiles at the most frequently used charging station for each scenario. The comparison reveals notable differences in station utilization patterns between the AFIR based and Traffic flow optimized layouts, as well as between the 350 kW and 1 MW charger configurations.

In the AFIR layout, the selected stations have a higher average occupation rate in three out of the four scenarios. Because AFIR hubs are spaced at larger intervals, they are fewer but larger in size. As a result, the demand at these stations is more consistent and shows smoother curves with less pronounced and frequent dips.

In contrast, in the traffic flow optimized layout, the demand curve appears more volatile. These stations, placed based on the ideal charging locations, are typically smaller and more localized. This leads to sharper peaks correlated with truck waves and a more volatile curve. The payoff for placing stations more aligned with actual vehicle behavior is more variable utilization and thus harder on the local grid.

Both station placement strategies share the same overall patterns, a strong surge with the morning fleet at dawn (6-10AM), followed by a second longer peak when trucks come home late in the afternoon . After 8PM, the demand tide retreats and remains lower until midnight in the traffic flow stations.

The impact of switching from a 350 kW charger to a 1 MW charger almost triples the instantaneous power draw when a truck plugs in, so the moment to moment demand spike becomes much higher. Because trucks charge at a higher rate, they reach their target SoC much faster. This leaves the daily energy almost unchanged. The trade of is clear, drivers gain shorter dwell times, but the grid must tolerate sharper power spikes.

In general, AFIR hubs provide more megawatt hours every day than the most heavily loaded demand driven site. In other words, concentrating capacity in a few large stations does not mean that chargers will be idle once electrification accelerates.

This comparison illustrates a key trade off: AFIR locations provide smoother station level demand curves but can be less efficient on the user level, while traffic flow based layouts are more user oriented and cost effective, but produce less consistent demand per station. Combining demand driven sites with batteries and complete energy management systems could capture the best of both worlds in 2030 and beyond.

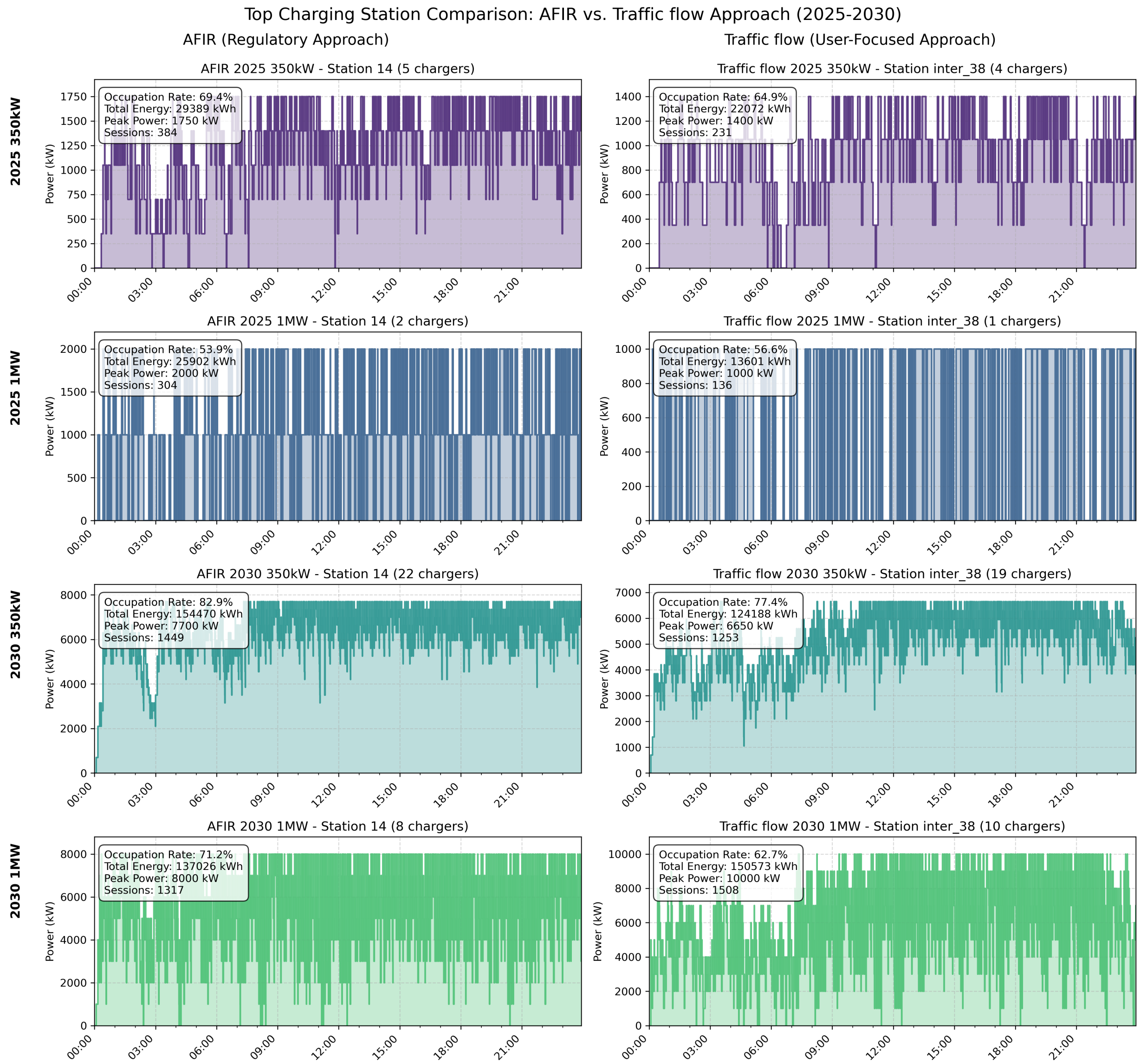


Figure 9: Power demand at the most frequently used station for each scenario

## 5.7 Spacial Comparison

This section evaluates how the spacial distribution of charging stations evolves under different planning strategies. For each scenario, the traffic layout and AFIR layout are compared. Spatial metrics are presented in structured tables and supported visually by maps. Key differences in total station count, regional spread, and co-location are analyzed to understand where the two approaches differ. The goal is to asses how well the AFIR regulation align with the real freight movement patterns captured by the traffic flow layout.

### 5.7.1 2025 - 350 kW chargers

Table 34 provides a comparison between the Traffic flow and AFIR station layout. About half of the sits are co-located, indicating that the regulatory spacing already captures many high demand areas identified by the demand driven model. These overlaps are visible as purple markers in Figure 10. A lot of remaining blue and red dots form visually distinct couples. It illustrates how the two approaches cover similar corridors but not on identical spots.

Both layouts serve the Northern corridor equally with 9 stations each. The traffic flow layout puts two extra stations to the east which makes sense because more truck traffic is recorded on the A1 and A30 routes in the east.

Table 34: Spatial comparison of charging station networks (Traffic flow vs AFIR regulation)

| **Metric** | **Traffic Flow** | **AFIR Regulation** |
|---|---|---|
| Stations Total | 21 | 20 |
| Overlapping Stations | – | 10 |
| Stations North | 9 | 9 |
| Stations East | 14 | 12 |
| Stations South | 12 | 11 |
| Stations West | 7 | 8 |

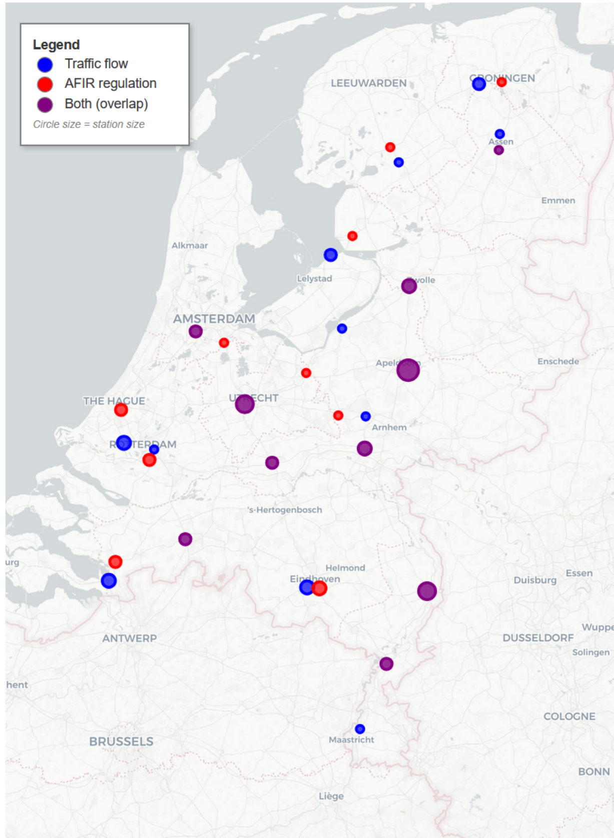


Figure 10: 2025 - 350 kW, Station location comparison Traffic flow vs AFIR

#### 5.7.2 2025 - 1 MW chargers

With 1 MW chargers, the traffic flow layout places 18 stations and the AFIR 19 35. Thirteen of those are located at the same location. So two thirds of the regulatory network now co-locates with high demand hubs. Compared with the 350 kW charger case, the stronger overlap indicates that both methods converge even more. This is because the traffic Traffic layout can meet local demand at fewer, larger hubs that often coincide with the AFIR grid.

The northern coverage remains identical. The traffic driven layout still leans a bit more east to serve the A1 and A30 route. The AFIR stations are more present in the western side. Again, red and blue couples are visible in Figure 11, although fewer then for the 350kW layout. This reinforces that the AFIR stations cover most high demand areas identified by the Traffic flow optimization.

Table 35: Spatial comparison of charging station networks (Traffic flow vs AFIR regulation, 350MW)

| **Metric** | **Traffic Flow** | **AFIR Regulation** |
|---|---|---|
| Stations Total | 18 | 19 |
| Overlapping Stations | – | 13 |
| Stations North | 8 | 8 |
| Stations East | 12 | 11 |
| Stations South | 10 | 11 |
| Stations West | 6 | 8 |

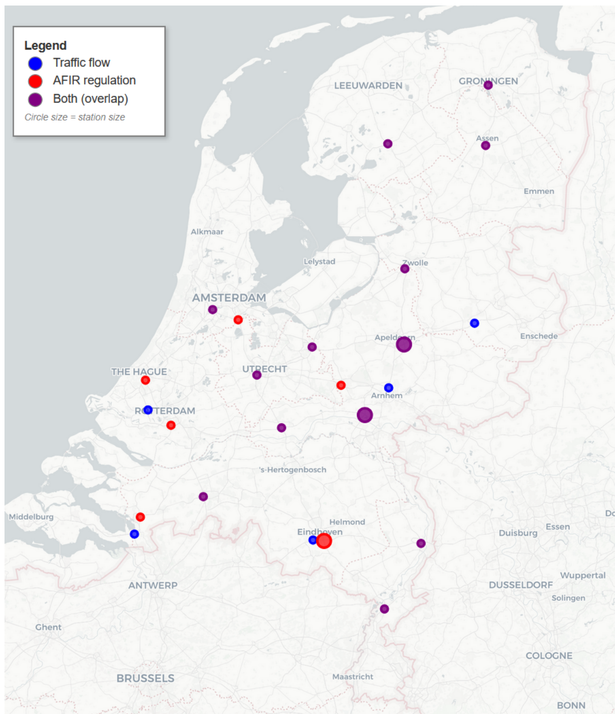


Figure 11: 2025 - 1 MW, Station location comparison Traffic flow vs AFIR

#### 5.7.3 2030 - 350 kW chargers

The traffic optimization now places 37 station, 3 more than the AFIR minimum of 34 with 350 kW stations as can be seen in Table 36. Halve of the AFIR sites are shared with the traffic flow layout. This means that as the demand increases, both strategies converge on the same power hubs.

The Northers coverage is nearly identical. East west balance has effectively evened out between the two planning layouts. The main difference is southern halve, where the traffic layout adds four sites (22 vs 18).

Table 36: Spatial comparison of charging station networks in 2030 (Traffic flow vs AFIR regulation)

| Metric | Traffic Flow | AFIR Regulation |
|---|---|---|
| Stations Total | 37 | 34 |
| Overlapping Stations | – | 18 |
| Stations North | 15 | 16 |
| Stations East | 23 | 22 |
| Stations South | 22 | 18 |
| Stations West | 14 | 12 |

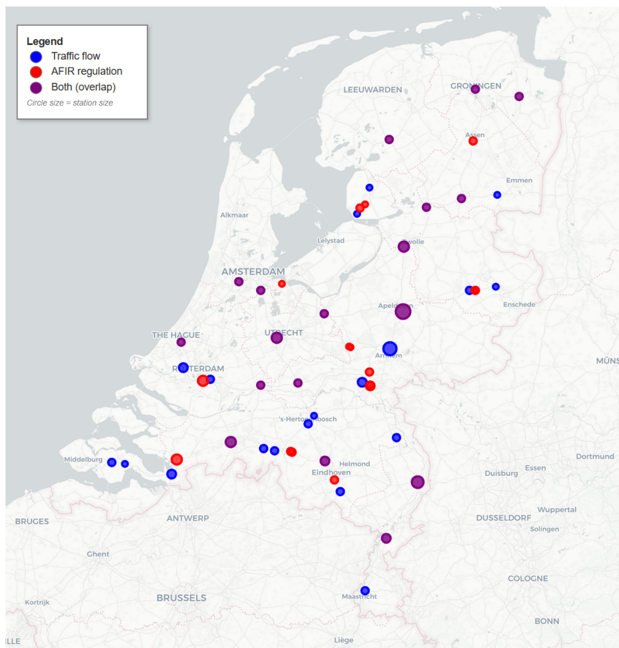


Figure 12: 2030 - 350 kW, Station location comparison Traffic flow vs AFIR

### 5.7.4 2030 - 1 MW chargers

Table 37 lists the spacial comparisons of the two charging station networks in 2030 using 1 MW chargers. Nineteen AFIR sites coincide with traffic flow locations, confirming that both approaches recognizes the densest freight charging hubs. The demand based optimization adds five extra stations in the South west corridor. These locations absorb the growth in cross border flows and avoid potential early charging penalties.

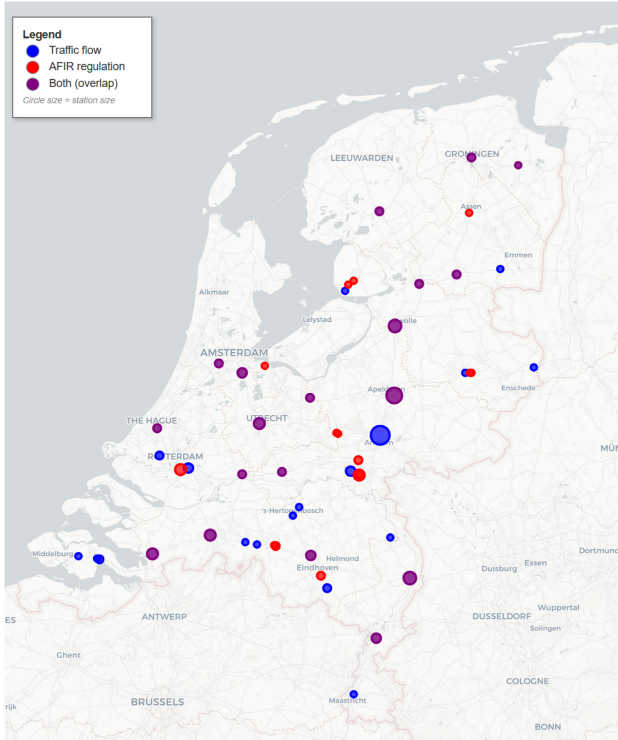


Figure 13: 2030 - 1 MW, Station location comparison Traffic flow vs AFIR

Table 37: Spatial comparison of the two charging station networks in 2030 (Traffic flow vs AFIR regulation, 1MW)

| **Metric** | **Traffic Flow** | **AFIR Regulation** |
|---|---|---|
| Stations Total | 37 | 34 |
| Overlapping Stations | – | 19 |
| Stations North | 14 | 16 |
| Stations East | 22 | 22 |
| Stations South | 23 | 18 |
| Stations West | 15 | 12 |

# 6 Conclusions and Recommendations

This study set out to model the charging demand curve at heavy-duty electric vehicle charging stations by optimizing station allocation while considering maximum wait times and grid capacity limitations. By simulating detailed truck route data and implementing a robust optimization framework, several important insights emerged.

## 6.1 Conclusions

**Secondary research questions:**

1. **How can real world truck trip data be used to simulate charging demand through SoC modeling?**

   Charging demand is simulated by calculating how much energy a truck uses during its trip. Each truck is reconstructed using GPS trajectories and given a battery size and energy consumption rate based on its type. As the trip progresses, the battery decreases. When it dips below a certain level, a charging event is created. These events include the time and location where charging likely would happen as well as the energy it would need. This method helps estimate realistic charging needs based on actual truck routes and driving patterns.

2. **What optimization method can be used to assign charging event to stations and time slots, while balancing total cost, grid limits, and wait times?**

   A Mixed-Integer Linear Programming (MILP) model is used to assign charging events to stations and time slots. The model decides which candidate station locations should be built, how many chargers of each type to install at each site, and when each truck is allowed to charge. It aims to minimize the total cost of the system, which includes the cost of building stations, installation and purchase cost of the chargers, grid connection costs, and penalty costs for events that would charge to early. These early charging penalties are characterized by needing another charging event to make it to the destination.

   The model includes several important constraints. It ensures that the total installed charging power at each station does not exceed the available grid capacity. Trucks can only be assigned to stations that are actually built, and the number of trucks charging at any given time cannot be higher than the number of available chargers. To guarantee sufficient network coverage, the model requires at least 90% of all charging events to be assigned. It also limits the total wait time per truck tour to avoid long delays. The model supports multiple charger types with different power levels, although one at a time, and allows each charging event to be assigned to one of several possible start times within a given time window.

This optimization approach helps design a cost effective charging network that meets operational needs while respecting technical limits and service quality.

3. **How do regulatory systems compare to demand driven stations layouts in terms of infrastructure cost, wait time, and scalability under different electrification scenarios?**

   In 2025, AFIR-regulated layouts achieve similar system coverage with slightly fewer stations and a marginally lower infrastructure cost. However, these savings come mainly from a longer maximum allowed wait time. Traffic flow optimized layouts, by aligning station placement with real truck movement, reduce the number of earl charging penalties and improve service quality at a slightly higher cost.

   In 2030, these differences become more pronounced. The AFIR layout relies on the minimum number of stations (34) needed to satisfy the regulatory spacing requirement. While this achieves formal compliance, it proves insufficient to absorb the increased electrified traffic. As a result, the number of early charging penalties increases more than fourfold, and overall infrastructure cost escalates significancy. Demand based layouts, which adapt placement to traffic and energy demand, nearly eliminate penalties and maintain service quality with lower total cost, demonstrating better scalability and system efficiency under higher electrification rates.

   The power demand curves reveal clear contrast between AFIR and demand based station layouts. AFIR stations show smoother and more stable usage profiles due to their larger size and wider spacing which helps distributing the demand more evenly throughout the day.

   In contrast, demand based stations exhibit sharper peaks and greater variability in station level usage. This is expected, as these stations are placed in high demand corridors and are more closely reflect actual truck behavior. While the demand is less predictable, the network operates more efficiently and delivers better overall performance.

**Primary research question: How can station locations and configurations be optimized based on simulated HDEV charging demand, considering reasonable wait times and grid limitations?**

Charging demand is estimated by simulating energy depletion and charging needs across truck routes using real world trip data and vehicle characteristics. These simulated charging events are then used as input for a MILP optimization model, which determines optimal station location and configurations. Once stations are placed, demand curves per station can be derived to evaluate utilization and performance. This integrated modeling framework enables infrastructure to be placed where and when its needed most, reducing early charging penalties, improving service quality, and optimizing resource allocation under growing electrification scenarios.

## 6.2 Recommendations

1. Extend Simulations to later future scenarios

   Future work should extend simulations to include later future scenarios beyond 2030. Thanks to DelftBlue [Delft High Performance Computing Centre (DHPC), 2024], we were able to run up to 2030 within the time constraints of this thesis. However, running and optimizing these simulations including all the preprocessing steps, is complex and could be a full research project on its own. Because future demand and technology developments are uncertain, its useful to plan for different scenarios (low, medium, high electric truck use). Future scenarios should also include possible improvements in batteries and chargers.

2. Integration of short detour re-routing

   Currently, the optimization model does not allow for minor re-routing to nearby chargers, potentially causing inefficiencies and excessive wait times at certain stations. Future work should integrate re-routing mechanisms capable of considering short detours. leveraging alternative paths from routing APIs like GraphHopper could significantly increase infrastructure utilization and service quality by distributing charging demand more evenly.

3. Include weather differences

   Future studies should incorporate the impact of weather conditions on charging needs and vehicle performance. Conditions like extreme cold, heat or rain can greatly change energy use.

4. Expansion to Cross-Border, Pan European scenarios

   While this study primarily addresses the Dutch transport network, future research should extend the simulation to a broader area.

5. Validation with Real Utilization Data
   Lastly, validating the model with empirical utilization data from existing charging infrastructure is crucial. Such validation would enhance the credibility and accuracy of the simulation results, allowing for better calibration of model parameters.

# 7 References


[Agenda, 2022] Agenda, N. C. I. (2022). Dutch national charging infrastructure agenda. Technical report, National Charging Infrastructure Authority.

[Bernard et al., 2022] Bernard, M. R., Tankou, A., Cui, H., and Ragon, P.-L. (2022). Charging solutions for battery-electric trucks. Technical report, International Council on Clean Transportation (ICCT).

[Borlaug et al., 2022] Borlaug, B., Moniot, M., Birky, A., Alexander, M., and Muratori, M. (2022). Charging needs for electric semi-trailer trucks. *Renewable and Sustainable Energy Transition*, 2. Article 100038.

[Brilliant.org contributors, 2024] Brilliant.org contributors (2024). Depth-first search (dfs). `https://brilliant.org/wiki/depth-first-search-dfs/`. Accessed: 2025-05-18.

[B.V., 2024] B.V., S. N. (2024). Tarieven 2024 elektriciteit grootverbruik.

[Cieslik and Antczak, 2023] Cieslik, W. and Antczak, W. (2023). Research of load impact on energy consumption in an electric delivery vehicle based on real driving conditions: Guidance for electrification of light-duty vehicle fleet. *Energies*, 16. Article 775.

[CleanTechnica, 2023] CleanTechnica (2023). Eu rules require ev fast-charging stations every 60 kilometers.

[Commission, 2025a] Commission, E. (2025a). Clean vehicles directive.

[Commission, 2025b] Commission, E. (2025b). Trans-european transport network (ten-t). `https://transport.ec.europa.eu/transport-themes/infrastructure-and-investment/trans-european-transport-network-ten-t_en`. Accessed: 2025-01-23.

[Company, 2023] Company, M. . (2023). Can public ev fast-charging stations be profitable in the united states?

[contributors, 2025] contributors, W. (2025). European green deal.

[Delft High Performance Computing Centre (DHPC), 2024] Delft High Performance Computing Centre (DHPC) (2024). DelftBlue Supercomputer (Phase 2). `https://www.tudelft.nl/dhpc/ark:/44463/DelftBluePhase2`.

[ElaadNL, 2025a] ElaadNL (2025a). Outlook logistiek - update 2025. Accessed: 2025-04-19.

[ElaadNL, 2025b] ElaadNL (2025b). Profielen voor logistiek – laadprofielen voor elektrische bestel- en vrachtauto's. Technical report, ElaadNL.

[EVBoosters, 2022] EVBoosters (2022). Outlook 2025: Europe's heavy-duty charging infrastructure for electric trucks.

[Federation, 2025] Federation, E. C. (2025). Levv-logic: Light electric freight vehicles in urban logistics.

[Forum, 2025] Forum, I. T. (2025). Micromobility: Policy insights and data.

[Hall and Lutsey, 2019] Hall, D. and Lutsey, N. (2019). Estimating the infrastructure needs and costs for the launch of zero-emission trucks.

[(IEA), 2024] (IEA), I. E. A. (2024). Global ev outlook 2024: Moving towards increased affordability.

[Laboratory, 2025] Laboratory, N. R. E. (2025). Electric vehicle fleet deployment guide.

[Link and Plötz, 2022] Link, S. and Plötz, P. (2022). Technical feasibility of heavy-duty battery-electric trucks for urban and regional delivery in germany—a real-world case study. *World Electr. Veh. J.*, 13(9):161.

[Mercedes-Benz, ] Mercedes-Benz. eactros 600 configurator. `https://www.mercedes-benz-trucks.com/int/en/trucks/eactros-600.html`. Accessed: 2025-04-19.

[Milence, 2025a] Milence (2025a). Fact sheet milence, january 2025.

[Milence, 2025b] Milence (2025b). Milence deploys its first megawatt charging system solution at the port of antwerp bruges.

[Morris, 2024] Morris, C. (2024). Shell opens megawatt charger for electric trucks and boats in amsterdam.

[Observatory, 2023] Observatory, A. F. (2023). European green deal: Ambitious new law agreed to deploy sufficient alternative fuels infrastructure. Accessed on January 22, 2025.

[of the European Union, 2024] of the European Union, C. (2024). Heavy-duty vehicles: Council signs off on stricter co emission standards.

[on Clean Transportation, 2023] on Clean Transportation, I. C. (2023). Global overview of government targets for phasing out internal combustion engine medium- and heavy-duty trucks.

[Plaza, 2023] Plaza, M. (2023). Shell establishes first energy hub for trucks in the netherlands.

[Rijkswaterstaat, 2024] Rijkswaterstaat (2024). Basgoed freight transport model.

[Statista, 2023] Statista (2023). Number of electric commercial vehicles in the netherlands, by vehicle type.

[TNO, 2021] TNO (2021). Duiding van het afir-voorstel op de benodigde opbouw van tank- en laadinfrastructuur in nederland. Technical report, TNO. Analysis of the AFIR proposal for the Netherlands.

[to Zero and CALSTART, 2022] to Zero, G. D. and CALSTART (2022). Global roadmap for reaching 100% zero-emission medium- and heavy-duty vehicles by 2040.

[van Cappellen et al., 2022] van Cappellen, L., Tol, E., Jongsma, C., Otten, M., and Schilling, J. (2022). Laden voor logistiek bij beperkte netcapaciteit. Technical report, CE Delft.

[Volvo, ] Volvo. Volvo electric truck specifications.

[Wood et al., 2017] Wood, E., Rames, C., Muratori, M., Raghavan, S., and Melaina, M. (2017). National plug-in electric vehicle infrastructure analysis. Technical Report NREL/TP-5400-67235, National Renewable Energy Laboratory.