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Master Thesis
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Enabling International Electric Truck Transport by Integrating Megawatt Charging Infrastructure in The Netherlands

An Agent-Based Simulation Approach

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Executive Summary

The transition towards zero-emission road freight transport is an important cornerstone of the European Union's climate strategy. Heavy-duty trucks account for 27% of carbon dioxide emission in Europe from road transport. The European Union has agreed on ambitious tailpipe emissions reduction targets for newly sold heavy-duty trucks of -90% in 2040 compared to tailpipe emissions from 2020. Battery Electric Trucks (BETs) are widely seen as a viable zero-emission alternative to diesel trucks. However, the adoption of BETs is constrained by practical limitations such as range, charging time and infrastructural availability. The introduction of the Megawatt Charging System (MCS) is expected to mitigate these barriers by enabling en-route recharging within the 45 minute mandatory truck driver breaks. This reduces the need for oversized batteries and enables long-haul trucks to go battery electric.

The Netherlands is with the largest European port one of the key locations for import and export in Europe. This means the Netherlands also has an important role to play in the transition towards BETs. The Netherlands has also set ambitious climate objectives that align with the European Green Deal. National policy aims to reduce CO_2 emissions by 60% by 2030 and achieve a fully zero-emission vehicle fleet by 2050. To meet these goals, the Dutch government is facilitating the transition to zero-emission logistics through the introduction of Zero-Emission Zones (ZEZs) in urban areas by 2025.

Current research on MCS deployment in the Netherlands is limited. While some studies provide European-level forecasts, they lack country-specific details. The only Dutch model, which is developed by Panteia, focuses solely on corridor intensity and neglects behavioral and temporal dynamics, this leaves a gap this study addresses. This study researches the placement of MCS infrastructure in the Netherlands to enable the transition towards BETs. This is done by using an agent-based simulation model. This type of model allows for individual simulation of each truck and therefore allows for more detailed behavioral patterns. The freight flows are derived from the BasGoed6 datasets which is based on real world road freight data from 2022. The candidate locations for MCS infrastructure are based on already existing Truck Parkings (TPs) and motorway service areas (VZP) in the Netherlands. To account for the current shortage of truck parking capacity, the model additionally introduces hypothetical parking location (DUMs) that represent potential future sites or areas where additional facilities would be required. The model calculates the charging behavior of the BETs and determines the charging demand for every TP and VZP.

One of the regulatory driving factors behind the exact placement of truck charging infrastructure is the Alternative Fuel Infrastructure Regulation (AFIR) of the European Union. AFIR dictates clusters of charging infrastructure to be place after every 60-100km on the TEN-T corridors. The size of the cluster needs to be atleast 1.4MW and consist of chargers with a minimal capacity of 350kW. This study however finds that individual chargers with a capacity of 350kW is insufficient to provide long-haul BETs with the opportunity to charge within the mandatory 45 minute break. Therefore, this study recommends placement of charging infrastructure of at least 800kW.

The model results provide insights into how charging demand would distribute across the dutch network over time. The first insight is about the spatial distribution of the charging demand. Charging demand is relatively clustered around truck parkings close to major freight corridors, such as the A16 corridor connecting the Port of Rotterdam to Belgium, the A67 corridor towards Venlo, and the A1/A15 connection towards Germany. This concentrates the energy demand mostly around Noord-Brabant and Gelderland followed by Zuid-Holland and Limburg. The remainder of the Netherlands also requires MCS infrastructure. However, the bulk of charging activity will occur along these major corridors. The map below illustrates how the energy demand would be distributed if 20% of all trucks were BETs.

Figure 1: Distribution of MCS locations at 20% electrification

Energy demand is intimately connected to energy grid capacity. The grid capacity in the Netherlands is currently limited and requires reinforcement to accommodate the load of MCS infrastructure. At only 20% electrification the expected daily energy demand in Noord-Brabant is already at 720,000 kWh, while Flevoland records the lowest demand with just 89.000 kWh/day. Importantly, the demand is highly concentrated within the grid zones rather than evenly spread across the province. An example is the truck parking near Venlo, the demand here is projected to reach 100.000 kWh/day, while the projected demand for Limburg in its entirety is just 430.000 kWh/day. At this scale, the site would need to be connected to the high-voltage grid rather than the medium-voltage grid. Furthermore, the energy demand is not spread over the day but concentrated at certain hours. This results in a peak energy demand of 1200 MW if the demand would be met. However, since charging infrastructure will not be build to satisfy peak demand this will be significantly lower in reality. 95% of all demand can already be met with peak loads lower than 400MW.

Currently policy makers are debating whether trucks should be allowed for longer than 4 hours at a VZP. This decision strongly influences where trucks spend the night and how charging demand is distributed. The Netherlands already faces a shortage of approximately 4,000 overnight parking spaces. Restricting overnight stays to designated TPs would shift sleeping trucks away from VZPs, increasing the pressure on TPs and increasing the parking shortage. On the positive note, this would eliminate competition between resting and charging trucks at VZP, ensuring continuous availability of MCS chargers. Therefore, the implementation of this policy is only viable if it is paired with an increase of parking space for overnight stay.

Taken together, this study demonstrates that the electrification of road freight is feasible but dependent on the alignment of infrastructure deployment, grid reinforcement and regulatory decisions. Charging demand is concentrated along major corridors, which highlight the need for a targeted deployment strategy of MCS chargers. The energy grid needs to be reinforced at specific grid zones, both the mid-voltage and high-voltage connections. Lastly, policy choices on resting areas directly impact the charging availability and should be combined by an increase of parking spaces for overnight stay.

Managementsamenvatting

De transitie naar emissievrij goederenvervoer over de weg is een belangrijke pijler van de klimaatstrategie van de Europese Unie. Zware vrachtwagens zijn goed voor 27% van de CO_2-uitstoot van het wegverkeer in Europa. De Europese Unie heeft ambitieuze reductiedoelen afgesproken voor de uitlaatemissies van nieuw verkochte zware vrachtwagens: -90% in 2040 ten opzichte van de uitlaatemissies van 2020. Battery Electric Trucks (BETs) worden breed gezien als een haalbaar emissievrij alternatief voor dieseltrucks. De adoptie van BETs wordt echter begrensd door praktische beperkingen zoals actieradius, laadtijd en beschikbaarheid van infrastructuur. De introductie van het Megawatt Charging System (MCS) zal naar verwachting deze barrières mitigeren door onderweg laden mogelijk te maken binnen de verplichte pauzes van 45 minuten voor truckchauffeurs. Dit verkleint de noodzaak van enorme batterijen en maakt het mogelijk dat langeafstands vrachtwagens volledig batterij-elektrisch kunnen rijden.

Nederland is met de grootste Europese zeehaven een van de belangrijkste landen voor import en export in Europa. Dit betekent dat Nederland ook een cruciale rol heeft in de transitie naar BETs. Nederland heeft bovendien ambitieuze klimaatdoelen vastgesteld die aansluiten op de Europese Green Deal. Nationaal beleid streeft naar een reductie van CO_2-emissies met 60% in 2030 en naar een volledig emissievrij wagenpark in 2050. Om deze doelen te bereiken faciliteert de Nederlandse overheid de transitie naar emissieloze logistiek door de introductie van Zero-Emission Zones (ZEZ's) in stedelijke gebieden vanaf 2025.

Huidig onderzoek naar MCS-uitrol in Nederland is beperkt. Hoewel enkele studies voorspellingen op Europees niveau bieden, ontbreken landspecifieke details. Het enige Nederlandse model, ontwikkeld door Panteia, richt zich uitsluitend op corridor intensiteit en negeert gedragsmatige en tijdsgebonden dynamieken. Dit veroorzaakt een kennis lacune die deze studie adresseert. Deze studie onderzoekt de plaatsing van MCS-infrastructuur in Nederland om de transitie naar BETs te ondersteunen. Dit gebeurt met behulp van een agent-based simulatie model. Dit type model maakt de simulatie van elke individuele vrachtwagen mogelijk en staat daardoor meer gedetailleerde gedragspatronen toe. De goederenstromen zijn afgeleid van de BasGoed6-dataset, gebaseerd op daadwerkelijke wegverkeers data uit 2022. De kandidaat locaties voor MCS-infrastructuur zijn gebaseerd op reeds bestaande Truckparkings (TP's) en verzorgingsplaatsen (VZP's) langs autosnelwegen in Nederland. Om rekening te houden met het huidige tekort aan vrachtwagen parkeerplaatsen introduceert het model bovendien hypothetische parkeerplaatsen (DUM's) die potentiële toekomstige locaties of gebieden vertegenwoordigen waar extra voorzieningen nodig zouden zijn. Het model berekent het laadgedrag van de BETs en bepaalt de laadvraag voor elke TP en VZP.

Een van de wettelijke drijvende factoren achter de exacte plaatsing van laadinfrastructuur voor trucks is de Alternative Fuel Infrastructure Regulation (AFIR) van de Europese Unie. AFIR schrijft voor dat clusters van laadinfrastructuur elke 60–100 km op de TEN-T-corridors worden geplaatst. De grootte van het cluster moet ten minste 1,4 MW zijn en bestaan uit laders met een minimale capaciteit van 350 kW. Deze studie constateert echter dat individuele laders met een capaciteit van 350 kW onvoldoende zijn om langeafstands BETs binnen de verplichte pauze van 45 minuten te laten laden. Daarom adviseert deze studie plaatsing van laadinfrastructuur van ten minste 800 kW.

De model resultaten geven inzicht in hoe de laadvraag zich over tijd over het Nederlandse netwerk zou verdelen. Het eerste inzicht betreft de ruimtelijke verdeling van de laadvraag. Laadvraag is relatief geclusterd rond truckparkings nabij belangrijke goederencorridors, zoals de A16 die de Haven van Rotterdam met België verbindt, de A67 richting Venlo, en de A1/A15 richting Duitsland. Hierdoor concentreert de energievraag zich vooral rond Noord-Brabant en Gelderland, gevolgd door Zuid-Holland en Limburg. De rest van Nederland heeft eveneens MCS-infrastructuur nodig, maar het grootste deel van de laad activiteit zal plaatsvinden langs deze hoofdassen. De onderstaande kaart illustreert hoe de energievraag zou worden verdeeld indien 20% van alle trucks BETs zouden zijn.

Figure 2: Verdeling van MCS-locaties bij 20% elektrificatie

Energievraag is nauw verbonden met de capaciteit van het elektriciteitsnet. De capaciteit van het net in Nederland is momenteel beperkt en vergt versterking om de belasting van MCS-infrastructuur te kunnen accommoderen. Bij slechts 20% elektrificatie bedraagt de verwachte dagelijkse energievraag in Noord-Brabant al 720.000 kWh, terwijl Flevoland de laagste vraag kent met slechts 89.000 kWh/dag. Belangrijk is dat de vraag sterk geconcentreerd is binnen netgebieden en niet gelijkmatig over de provincie is verspreid. Een voorbeeld is de truck parking nabij Venlo; de vraag daar wordt geraamd op 100.000 kWh/dag, terwijl de geraamde vraag voor heel Limburg slechts 430.000 kWh/dag is. Op deze schaal moet de locatie worden aangesloten op het hoogspanningsnet in plaats van het middenspanningsnet. Bovendien is de energievraag niet gelijkmatig over de dag verdeeld, maar geconcentreerd in bepaalde uren. Dit resulteert in een piekvermogen van 1.200 MW als volledig aan de vraag zou worden voldaan. Omdat laadinfrastructuur niet wordt geplaatst om piekvraag op te vangen, zal dit in de praktijk aanzienlijk lager uitvallen. 95% van de totale vraag kan al worden bediend met piekbelastingen onder de 400 MW.

Beleidsmakers debatteren momenteel of trucks langer dan 4 uur op een VZP mogen staan. Deze beslissing beïnvloedt sterk waar trucks overnachten en hoe de laadvraag wordt verdeeld. Nederland kampt al met een tekort van circa 4.000 overnachtingsplekken. Het beperken van overnachtingen tot aangewezen TP's zou slapende trucks van VZP's wegsturen, waardoor de druk op TP's toeneemt en het tekort aan parkeerplaatsen groeit. Positief is dat dit de concurrentie tussen rustende en ladende trucks op VZP's zou wegnemen, wat de continue beschikbaarheid van MCS-laders waarborgt. De invoering van dit beleid is daarom alleen haalbaar als het gepaard gaat met een toename van het aantal parkeerplaatsen voor overnachtingen.

Samenvattend laat deze studie zien dat elektrificatie van het goederenvervoer op de weg haalbaar is, maar afhankelijk is van de afstemming tussen de uitrol van de infrastructuur, versterking van het energienet, en beleidskeuzes. Laadvraag concentreert zich langs hoofd corridors, wat de noodzaak onderstreept van een gerichte uitrolstrategie voor MCS-laders. Het elektriciteitsnet moet op specifieke locaties worden versterkt, zowel op middenspannings- als hoogspanningsaansluitingen. Ten slotte hebben beleidskeuzes over rustplaatsen directe impact op de laad beschikbaarheid en moeten zij worden gecombineerd met een uitbreiding van het aantal parkeerplaatsen voor overnachtingen.

Contents

Nomenclature

Abbreviations

ABM	Agent-Based Model
AFIR	Alternative Fuels Infrastructure Regulation
BET	Battery-Electric Truck
CBS	Centraal Bureau voor de Statistiek (Statistics Netherlands)
CCS	Combined Charging System
DSO	Distribution System Operator (regional grid operator)
DUM	Dummy location (hypothetical charging site)
ETISplus	European Transport policy Information System (dataset)
EU	European Union
MCS	Megawatt Charging System
NDW	Nationaal Dataportaal Wegverkeer
NWB	Nationaal Wegenbestand (Dutch road network)
OD	Origin–Destination
SOC	State of Charge
TEN-T	Trans-European Transport Network
TP	Truck Parking (secured facility)
TSO	Transmission System Operator (national high-voltage grid operator)
VZP	Verzorgingsplaats (Dutch motorway rest area)
ZEZ	Zero Emission Zone

Symbols and Variables

D_{od}	Shortest path distance between origin o and destination d (m)
$P(o,d)$	Set of paths between origin o and d
$\ell(e)$	Length of edge e in the road network (m)
S_i	Score of charging station i in search algorithm
d_i	Shortest path distance to station i (m)
w_i	Estimated waiting time at station i (min)
θ_i	Directional alignment factor (1 if aligned, 3 otherwise)
t_i	Type penalty for station i (1 = real, 5 = dummy)
v	Truck speed (m/min)
E	Total energy consumption (J)
η	Drivetrain efficiency
m	Vehicle mass (kg)
α	Mass-dependent energy coefficient (J/kg)
β	Mass-independent energy consumption (J)
a	Vehicle acceleration (m/s^2)
g	Gravitational acceleration (9.81 m/s^2)
θ	Road slope angle (rad)
f_r	Rolling resistance coefficient
ρ	Air density (kg/m^3)
C_d	Aerodynamic drag coefficient
A_f	Frontal area of truck (m^2)
Δt	Simulation time step (min)

1 Introduction

The transition towards battery electric trucks (BETs) addresses an important societal challenge, reducing greenhouse gas emissions and air pollution for road freight. The challenge is part of a wider system that depends on infrastructure, grid capacity, logistics, and regulation. A major policy barrier in this context is the shortage of well-planned charging infrastructure. This creates a bottleneck for fleet electrification and raises concerns about the balance of energy demand (Herlt & Hildebrandt, 2023; Lange et al., 2024). The lack of a well-planned charging infrastructure and inaccurate grid requirement forecasting can result in an hindrance of the adoption of BETs. This would slow the progress towards sustainability targets.

This study aims to provide policy-relevant insights by identifying possible placement and configuration of the charging infrastructure using agent-based simulation. The model identifies the location and configuration by predicting the spatial and temporal charging demand of BETs. Unlike static models, agent-based simulation allows for dynamic modeling of individual truck behavior (Nguyen et al., 2021). This data-based approach can therefore be aligned with national and European climate and transport regulation. The findings of this research will support policymakers in designing regulations that ensure an efficient and scalable transition to zero-emission freight transport.

1.1 Social and Economic Relevance

The transition towards BETs is aligned with the national and European policies to reduce the greenhouse gas emissions and can be considered an important step towards achieving the sustainability goals of the Netherlands (ACEA et al., 2022; RVO, 2024). Road freight only constitutes a small portion of the total road traffic but it accounts for 27% of the road transport emissions in Europe. This makes the electrification of road freight a key priority (Speth, Sauter, & Plötz, 2022). The European Union (EU) aims that CO_2 emissions from newly registered heavy-duty vehicles to be reduced by 30% in 2030 comparison to current levels (European Parliament and the Council of the European Union, 2023). Analyses show that this is only possible when using zero emission vehicles (Breed et al., 2021). To facilitate this transition the charging infrastructure for BETs needs to be expanded across Europe. The availability of charging infrastructure is therefore crucial for this transition. Without charging infrastructure the purchase of electric trucks will not be a viable alternative for logistic providers. Insufficient charging infrastructure could lead to unexpected waiting times or detours and therefore monetary losses(Herlt & Hildebrandt, 2023; Osieczko et al., 2021)

BETs are not the only zero emission vehicle that could be considered the solution to transport emissions, fuel cell electric vehicles (FCEV) have also been suggested. FCEV produces energy by transforming hydrogen into electricity. Unfortunately, this comes with downsides, of which the most important one is the efficiency of the creation of hydrogen. The method of creating hydrogen is called electrolysis, this is the method of using electricity to split water into hydrogen and oxygen. The commercially available electrolysis method has an efficiency of 60%, resulting in a high energy loss (Burton et al., 2021).

Besides the environmental benefits there is also a significant economic potential to the electrification of road freight. BETs offer lower operational costs than diesel trucks due to reduced fuel and maintenance expenses. This makes them an increasingly attractive alternative for logistic companies (Breed et al., 2021; Link, Stephan, et al., 2024; Osieczko et al., 2021). The investment in charging infrastructure itself can also serve as a powerful economic stimulus. According to Herlt and Hildebrandt, 2023, the roll out of MCS chargers can drive job creation across construction and renewable energy. These investments can also create new business models for truck parkings (TPs).

The last challenge is to ensure equitable access of the charging infrastructure across the Netherlands. This means the creation of a well-distributed network of charging infrastructure to prevent the formation of areas inaccessible for BETs. This could provide a challenge in especially less populated rural areas (ACEA et al., 2022).

1.2 Knowledge gap

The deployment of BET charging infrastructure is a research topic that has only been approached in recent years (Alam & Guo, 2023). The importance of the research is found in the topics intersection of sustainable transportation, energy systems and logistics. Electrifying freight transport is widely regarded as an important strategy to reduce greenhouse gas emissions and dependence on fossil fuels (Herlt & Hildebrandt, 2023). However, the existing research has significant gaps in understanding the placement of charging infrastructure, especially in country specific details (Alam & Guo, 2023). Most research use a more global approach for Europe, lacking significant details such as real locations or energy grid (Bertucci et al., 2024; Shoman et al., 2023). Furthermore, most research uses a static approach instead of a dynamic approach such as agent-based modeling (ABM).

Agent-based modeling is a dynamic approach in which every truck is simulated as an individual agent. This means that decision making can be done on individual level. Therefore ABM is able to capture the complexity of logistics operations and decision-making(Lu et al., 2022; Menter et al., 2023; Mishra et al., 2022; Nguyen et al., 2021).

This study contributes to the literature by employing agent-based simulation in the Netherlands to model truck behavior.This method is uniquely suited to capture the complexity of logistics operations and individual vehicle decision-making. Unlike the static models used by previous research, agent-based approaches allow for the dynamic evaluation of truck charging demand, accounting for variables such as driving routes, human behavior, energy consumption patterns, and location constraints (Lu et al., 2022; Menter et al., 2023; Mishra et al., 2022; Nguyen et al., 2021). The integration of human behavior, grid constraints, and traffic data into the simulation further enhances its applicability and robustness, filling a gap in existing modeling frameworks. (Menter et al., 2023; Nguyen et al., 2021)

By advancing the methodology for modeling and planning electric truck charging infrastructure, this study bridges the gap between theoretical research and practical implementation. Its findings are expected to help for future research in sustainable freight transportation and contribute to achieving European Union climate targets (ACEA et al., 2022; Sauter et al., 2021).

1.3 Scope

The scope of this research is limited to the placement of megawatt-scale charging infrastructure for battery-electric trucks (BETs) within the Netherlands. The study explicitly focuses on the Dutch highway network, defined as all A-roads and a selected number of key N-roads that play an essential role in freight transport. Within this network, existing motorway service areas (VZPs) and secured truck parkings (TPs) are considered as the primary candidate locations for charging infrastructure.

The analysis is restricted to public and semi-public facilities along national freight corridors. This does not include private depots or company-owned charging sites. By doing so, the study addresses the infrastructure relevant for international long-haul transport and cross-border logistics. This is in line with European Union objectives for interoperable charging along the Trans-European Transport Network (TEN-T).

While the geographical focus is on the Netherlands, the model incorporates European logistic behavior by simulating all truck movements from or to the Netherlands. This ensures that the analysis reflects both the national infrastructure context and its role within the wider European freight system.

1.4 Research Questions

Given the gaps identified in the literature, this study aims to answer the following main research question:

Where should megawatt-scale charging infrastructure be placed in the Netherlands to best support battery electric truck transport, based on dynamic agent-based modeling?

This main question directly addresses the potential problems in the placement of charging infrastructure. However, the main question is fairly complex, to comprehensively address the main research question, the following sub-questions are formulated:

1. What are the key logistics and travel patterns of road freight trucks in the Netherlands?
2. How can policy interventions and regulatory frameworks impact the placement and utilization of charging infrastructure?
3. What are the energy demand implications of large-scale electric truck adoption?

These sub-questions ensure a structured approach by breaking down the main research question into manageable components, linking each aspect to the identified knowledge gaps and research objectives.

1.5 Case Study: MCS in The Netherlands for Battery Electric Trucks

This research focuses on the Netherlands as a case study for the placement of megawatt-scale charging infrastructure, while also including European logistic road traffic. The Netherlands is particularly suitable for a case study due to its central role in European logistics. It has some of the busiest freight corridors and ports in the EU, forming important nodes in the Trans-European Transport Network (TEN-T). Studying the Netherlands therefore provides a highly detailed national perspective with international importance.

Most existing studies approach the challenge of charging infrastructure deployment from a European perspective, which is essential for achieving cross-border interoperability. However, this leaves limited scope for capturing country-specific dynamics. For the Netherlands, the only dedicated study on megawatt charging infrastructure placement has been conducted by Panteia (Panteia, 2025). Their model employs a static corridor-based approach, allocating charging demand to existing parking facilities based on corridor traffic intensity and projected growth. While this provides valuable insights into expected demand and parking capacity, the method remains static and does not account for dynamic truck-level behavior such as route adjustments, queuing, battery status or travel times.

Given that European legislation, such as the Alternative Fuels Infrastructure Regulation (AFIR), sets mandatory minimum targets for charging infrastructure but does not specify detailed placement strategies at the national scale, there is a clear research gap (European Parliament and the Council of the European Union, 2023). This study therefore applies an agent-based simulation approach to model the individual behavior of electric trucks in the Netherlands, enabling a dynamic comparison with the existing static model of ElaadNL and Panteia. By doing so, it aims to validate and complement static corridor-based projections, identify potential mismatches, and provide actionable insights for policymakers and infrastructure planners.

In this study, the Dutch road network is defined as comprising all A-roads, supplemented by a selection of key N-roads (listed in Appendix A, Section A.4). Within this network, the Netherlands hosts 288 verzorgingsplaatsen (VZPs), motorway service areas for trucks, and 82 larger secured truck parkings (TPs). These sites are taken as the primary candidate locations for battery-electric truck (BET) charging infrastructure. Since these facilities have finite parking capacity, the model also incorporates 211 hypothetic “dummy” (DUM) locations. These represent potential additional charging sites that can be utilized when existing facilities reach their maximum capacity. Their inclusion allows the model to signal where capacity shortages may arise and to highlight the potential necessity of expanding infrastructure beyond current facilities.

2 Literature Study

Existing research on electric truck charging infrastructure primarily revolves around infrastructure placement, technical feasibility, energy grid integration, and traffic modeling, with increasing attention to policy implications and scalability. While significant progress has been made in understanding the technical and economic dimensions of charging networks, the integration of agent-based modeling (ABM) to capture real-world logistics behaviors and grid constraints remains underexplored. Research which includes the Netherlands also lacks detailed specifications of infrastructure placement. This review highlights gaps that remain in current research.

This section will begin with the search methodology employed for this research and will then delve deeper into theoretical and practical aspects surrounding the topic of MCS deployment. Starting with the methodologies typically used to study the deployment locations for MCS. Continuing into the specifics of MCS and BETs, the state and problems with energy grid integration, prognoses of BET deployment growth, policy interventions, and finally end with the usage of ABM in logistic modeling.

2.1 Search Methodology

To establish a solid foundation for this study, a systematic review of existing literature was conducted, focusing on electric truck charging infrastructure, agent-based modeling (ABM), logistics network planning, and Megawatt charging systems. The search was carried out using WorldCat TU Delft Catalogue, Scopus, and Google Scholar, chosen for their broad interdisciplinary coverage.

Queries were designed to align with the core problem of strategically planning the placement of electric truck charging infrastructure. This resulted in search terms including electric trucks, logistics, megawatt charging infrastructure, grid capacity and agent-based modeling.

Appendix A.8 contains a more in depth reconstruction of the approach.

2.2 Node-, Path-, and Tour-based Methods for planning charging infrastructure

In the context of charging infrastructure planning, three major modeling approaches are commonly distinguished: node-based, path-based, and tour-based methods. Each approach differs in how demand is represented and how charging station placement is optimized (Deb et al., 2018; Metais et al., 2022).

Node-based approaches formulate the problem as a facility location model, where charging stations are located at network nodes to cover demand (Deb et al., 2018; Metais et al., 2022). These models, such as the Set Covering Location Model (SCLM) or the Maximum Covering Location Model (MCLM), aim to ensure accessibility within a predefined distance threshold. They provide a relatively static representation of demand, making them computationally tractable and suitable for large-scale network planning. However, they may oversimplify user behavior, as they do not explicitly capture the dynamics of trip chaining or real-world driving patterns. This makes node-based a scalable approach but it assumes homogeneous demand and fails for heterogeneous truck behavior

The ElaadNL and Panteia corridor model (Panteia, 2025) is based on the traffic intensity at each corridor, the intensity determines the charging demand at the charging location (node). their model would therefore formally be considered a node-based method.

Speth, Sauter, and Plötz, 2022 and Speth, Plötz, et al., 2022 are two other examples of node-based approaches. They place charging locations for BET at regular intervals along German and European highways and use local traffic volumes as an indicator for node-based charging demand. Using a queuing model, they determine the necessary number of charging points for each location.

Path-based models focus on vehicle flows along origin–destination (OD) paths (Deb et al., 2018; Metais et al., 2022). Charging stations are placed along routes with the highest traffic intensity to maximize coverage of feasible trips. This approach explicitly accounts for range limitations and the need for en-route charging. While more realistic than node-based models in capturing mobility patterns, path-based methods are still limited in that they treat trips as independent OD pairs, neglecting the broader sequence of activities that characterize actual travel behavior.

Jochem et al., 2019 used this approach to calculate a European charging network for BETs with several hundred charging stations along the TEN-T network.

Speth et al., 2025, Sauter et al., 2021 and Lange et al., 2024 are three other papers using a path-based approach by calculating the approximately locations of charging stations across Europe.

Whitehead et al., 2021 has used GPS data from trucks to create an origin-destination matrix in Queensland Australia. GPS data would be very interesting for tour-based methods. However, this data was de-identified, therefore multiple trips could not be connected to each other and this paper also remained a path-based method.

Tour-based (or activity-based) models extend the path perspective by considering complete travel chains, including intermediate stops and dwell times (Deb et al., 2018; Metais et al., 2022). By modeling the full set of activities within a tour, these methods allow a more accurate representation of when and where charging can occur, particularly during parking opportunities. Tour-based approaches therefore capture heterogeneity in user behavior and provide a richer behavioral foundation for planning. However, they require detailed mobility data and are computationally more demanding, which can limit their applicability in large-scale studies.

Bertucci et al., 2024 is the only paper that uses a tour-based method for a case study in the Netherlands but he only uses the tours to determine optimal charging configuration at a single distribution hub in the Netherlands, not multiple charging locations.

Node-based approaches offer simplicity and scalability, path-based methods improve realism by considering trip feasibility, and tour-based approaches provide the most accurate behavioral representation at the cost of higher data and computational requirements. On the topic of BET charging infrastructure placement early research was mostly done using node-based approaches, path-based approaches have been used for newer research but tour-based approach has been underexplored.

2.3 Megawatt Charging System (MCS) specifications

The electrification of road freight trucks requires charging powers well beyond passenger vehicle fast-charging technology. The Megawatt Charging System (MCS) has emerged as the industry's standardized solution, developed under the CharIN initiative and currently being integrated into European infrastructure planning. It is specified to support charging powers up to 3.75 MW in theory (1250 V, 3000 A), enabling battery-electric trucks to recharge a substantial portion of their energy storage within the mandatory 45-minute driver rest period defined by EU regulation (European Parliament and the Council of the European Union, 2015) (CharIN, 2022; Schneider et al., 2023). Currently, the maximum achieved charging power of the MCS is capped at 1.2 MW, this is still more than enough to charge a substantial amount in the mandatory resting period (Moorthy et al., 2022). This capability makes MCS a important enabler for long-haul electrification by shortening charging duration.

MCS relies on new connector designs, enhanced thermal management, and improved electromagnetic compatibility to accommodate currents an order of magnitude higher than the Combined Charging System (CCS) (CharIN, 2022). Research further highlights that for typical one-stop driving strategies, charging powers of approximately 0.8 MW combined with battery capacities around 600 kWh are sufficient to reach parity with diesel operations, while higher charging powers mainly enable battery downsizing under multi-stop strategies (Schneider et al., 2023). System architecture concepts propose multiport stations with direct medium-voltage grid connection and integration of storage and renewable energy resources to mitigate grid load fluctuations and ensure resilience (Makoschitz, 2022; Moorthy et al., 2022). In practice, such hubs are designed to serve several trucks at once while smoothing demand on the grid through dispatch control. (Black & Veatch Corporation, 2021).

At the European level, MCS is explicitly embedded in regulatory and infrastructure roadmaps. The Alternative Fuels Infrastructure Regulation (AFIR) requires Member States to deploy high-power truck charging pools along the TEN-T network at 60 km intervals by 2030 (European Parliament and the Council of the European Union, 2023). Recent optimization studies show that a

European network of approximately 1000 MCS locations could already cover over 90% of long-haul battery truck flows by 2030, with priority given to highway intersections and major freight corridors (Lange et al., 2024). Large datasets containing truck stop and parking locations in Europe already exist, these locations are especially suitable for early MCS adoption as they are located at high intensity corridors and provide truck parking. (Link & Plötz, 2024; Speth & Plötz, 2021).

2.4 Energy Grid Integration and System Impacts

Deploying megawatt-scale charging is as much an energy system challenge as it is a logistics one. Megawatt charging systems for battery electric trucks are rated between 1 and 3.75 MW per charger, this means substation have to be connected to the medium-voltage distribution grid rather than the high-voltage transmission network. this means that regional grid operators (DSOs) such as Liander, Stedin, and Enexis in the Netherlands will play a central role in enabling the rollout of charging hubs. Current congestion in the Dutch medium-voltage grid already poses constraints for connecting new electricity demand, highlighting a key bottleneck for scaling MCS deployment (ACEA et al., 2022).

Studies consistently emphasize that unmanaged charging of electric trucks would lead to significant local grid reinforcement needs. For example, the European EV Charging Masterplan estimates that grid upgrades worth approximately €41 billion are required across Europe by 2030 to accommodate the charging demand of commercial vehicles (ACEA et al., 2022). Similarly, Makoschitz, 2022 suggest that clustered megawatt-scale charging hubs can impose peak loads exceeding the capacity of typical medium-voltage distribution transformers by factors of 2–3, underscoring the need for demand-side management and grid reinforcement. This would necessitate costly grid expansion unless load-shifting strategies are adopted.

Several strategies are proposed to mitigate these system impacts. Smart charging and energy management systems can align charging with periods of lower grid stress or higher renewable availability (Makoschitz, 2022). Furthermore, on-site energy storage and integration of local renewable energy sources can buffer load peaks and reduce grid dependency. Lastly, multiport MCS hubs are increasingly designed with modular power electronics that allow dynamic power allocation and a stable grid load profile (Moorthy et al., 2022).

At the European level, the Alternative Fuels Infrastructure Regulation (AFIR) mandates minimum power levels for publicly accessible charging pools along the TEN-T network, implicitly requiring coordination between infrastructure operators and DSOs to guarantee grid capacity (European Parliament and the Council of the European Union, 2023). Yet, the temporal and spatial mismatch between logistics demand and grid availability remains an important research gap. Existing studies largely assume sufficient connection capacity will be made available, while the real-world permitting processes and capacity constraints suggest a strong need for co-optimization between logistics planning and power system reinforcement.

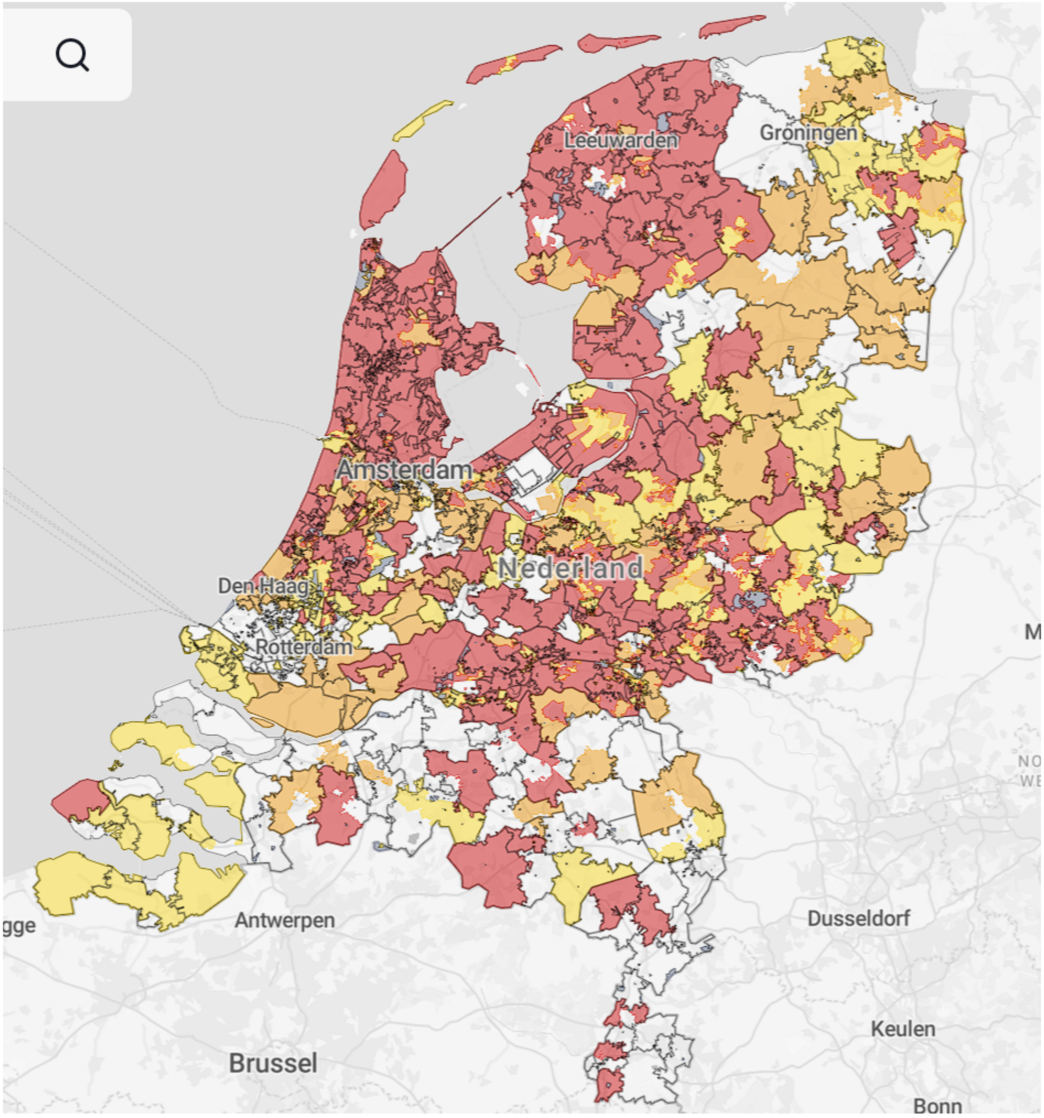


Figure 3: Current congestion in the Dutch electricity distribution grid (Netbeheer Nederland, 2025). Red areas indicate locations where no additional grid capacity is available, orange/yellow represent constrained capacity, and white areas show regions with available capacity.

The map in Figure 3 illustrates the current state of electricity grid congestion in the Netherlands at the medium-voltage level, as reported by regional distribution system operators (DSOs). Large parts of the country, particularly in the Randstad (except Port of Rotterdam), the northern provinces, and along major logistics corridors, are marked in red, indicating that no new large-scale connections can currently be made. Orange and yellow regions represent partial constraints, where limited capacity remains available. White areas show unconstrained grid zones.

This situation demonstrates an important bottleneck for the rollout of megawatt-scale charging infrastructure. Since multi-megawatt charging stations are typically connected to the medium-voltage grid, they depend directly on DSO capacity. The prevalence of congestion implies that the siting of charging infrastructure cannot be determined by logistics factors alone but must also consider local grid availability. In practice, this means that alignment between transport planning and grid reinforcement is essential: locations with the highest transport demand may coincide with some of the most grid-constrained regions, delaying implementation unless smart charging, on-site storage, or grid upgrades are introduced.

2.5 Policy, Regulation, and Governance

The roll out of megawatt-scale charging infrastructure is shaped not only by technology and grid capacity, but also by the regulatory framework that governs its deployment. Policy plays a decisive role in setting minimum infrastructure requirements, coordinating cross-border networks, and ensuring interoperability across manufacturers and operators.

At the European level, the Alternative Fuels Infrastructure Regulation (AFIR), adopted in 2023, sets binding targets for the deployment of heavy-duty charging infrastructure along the TEN-T corridors (European Parliament and the Council of the European Union, 2023). Specifically, it mandates that by 2030 publicly accessible charging pools of at least 1.4 MW must be installed every 60 km on the TEN-T core network, with individual recharging points capable of delivering at least 350 kW. This represents a major shift from the previous directive framework, as Member States are now legally required to deliver minimum levels of charging capacity. AFIR thereby provides legal certainty for investors and operators, but also places significant pressure on distribution system operators (DSOs) and governments to resolve existing grid congestion before the 2030 deadline. AFIR sets minimum criteria for European wide implementation but no strategies for site locations.

Additional European legislation further accelerates the transition towards zero-emission freight transport. Regulation (EU) 2019/1242 sets CO_2 emission performance standards for new heavy-duty vehicles, requiring a 15% reduction by 2025 and a 30% reduction by 2030 compared to 2019 levels (European Parliament and the Council of the European Union, 2019). These targets create direct demand for zero-emission trucks and high-power charging infrastructure. EU Directive 96/53/EC also provides a weight allowance of up to 2 tonnes for zero-emission trucks to partially offset the penalty of the additional battery weight (European Parliament and the Council of the European Union, 2019). Earlier legislative frameworks on trucker rules, such as Regulation (EU) No 561/2006 on driving and rest times, continue to influence the temporal and spatial pattern of charging demand, as they define mandatory 45-minute breaks every 4.5 hours of driving (European Parliament and the Council of the European Union, 2015). This regulation effectively aligns the technical capabilities of MCS with existing rest schedules.

National policies also affect the feasibility of integrating charging and rest. The Netherlands has had experiments with a restricted parking duration at resting areas (VZP) of four hours (Klem, 2022). This experiment is also rumored to be implemented in the future. While intended to optimize parking availability, these restrictions could constrain the ability of drivers to combine long rest periods with overnight charging, potentially reducing the attractiveness of certain sites for MCS deployment.

A further governance instrument that directly shapes the uptake of zero-emission trucks and associated charging infrastructure is the introduction of Zero Emission Zones (ZEZs) for urban logistics. In the Netherlands, more than 30 municipalities, including The Hague, Rotterdam, and Amsterdam, plan to implement ZEZs by 2025, banning access for conventionally fueled delivery trucks and requiring zero-emission vehicles for city logistics (Bertucci et al., 2024). These zones are embedded in the national Climate Agreement, which mandates that all new delivery vehicles entering urban ZEZs must be zero-emission from 2025 onwards. The ZEZ policy therefore accelerates the demand for battery-electric trucks (BETs) and amplifies the urgency for charging hubs both in urban areas and along key freight corridors. While ZEZs primarily target last-mile and distribution vehicles, they have spillover effects for long-haul transport. Fleet operators increasingly require interoperable charging infrastructure that allows seamless operation across ZEZ-compliant cities and long-distance corridors.

Several strategic roadmaps complement these legislative foundations. The European EV Charging Masterplan estimates that approximately 40000 fast charging points for trucks and buses are needed by 2030, with around 51 fast chargers per 100 km on the core TEN-T corridors (ACEA et al., 2022). Similarly, McKinsey projects that more than 300,000 charging points for medium- and heavy-duty vehicles will be required across Europe by 2030, demanding capital investments of €7 billion by that date (Herlt & Hildebrandt, 2023). These projections emphasize the scale of coordinated action required among fleet operators, infrastructure providers, financial institutions, and regulators.

Governance challenges arise at multiple levels. First, coordination is needed between European policy and national implementation strategies, which vary in ambition and speed. Second, harmonization of technical standards such as the Megawatt Charging System (MCS) is important to prevent fragmentation of the European freight transport network (CharIN, 2022). Third, the regulatory frameworks for grid access and permitting differ across Member States, with long waiting times for grid connections frequently cited as a barrier (Lange et al., 2024). Finally, governance extends to operational aspects, such as ensuring nondiscriminatory access to public charging stations, transparent pricing mechanisms, and interoperability of payment systems.

2.6 Battery-Electric Trucks (BETs)

The technological readiness and economic competitiveness of battery-electric trucks (BETs) are key determinants of charging infrastructure demand. While the first commercial models have been introduced by major manufacturers such as Volvo, Daimler, and MAN, the large-scale adoption of BETs depends on vehicle range, battery cost trajectories, payload implications, and operational suitability across logistics segments.

BETs require significantly larger battery capacities than passenger cars due to their weight and duty cycles. Early studies suggest that urban and regional trucks can operate effectively with 200–400 kWh battery packs, while long-haul trucks typically require 600–1000 kWh to cover daily distances of 400–800 km (Galassi & Rapone, 2021; Osieczko et al., 2021). This results in vehicle weights several tonnes higher than comparable diesel trucks, reducing payload capacity and influencing vehicle economics. Nevertheless, EU Directive 96/53/EC provides a weight allowance of up to 2 tonnes for zero-emission trucks to partially offset this penalty (European Parliament and the Council of the European Union, 2019).

Energy consumption for BETs varies considerably by context. Typical values for long-haul trucks range between 1.1 and 2.0 kWh/km, implying daily energy demands of up to 1,000 kWh for a 40-ton vehicle (Mareev et al., 2017). Urban distribution shows lower and more predictable demand, though traffic conditions such as stop-and-go patterns can significantly increase consumption (Basso et al., 2019; Mamarikas et al., 2022).

The economic viability of BETs is strongly linked to the trajectory of battery costs. Recent analysis shows that the cost of lithium-ion batteries for heavy-duty applications has declined by over 80% since 2010, and is expected to fall below $200 per kWh by 2030 (Link, Stephan, et al., 2024). Lower battery costs improve the total cost of ownership parity with diesel trucks, particularly in segments with high utilization rates and predictable routes. Moreover, BETs benefit from lower maintenance costs and higher drivetrain efficiency, although their capital costs remain substantially higher in the short term.

Operationally, BET adoption varies strongly by use case. Urban and regional distribution are considered early adopters due to shorter and more predictable routes, depot charging opportunities, and alignment with zero-emission zone (ZEZ) policies in European cities (Bertucci et al., 2024; Herlt & Hildebrandt, 2023). By contrast, long-haul applications face greater barriers: limited range, charging downtime, and the need for high-power en-route charging infrastructure. Here, the Megawatt Charging System (MCS) is viewed as an important enabler, as it allows trucks to recharge during the 45-minute mandatory rest breaks required by EU law (Schneider et al., 2023).

Fleet transition dynamics are further influenced by the logistics industry structure and regulatory pressure. The regulatory pressure coming from the EU CO_2 standards for heavy-duty vehicles mandate transition towards zero emission trucks (European Parliament and the Council of the European Union, 2019). At the same time, the industry exists out of a lot of small operators, which makes investments into zero emission trucks more risk-sensitive (Osieczko et al., 2021). The heterogeneity of the industry implies that large operators with capital and private charging depots may electrify earlier, while small hauliers may delay adoption until public MCS networks are established.

2.7 Projected Adoption of Battery-Electric Trucks

The large-scale deployment of charging infrastructure is tightly linked to the market uptake of BETs. Recent projections from ElaadNL's Outlook Logistiek 2025Q1 provide scenario-based estimates of BET adoption through 2050. The Dutch truck fleet currently numbers about 165000 vehicles and is expected to remain relatively stable, reaching approximately 173000 by 2050 (ElaadNL, 2025).

In the updated outlook, early adoption has been revised downwards compared to previous forecasts due to delays in manufacturer rollouts and the initially smaller impact of zero-emission zones. Nevertheless, BET penetration is expected to accelerate significantly in the 2030s, driven by stricter

EU CO_2 standards, national subsidy schemes, and the declining total cost of ownership relative to diesel.

The scenarios show strong growth trajectories:

- In the **low scenario**, BETs account for only 6% of the fleet in 2030 but grow to 76% by 2050.
- In the **medium scenario**, 15% of trucks are electric by 2030, increasing to 85% by 2050.
- In the **high scenario**, uptake reaches 18% in 2030 and 94% in 2050.

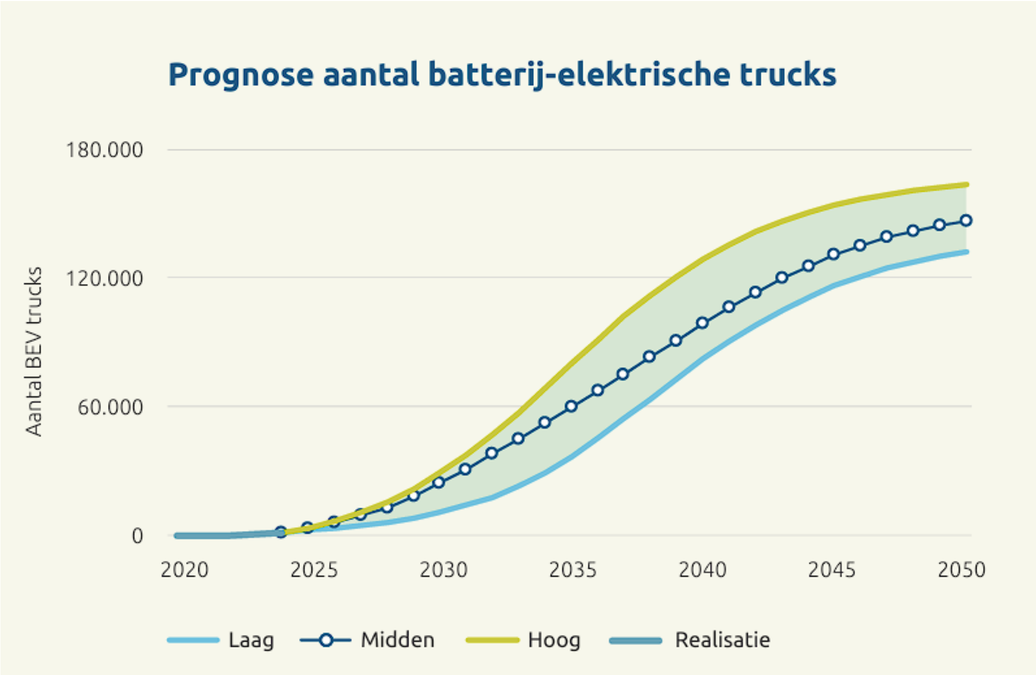


Figure 4: Prognosis ElaadNL for BET's in the Netherlands (ElaadNL, 2025)

In absolute terms, this translates to approximately 24000-29000 battery-electric trucks on Dutch roads by 2030, depending on the scenario, rising to 132000–164000 vehicles by 2050 (ElaadNL, 2025). Across all scenarios, hydrogen trucks play only a marginal role due to persistently high fuel costs, with BETs expected to dominate the heavy-duty zero-emission segment.

These projections underline that while short-term adoption will remain modest, long-term electrification of the truck fleet is virtually inevitable. This reinforces the urgency of aligning charging infrastructure planning with expected uptake curves. Even the low scenario implies a multi-decade ramp-up requiring widespread corridor and depot-based megawatt charging infrastructure.

2.8 Logistic Modeling and Agent-Based Modeling (ABM)

logistic modeling is central to evaluating the placement and utilization of charging infrastructure, since the spatial and temporal distribution of truck flows determines charging demand. Traditional approaches rely on aggregate traffic assignment or origin–destination (OD) models, which estimate flows between regions and assign them to network paths. While these methods are computationally efficient and suitable for large-scale planning, they often fail to capture the heterogeneity of logistics operations, such as variations in departure times, delivery schedules, and driver behavior (Nguyen et al., 2021).

Agent-Based Modeling (ABM) has been proposed as a complementary approach that addresses these shortcomings. In ABM, individual vehicles, drivers, or companies are modeled as agents with decision-making rules, interacting within a simulated transport network. This enables the explicit representation of logistics processes such as tour chaining, time-dependent driving speed, variable energy consumption , and time-dependent routing. By capturing the micro-level behaviors that aggregate models abstract away, ABM provides a detailed basis for analyzing when, where, and how trucks will require charging (Galassi & Rapone, 2021).

At the same time, ABM comes with challenges. Models require highly detailed data on trips, tours, and logistics chains, which are often proprietary or incomplete. They are also computationally intensive, limiting scalability to region or small national levels compared to aggregate OD approaches (Nguyen et al., 2021). Consequently, much of the literature still applies node- or path-based methods at large scale, while ABM remains primarily used in regional or case-specific studies.

Several recent studies have applied ABM specifically to freight transport and charging. Mishra et al., 2022 outline a conceptual framework for agent-based transport models, emphasizing the requirements for data granularity, behavioral realism, and scalability. Their work shows how ABM can capture the interactions between infrastructure, vehicles, and users in ways that aggregate models cannot. Building on this, Bertucci et al., 2024 use an ABM to optimize charging infrastructure and fleet operations for battery-electric trucks for a single distribution hub in the Netherlands, showing how agent-based simulation can reflect operational constraints such as delivery schedules, battery capacities, and grid limits. On a larger scale, Lu et al., 2022 develop a long-haul freight transport model for Germany, where freight agents represent daily truck movements across the national network based on NUTS3-level flow data. Their model generates nearly one million long-haul truck trips per day and can be used as a foundation for logistic ABM models.

2.9 Stakeholders Integration MCS Infrastructure

The integration of MCS infrastructure is a complex problem influenced by many stakeholders. To illustrate the influence and interest of these stakeholders a Power-Interest (PI) grid was created. The four quarters in the PI-grid give an indication of the actions required for each organization involved. Organizations within the high-power but low-interest quarter require to be kept in the loop and satisfied, these organizations should be dealt with cautiously as they hold power but there interest is not necessarily aligned. Organizations in the high-interest, high-power quarter have the largest impact on the projects success and require close communication and cooperation. Organizations in the high-interest, low-power quarter are often very insightful and can be an important help in the roll out. Lastly, organizations in the low-power, low-interest quarter require no excessive communication. The PI-grid for the integration of MCS infrastructure can be found below in figure 5.

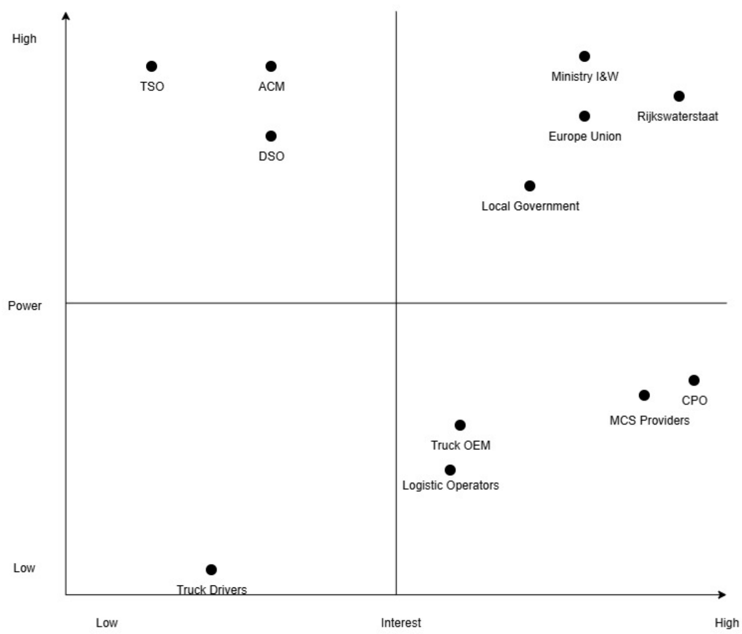


Figure 5: Stakeholder Power-Interest Grid for the integration of MCS infrastructure

The organizations are divided into the four quarters as follows:

High-interest, High-power

- **Rijkswaterstaat** is the administrative organization of the Ministry of Infrastructure and Water Management and is directly responsible for the management of VZP. Therefore, they dictate how the parking spaces at 288 VZP are allocated. This means they have the power to influence the pace in which MCS is rolled out by using MCS in their VZP configurations or not. As Rijkswaterstaat is also responsible for the safety, traffic flow and parking capacity. This means their responsibilities are intertwined with with the integration of MCS, combined with their high power this makes them an crucial actor within this development.
- **The Ministry of Infrastructure and Water Management (I&W)** defines the rules to which the integration of MCS infrastructure should adhere. There interest lies with improving the sustainability of the mobility sector without interrupting the traffic flow and safety. As they have a broad selection of interests and there involvement is less operational their interest are considered lower than Rijkswaterstaat which is operationally involved as well.
- **European Union** dictates the rules to which the Ministry of I&W should adhere. They have an interest in the increased sustainability of Europe as a whole but are not involved in the details of this operation.
- **Local Government**, such as municipalities and provinces, control the zoning plans and building permits around each parking location. Therefore, they need to approve all the development plans surrounding the realization of the MCS infrastructure. This makes them an important organization that requires substantial cooperation.

High-interest, Low-power

- **MCS providers** such as Kempower or ABB Group hold a high interest in the development of MCS as this is the main driving factor behind their sales. Their production capacity can hinder or increase the roll out pace of MCS infrastructure but ultimately they are dependent on Parking Operators such as Rijkswaterstaat for the demand.
- **Charging Point Operators (CPOs)** their business model is dependent on MCS and older versions such as CCS. This makes them highly interested in the development but ultimately they are also dependent on the demand.
- **Truck OEMs** are responsible for the development of trucks capable of using MCS. As their interests follows the interest of the truck market, their interest are aligned with the demand. Without development of MCS capable trucks the truck technology could be lagging behind and slowing down the integration of MCS.
- **Logistic Operators** can benefit from the integration of MCS infrastructure as the operational costs of BETs are lower than the operational costs of conventional trucks (Link, Stephan, et al., 2024). As the primary users of BETs and MCS infrastructure they will have an influence of the pace of the roll out.

Low-interest, High-power

- **The transmission system operator (TSO)** are responsible for the maintenance and development of the High voltage network. TSO in the Netherlands is TenneT and they therefore carry this responsibility. The high-voltage network is required for the connection and expansion of the mid-voltage network, without the expansion of the high-voltage network the mid-voltage network is limited in its capacity. The lack of capacity could cripple the entire MCS roll out. Since MCS is just one of the many usages of the energy network the interest of TenneT is not particularly high. However, their involvement is crucial in the successful integration of MCS infrastructure.
- **Distribution System Operator (DSO)** oversee the maintenance and development of the mid-voltage network. The Netherlands has multiple DSOs such as Stedin, Liander, Enexis etc. MCS infrastructure is directly connected to the mid-voltage grid, DSOs therefore have an higher interest in MCS than TenneT. However, as DSOs are dependent on TenneT for the expansion of their capacity, DSO hold less power. However, a lack of DSO cooperation or expansion will significantly impact the integration of MCS infrastructure in the Netherlands.

- **Authority for Consumers and Markets (ACM)** holds the power to prioritize projects on the power grid. Generally the Netherlands holds a First in First out (FIFO) approach to connecting to the power grid. However, certain projects such as hospitals can gain priority. ACM is the organization which determines whether a project falls under the priority or not. This means the ACM holds to power to significantly boost the roll out of MCS infrastructure.

3 Methodology

3.1 Research Design

The research design provides the overall structure through which the objectives of this study are addressed. It defines the logical sequence that connects the research questions to the data collection, modeling approach, analysis, and conclusions. This thesis follows a model-based research design, in which empirical insights, conceptual modeling, and computational experimentation are integrated to study the spatial and behavioral dynamics of MCS deployment for BETs in the Netherlands.

The study combines elements of exploratory and quantitative research. It is exploratory in identifying the relevant infrastructural, behavioral, and policy factors that influence MCS adoption. It is quantitative in testing the effects of these factors through agent-based simulation. The design is iterative and cyclic, meaning that insights from each phase inform subsequent refinements of both the conceptual model and the empirical assumptions.

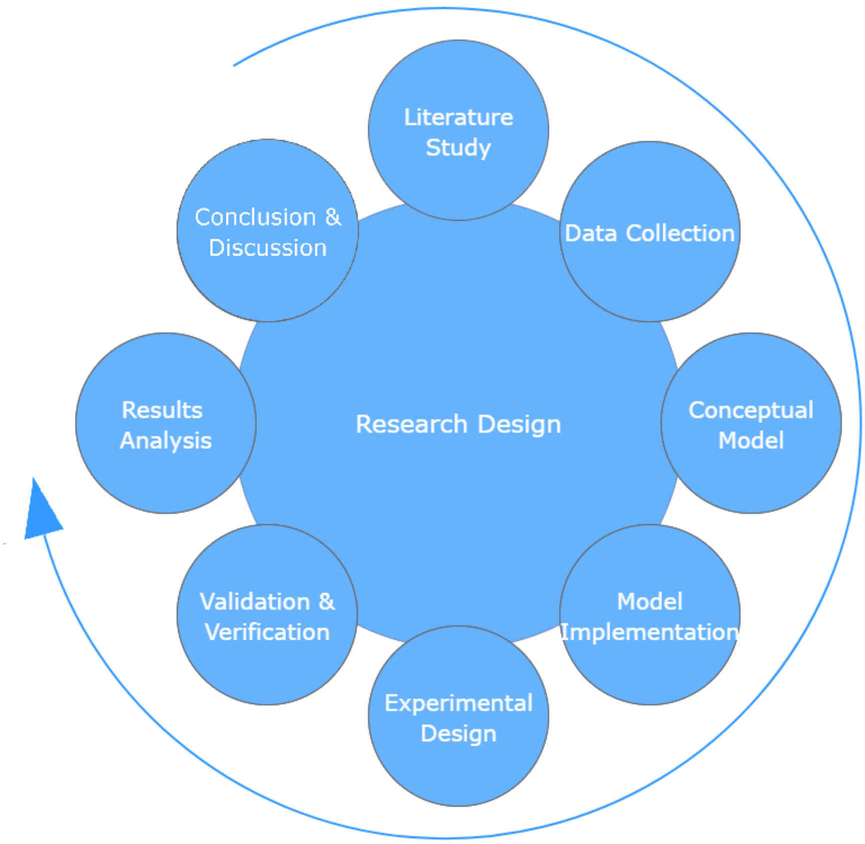


Figure 6: Research Design

As illustrated in Figure 6, the research process consists of eight phases.

1. **Literature Study** is used to establish the theoretical and technological foundations of MCS and truck electrification.
2. **Data Collection** and preprocessing of empirical freight, road network, and truck stop data are required for the use in the agent-based model.
3. **Conceptual Model** describes the behavior for the truck agents and the infrastructure, including assumptions used.
4. **Model Implementation** explains how the agent-based simulation was created and which software was used.
5. **Experimental Design** describes the scenarios written and the parameters chosen for the sensitivity analysis.

6. **Validation and Verification** of the model by comparing simulated outcomes with empirical data and theoretical expectations.

7. **Results Analysis** interprets the outcomes of the scenarios and policies.

8. **Conclusion and Discussion** outline the main findings, acknowledge model limitations, and provide recommendations for future research and practical implementation.

This iterative approach ensures that each stage contributes to a progressively more accurate representation of battery electric road freight transport. The conceptual model establishes behavioral patterns to which trucks should adhere, while the empirical data can be used for verification of this behavior. The combination of results and discussion ensure that the expectations are also compared to the results.

3.2 Data Required

This design requires an extensive amount of data to be able to correctly simulate road freight transport and truck behavior. Section 4.4.2 contains the full details of data processed and used in the model. The data used can be categorized in three parts:

1. **Environment:** This contains the road network and existing parking infrastructure. This data is required for the agents to interact with.

2. **Behavioral Patterns:** This includes behavior of trucks such as departure times and their average speed profiles.

3. **Logistic Patterns:** specifically a tour dataset that is similar to the tours made daily by trucks.

Together this data can be used to create a simulation environment that represent a simplified version of the road freight transport in the Netherlands. By the inclusion of additional behavior for charging the model can be transformed into a model that estimates charging demand and can be used for exploratory research into this subject.

3.3 Analysis Method

The goal of the result analysis is to be able to make statements and recommendations about the main research question (MQ):

"Where should megawatt-scale charging infrastructure be placed in the Netherlands to best support international electric truck transport, based on dynamic agent-based modeling?"

This can be done by answering the sub-questions which were formulated in section 1.4.

SQ1: What are the key logistics and travel patterns of road freight trucks in the Netherlands?

To find the key logistics and travel patterns this research will perform a spatial and statistical analysis on a combinations of datasets. Eurostat and CBS have datasets that provide intel on the country to country flow of road freight trucks. NDW has datasets that contain the intensity of trucks across corridors. The Logistic Road Freight module of Basgoed6 contains the daily tours of trucks for 5 working days in the year 2022. Together these datasets contain enough information to recreate the traffic flow of road freight trucks in the Netherlands and to validate the model.

SQ2: How can policy interventions and regulatory frameworks impact the placement and utilization of charging infrastructure?

Policy and regulatory effects are evaluated by running targeted scenarios in the agent-based model. For the first scenario the rules for sleeping overnight at motorway service areas (VZP) will be prohibited. The second scenario will deploy not just MCS but the CCS charging technology as well. These changes are implemented as location constraints and capacity settings in the model. Results are compared on max-users per location and the extent of unmet charging demand in the form of dummy locations.

SQ3: What are the energy demand implications of large-scale electric truck adoption?

To determine the energy demand implications of the electric truck adoption this research will analyze simulation outputs. The Charging logs generated by the ABM provide spatial and temporal kWh demand overview. These are aggregated per region in the Netherlands, and converted to load curves at different penetration levels. To ensure accuracy, assumptions on truck battery sizes and charging powers will be consistent with current literature. Grid-related implications will be assessed by mapping charging hotspots against medium-voltage grid accessibility in the Netherlands. This produces a quantitative outlook of energy demand intensity and grid stress under progressive electrification.

3.4 Model Validation and Verification

Model verification and validation ensure that the agent-based model produces reliable and interpretable results. Verification focuses on the internal consistency of the model and the correct implementation of its logic, while validation examines whether the model outcomes align with empirical and theoretical expectations.

First, the datasets were validated by cross-checking the processed freight that crosses the borders with data from CBS and Eurostat. This ensures that the directional flow of trucks matches the expected flows.

Second, sensitivity testing was used to verify the model behavior and its robustness. The sensitivity analysis tests how key parameters affect the key performance indicators selected in section 4.3. These results are verified by comparing them to the expected behavior, the magnitude of the effects is also interesting for further recommendations.

Furthermore, as the searching algorithm (section 4.5.1) was not taken from previous research but developed during this thesis. A small analysis was performed to check which value for the directional threshold would be most fitting.

Finally, the stochastic variability was verified by running multiple simulations with different random seeds. The variation between these seeds was measured to see if seed differences significantly influences the model. This was done to determine whether the amount of seeds in the scenarios was enough to gain significant results.

3.5 Modeling Approach

This research employs an agent-based modeling approach to explore the spatial and behavioral effects of truck charging. ABM is suited for system in which emerge from lots of interactions of heterogeneous agents. In the case of BET charging it is the interactions between individual trucks, charging locations and the road network. To explain the modeling approach in greater detail, the ODD protocol has been used in the next section 4. The ODD protocol (Overview, Design Concepts, Details) provides a structured way to present a complete overview of the model (Grimm et al., 2020).

4 Agent-based Model

The link to the entire python code for the model can be found in appendix A.1

This Section presents the agent-based model (ABM) developed to simulate the behavior of electric freight trucks and their interaction with charging infrastructure. The aim of the model is to explore how spatial availability of chargers and individual truck behavior influence charging demand patterns under varying infrastructural and behavioral scenarios.

To ensure transparency and reproducibility, this model description follows the ODD protocol (Overview, Design concepts, Details) (Grimm et al., 2020). The ODD framework is a widely used standard for documenting agent-based models across disciplines. It provides a structured way to present the purpose of the model, the entities and processes it includes, the underlying design concepts, and the technical details of implementation. By following this protocol the model should be easily reproducible by other researchers.

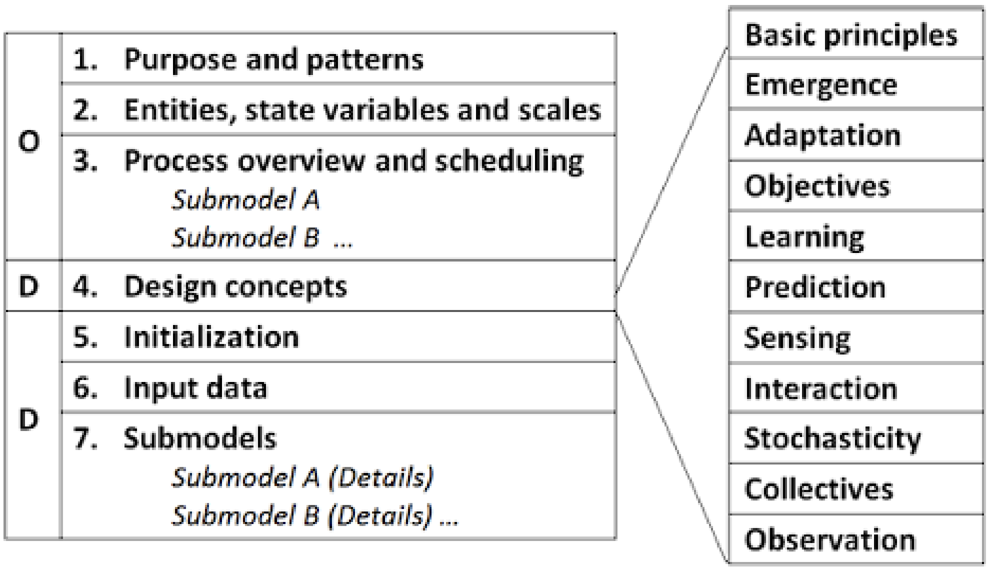


Figure 7: Structure of model descriptions following the ODD protocol (Grimm et al., 2020)

4.1 Overview

4.1.1 Purpose and patterns

The purpose of the agent-based model is to investigate where MCS infrastructure should be located in the Netherlands to support international BET transport. The model is designed to reproduce the spatial and temporal dynamics of freight movements and charging demand under European driving regulations. By simulating individual truck behavior, including routing, energy consumption, rest breaks, and charging choices, the model allows the assessment of infrastructure performance, such as utilization, queuing, and energy demand. The overarching goal is to provide decision support for planning charging locations that minimize logistics disruptions while aligning with regulatory, technical, and operational constraints.

4.1.2 Model Boundaries

The model is designed to analyze the deployment and utilization of megawatt charging infrastructure (MCS) for BETs in the Netherlands, in the context of national and international freight transport. Its boundaries are defined as follows:

- **Spatial scope:**
  - The network includes the Dutch highway system (A-roads) and a select few N-roads which can be found in appendix A.4.

- motorway service areas (VZP) and truck parkings (TP) are directly connected with the highway system
- International load and unload points are directly connected to border nodes in the Netherlands and have the Euclidean distance as length

- **Temporal scope:**
  - The model simulates truck movements and charging decisions over a period of five working days.
  - The model runs in time steps of 1 minute.
- **Agents:**
  - Only battery-electric trucks are simulated, this includes long and short haul.
  - Other powertrains (diesel, fuel cell) are excluded, except in traffic jams which are imitated.
  - Truck drivers are indirectly modeled through regulatory rest and driving time constraints which they strictly adhere to (**european_parlement_european_legislative_2015_trucker_rules_2**
- **Environment:**
  - VZP and TP are based on already realized locations, DUM are hypothetic to indicate lack of supply.
  - Grid capacity constraints are excluded at charging locations except in a special scenario.
  - Depot charging is only included at start and end locations.

4.1.3 Entities, state variables and scales

The primary entities in the model are BETs, charging infrastructure, and the road network environment.

- **Battery-electric trucks (agents)** are autonomous decision-making entities. Each truck is characterized by dynamic state variables such as state of charge (SOC), driving speed, location, energy consumption and route. Static attributes include maximum battery capacity and search threshold.
- **Charging infrastructure** consists of fixed nodes representing parking locations which can have megawatt-scale charging stations. Each location has a defined number of max charging points and queuing capacity. three types of sites are modeled: small resting areas (VZP), truck parking (TPs) locations that also allow overnight rest, and dummy locations which are not real but are used to indicate the need for new locations.
- **Load/Unload points** are fixed origins and destinations of trips, defining freight demand in the network.
- **Road network** forms the environment through which trucks travel, represented as a graph of links and nodes with associated distances and road type classifications. The road network consists out of all A-roads and a few important N-roads, the N-roads are specified in appendix A section A.4.

In Appendix A.5 figure 34 an extensive list can be found with all variables that influence the model, trucks and the locations.

The temporal scale of the simulation is one-minute timesteps, chosen to accurately present charging durations and compliance with European driving and rest regulations. The spatial scale is the Dutch national road network, including major highways and selected N-roads relevant for freight traffic. European freight traffic to or from the Netherlands is simulated but the European road network is simplified and uses euclidean distances. The simulation horizon spans five workdays to reproduce realistic tour patterns and charging demand distributions.

4.2 Design concepts

The ODD protocol prescribes that design concepts should capture the key modeling ideas that explain why and how the system behaves as it does. They clarify which mechanisms are explicitly modeled, which outcomes emerge indirectly, and which simplifications are made.

- **Basic principles:** Truck behavior follows European regulations on driving and rest periods (European Parliament and the Council of the European Union, 2015), physical constraints of battery-electric trucks such as battery size and speed, and constraints on max charging speed for chargers. Decisions and behavior are mainly rule-based but departure time and routes picked are stochastic, supported by deterministic variation in travel speed and behavior.
- **Emergence:** Outcomes in the model, such as where charging demand concentrates and station occupation rate are not programmed directly. Instead, they result from the combined behavior of many individual trucks making their own decisions about when and where to stop.
- **Adaptation:** Trucks adapt their routes when working time or state-of-charge (SOC) thresholds are reached. Agents may divert to alternative charging sites when necessary, balancing detour distance and queue length.
- **Objectives:** Agents seek to complete their assigned tours while minimizing detours, waiting time, and while remaining compliant with rest-time regulations.
- **Learning:** The model does not include learning mechanisms. Each agent reacts only to its current state and environment; behavior does not evolve over repeated tours.
- **Prediction:** Agents are assumed to have full knowledge of the road network and real-time charger availability. This simplification reflects anticipated digitization of logistics but abstracts from uncertainty in information exchange.
- **Sensing:** Trucks monitor their own SOC, accumulated driving and rest time, and distance to potential charging sites or unload location. Charging infrastructure monitors occupancy and queues to manage allocation of trucks.
- **Interaction:** Interaction occurs indirectly at charging stations through competition for limited connectors and parking spaces. Queues embody the effects of these interactions. Furthermore, interaction occurs indirectly in road congestion due to lower driving speeds at peak hours.
- **Stochasticity:** Randomness is included in departure times and route assignment. Departure times are based on a discrete probability distribution, route assignment is uniform random. These stochastic elements create heterogeneity in charging demand while still reflecting realistic scenarios. All other behavior and variables are deterministic.
- **Collectives:** Trucks act independently and are not modeled as coordinated fleets. Collective effects emerge only through aggregation of many individual choices.
- **Observation:** Outputs include charging demand per site, utilization rates, queue length distributions, temporal demand curves, and travel times. These provide indicators of infrastructure adequacy under different scenarios.

4.2.1 Behavioral Flows and Diagrams

To model the behavior of truck drivers, it is first necessary to chart their real-world behavior and translate it into a conceptual model that can be implemented in the agent-based system. Figure 8 below presents a simplified behavioral flow of a typical truck driver performing a tour.

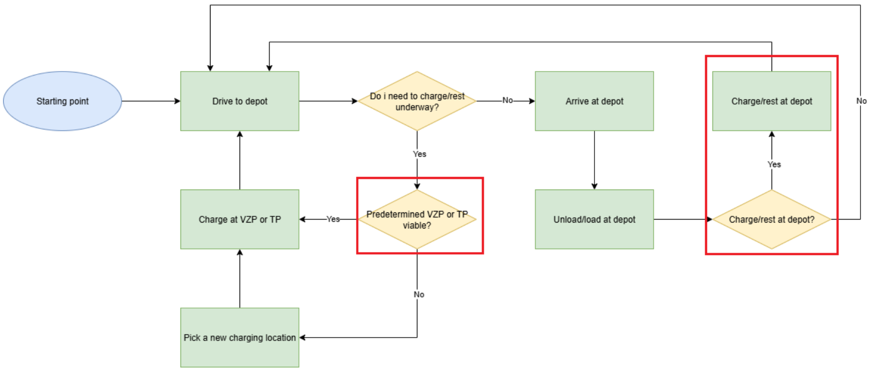


Figure 8: Behavioral flow of a truck driver

Two key processes in the figure are highlighted in red: (1) the predetermined selection of a VZP or TP location, and (2) the possibility of charging at depots.

Depot charging depends on the availability of chargers and whether they are publicly accessible. Assessing whether a depot will install chargers in the future and whether these will be publicly available lies outside the scope of this research. Consequently, this behavior was not modeled, except for two locations: the Port of Rotterdam and Schiphol. These sites are assumed to construct and provide access to charging facilities due to their scale and high likelihood of early deployment.

The second highlighted process concerns the predetermined choice of a VZP or TP charging location. Logistic operators typically plan routes and activities for their trucks in advance. This planning process would likely include selecting preferred charging sites. However, such decisions depend on several variables, some of which are beyond the scope of this research. In reality, truck drivers may deviate from these predetermined locations due to unforeseen circumstances such as traffic delays or long waiting times at the selected charging site. Therefore, the model determines the charging location real-time (model time), based on a limited set of influencing variables. The diagram in Figure 9 illustrates the key variables that directly influence this decision-making process for predetermining charging locations.

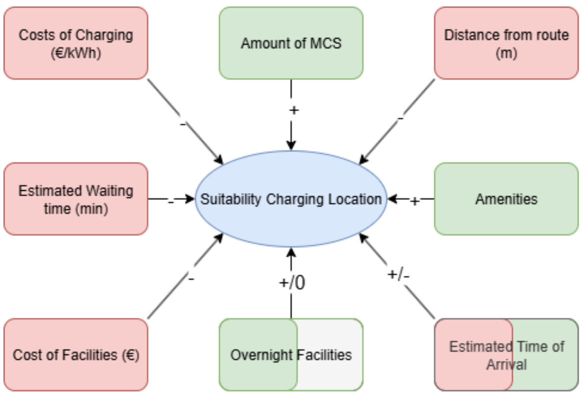


Figure 9: Variables influencing charging location suitability

Figure 9 also contains several variables that fall outside the scope of this research but are important. For instance, both charging costs and facility costs are not included. Likewise, amenities such as restaurants or showers are not considered in the model. The primary decision factors incorporated into the conceptual model are the estimated time of arrival, available capacity, and distance from the route.

Based on these decision-making variables and behavioral assumptions, a conceptual behavioral flow was developed for truck drivers, which serves as input for the agent-based model.

4.2.2 Conceptual Flow of Truck Behavior

The agent-based model follows a discrete-event simulation logic in which battery electric truck (BET) agents progress through a sequence of states based on internal conditions and environmental interactions. The conceptual flow can be summarized as follows:

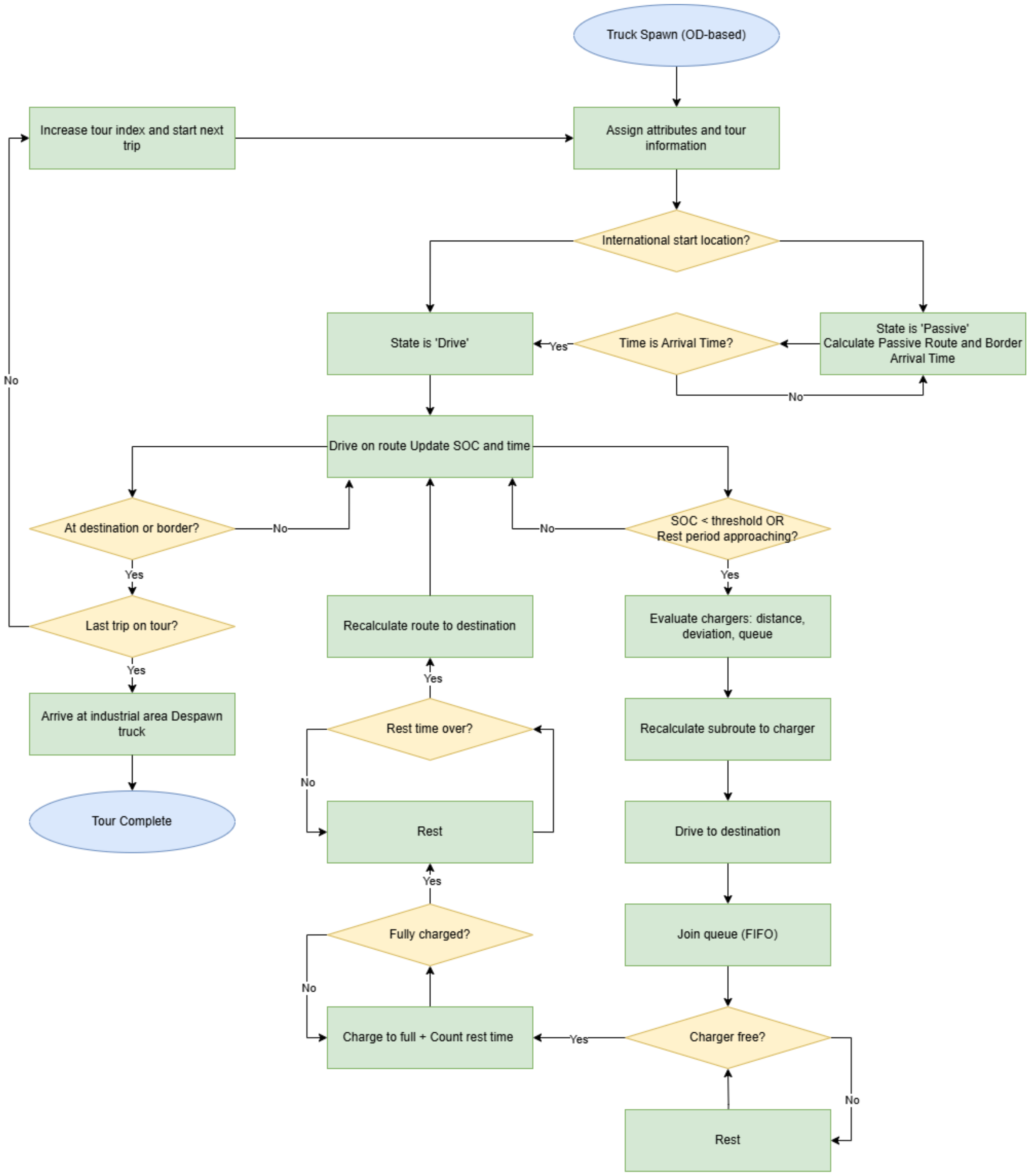


Figure 10: Concept Agent Behavior Flow

1. **Initialization**: Each agent is initialized with a predefined origin-destination pair, truck attributes (e.g., battery capacity, energy consumption, driver speed variation), and a starting time derived from a temporally disaggregated OD matrix.

2. **Trip start and route assignment**: Upon spawning, the truck is assigned a static route from origin to destination. This route is recalculated only when detouring to a charging location.

3. **Driving state**: The agent enters the driving state, consuming battery energy and accumulating driving time. Driving speed is determined by road type and time-of-day profiles.

4. **Charging decision trigger**: When the battery state of charge falls below a predefined threshold or a required rest period is approaching, the agent initiates a charging location search.

5. **Charging location selection**: The agent evaluates nearby charging stations based on travel distance, deviation from the route, and current queue length. A charger is selected and a sub-route to that location is created.

6. **Arrival and queueing**: Upon arrival at the charging location, the agent joins a FIFO queue if all chargers are occupied. Otherwise, it immediately begins charging.

7. **Charging and resting**: The agent charges up to full capacity or until a predefined SOC level is reached. If a rest period is also required, charging time counts toward that rest. Any remaining required rest time is completed after charging.

8. **Route resumption**: After charging and rest are completed, the agent calculates a new route from the charging location to the final destination and resumes driving.

9. **Trip completion**: Upon arrival at the destination (a load/unload location), the agent is removed from the simulation.

This flow is repeated for each truck agent independently. All updates occur at one-minute intervals. Charger availability and queue states are updated synchronously based on agent arrivals and departures.

4.2.3 Model Assumptions

Table 1: Modeling assumptions

Category	Assumption	Implication
Population & demand	Only battery-electric trucks are modeled.	No competition for parking/chargers from non-BETs; utilization may be optimistic.
Population & demand	Electrification is a fixed share of tours; non-electrified tours are removed.	Total truck demand is exogenous; no induced/suppressed demand effects.
Population & demand	tour demand is externally given; spawn timing drawn from an empirical minute-of-day distribution.	Temporal profiles come from inputs.
Geography & network	Only the Netherlands highway network and rest/parking locations are modeled; urban last-mile and depots are out of scope.	Results apply to corridor charging, not urban logistics or depot operations.
Geography & network	Outside-NL travel is simplified: inbound trips are treated as a time block; outbound trips end at the border.	Cross-border charging/queuing outside NL is not represented.
Operations & behavior	Drivers follow EU rest rules strictly (first 45-min break after $\sim$4.5 h; daily rest once duty time reached).	No early/late deviations, split breaks, or enforcement slack; behavior is idealized.
Operations & behavior	No waiting or dwell times at loading/unloading locations.	Stationary delays at origins/destinations are ignored; throughput may be optimistic.
Operations & behavior	No depot charging en route; trucks start full and only charge at public stations during trips.	Understates depot-centric strategies and their impact on public network load.
Operations & behavior	Routing always follows shortest path by distance and direction (not by time; no congestion routing).	Route choice is not optimized for traffic.
Operations & behavior	Charging decision is short distance not strategic: trigger at low state-of-charge or near mandated breaks; no trip-level optimization.	May miss globally optimal stop plans; realistic for many operators.
Charging & capacity	Sleepers occupy capacity; if sleeping demand $\geq$ capacity, a site is flagged as full.	Night-time capacity can be fully consumed by sleepers, blocking chargers.
Charging & capacity	No non-EV occupancy of parking/charging bays.	Available capacity may be overestimated versus reality.
Charging & capacity	VZP sleeping prohibition is off by default.	Thought likely sleeping prohibition is not a realised policy yet.
Charging & capacity	A short local radius is used for station availability (30km)	Puts a hard bound on detour willingness.
Queueing & choice	Maximum acceptable queue is capped at 20% of capacity; longer queues are effectively avoided.	Models queue-averse behavior; reduces extreme waiting times by assumption.
Energy & vehicle	All trucks share one battery size and start trips full; no degradation over time.	Understates variability across fleets and aging effects.
Energy & vehicle	Energy use from longitudinal physics on flat terrain; no hills, weather, auxiliary loads, or regenerative braking.	Consumption and therefore charging needs are partially idealized.
Energy & vehicle	Fixed drivetrain efficiency; no speed/load dependence.	Ignores efficiency penalties at high/low loads.
Energy & vehicle	Charging power is constant (e.g., 1.2 MW for MCS, 100 kW for CCS); no losses.	Likely understates charge times and overstates throughput.

Continued on next page

Category	Assumption	Implication
Market & policy	No prices/tariffs	Purely physical/behavioral utilization, not economic dispatch or market friction.
Market & policy	No endogenous investment, siting, or expansion decisions.	results are not an optimization outcome.
Data & calibration	Speed profiles by road class are exogenous time series; speeds do not feed back from simulated traffic.	Travel time depends on inputs, not congestion.
Special case	in Port of Rotterdam and Schiphol trucks allow opportunistic top-ups	Simplifies a local pattern; can inflate those sites utilization.
Population & demand	Base-year tours (2022) are reused for all electrification phases (no growth/decline across scenarios).	Results reflect a static freight baseline; utilization may be misestimated if demand evolves.
Energy & vehicle	Constant vehicle/load weight across trips (no payload differentiation).	Energy use and range ignore payload variation; charging needs may be biased for heavy/light trips.

4.3 Key Performance Indicators (KPIs)

To keep results readable and comparable across scenarios, KPIs are organized in three layers (Figure 11): vehicle-level outcomes for individual trucks/tours, which aggregate up to station-level performance for each charging location, which in turn aggregate up to system-wide indicators for the whole public network. Units are shown in the figure to make interpretation unambiguous.

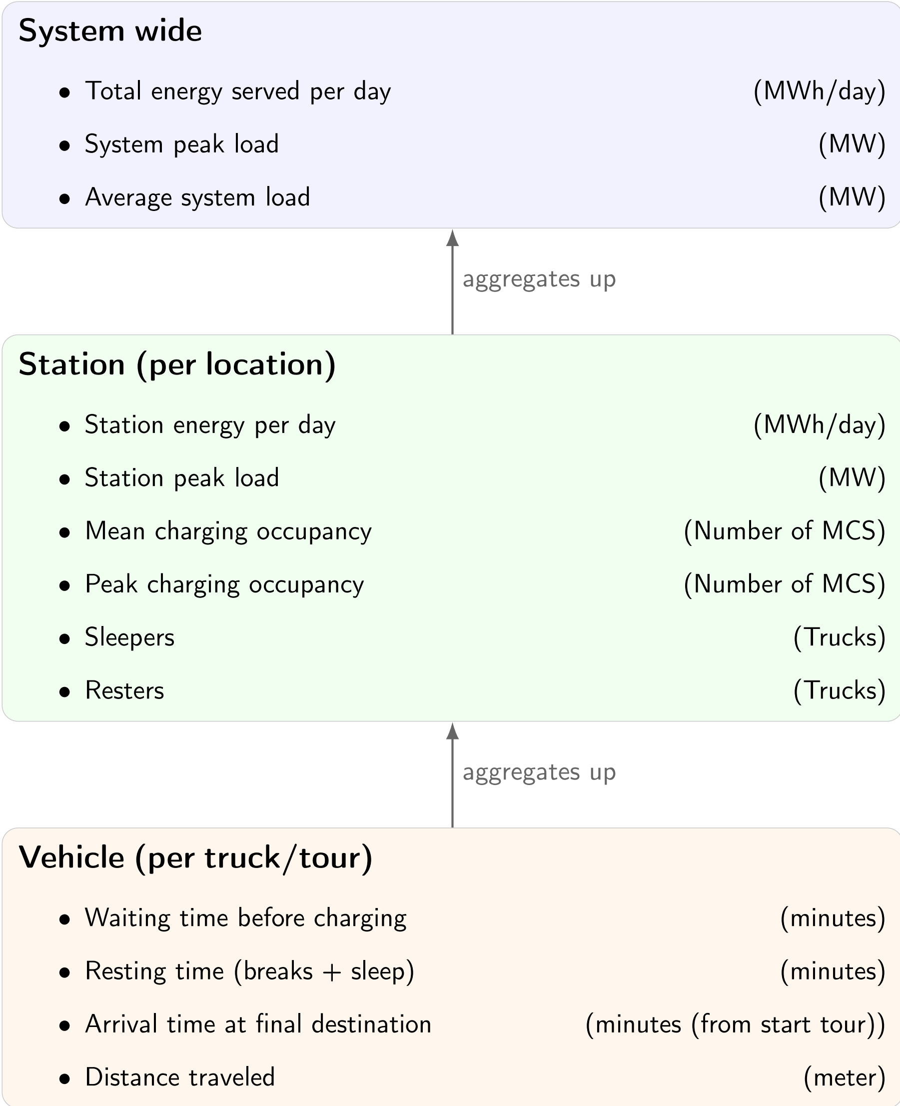


Figure 11: Key Performance Indicators per aggregation level

Why these KPIs?

- **System wide** Total energy per day, system peak load, average system load captures throughput and grid stress. These are the headline numbers for planners and DSOs.
- **Station (per location)** Station energy per day, station peak load, mean and peak charging occupancy in number of MCS in use, trucks sleeping, and trucks resting shows how individual sites are used and where parking capacity is tied up by.
- **Vehicle (per truck/tour)** Waiting time before charging, resting time, arrival time from tour start, distance traveled reflects the user experience and operational impacts that ultimately drive station and system outcomes.

How they are computed
KPIs are derived directly from the simulation logs. Each minute, the model records how many trucks are charging, resting, sleeping, or waiting at every station. From the charging logs the energy per station and system can be derived. The mean charging occupancy is the average number of MCS

in use across the day, and the peak charging occupancy is the highest number observed. Sleepers and resters are the counts of trucks in those states at a site at a given moment. Vehicle metrics use the truck logs: waiting time adds up time spent before a charge begins, resting time covers statutory 45-minute breaks plus overnight sleep, arrival time is measured from tour start to the final destination, and distance traveled is the realized route length (including detours).

Reporting conventions
Unless stated otherwise, KPIs are calculated per run and then averaged across random seeds. Daily values refer to a full 24-hour window but exclude day 1 because this day serves as warmup for the model. Stations have a heterogeneous utilization, to prevent peak influence means and peaks are presented for the 95% quantile.

4.4 Details

4.4.1 Initialization

At the beginning of each run, the model constructs the networked environment, creates stationary infrastructure agents, prepares the truck spawning logic, and sets global clocks and parameters.

- **Global parameters and scenarios** The model reads scenario inputs and sets fixed constants:
  - **Scenarios:** ccs_scenario (CCS instead of MCS at night), vzp_scenario (sleep allowed at VZPs when False), electrification (share of tours electrified), random seed.
  - **Vehicle/behaviour:** battery capacity (kWh), maximum queue (fraction of parking count usable as queue, default 0.2), search threshold (m), timestep (min).
  - **Energy model constants:** mass, air density, drag area, rolling resistance, gravity (used in the energy consumption function), drivetrain efficiency.
  - **Timekeeping (min):** first rest time = 270, second rest time = 585, length of day = 1440.
  - **Speeds:** lookup tables for A- and N-roads are loaded; the minute index selects the current mean speed each step.
- **Road network (environment)** The Dutch network is created as a directed graph G, with link attributes including length and a road code (i.e. A7). All coordinates are in EPSG:3035.
- **Load/unload nodes** Origins and destinations are created as Load/Unload point agents from the tour file. A dictionary load_unload_dict maps (x, y) to the corresponding agent.
- **Charging and rest infrastructure** Points of interest are read from a CSV file, projected to EPSG:3035, and filtered to $Pvracht \geq 0.01$. For each record:
  - **VZP** agents represent motorway service areas.
  - **Dummy** agents represent candidate or artificial locations.
  - **Parking** agents represent truck parking areas.

  Each site stores its position, a nominal capacity, empty lists of connected users and CCS chargers, a queue, and separate resting lists (rest, sleep). Charging rates are initialized as 1200/60 kWh/min for MCS-type sockets (scaled by timestep) and 100/60 kWh/min for CCS chargers. Dummy sites use a very high nominal capacity to represent unconstrained capacity. A global station dictionary maps coordinates to the corresponding agent, and sets of station positions are cached for routing.
- **Truck spawning** Multi-trip tours are generated from the tour data. Origin and destination coordinates are linked to the nearest network nodes, and trips that both start and end outside the Netherlands are removed. From the remaining tours, a share is sampled based on the chosen electrification rate. Departure times for the first trip in each tour are assigned using an empirical distribution of departure probabilities across the week. Once a truck is spawned, it follows its complete tour sequence, with subsequent trips executed in order.
- **Agent default.** When a truck is spawned, it is created with:

- initial state set to drive unless international start, battery equal to its maximum capacity, a constant base speed updated each step by road class tables, and energy consumption calculated through the battery consumption function. International starts begin in the state passive.
- tour bookkeeping (sequence, tour index), timekeeping variables (work time, driven time, resting time), and international flags for passive parts at the Dutch border.
- a routing path from start to end (shortest by distance).
- decision thresholds and search limits, such as maximum queue tolerance and search radius.

- **Clocks and logs** Global counters are initialized to zero, including simulation steps, total time, and arrivals. Minute-of-day and day-of-week clocks are set to track compliance with rest rules and speed profiles.

4.4.2 Input data

The model relies on several external datasets to initialize agents, construct the road network, and define freight demand.

- **Road network** The Dutch highway network, consisting of all A-roads and a selected set of important N-roads, is used as the spatial backbone of the model (see Appendix A.4). The network is represented as a directed graph with distances as edge weights and road types (A/N) stored as attributes to determine speed and energy consumption.
- **Tour-based demand** The detailed multi-trip tours are derived from a dataset of carrier movements in the Netherlands, ensuring realistic temporal and spatial freight patterns. The dataset is the Logistic Road Freight module of BasGoed6 and is not publicly available. The data has been validated in section 6.1
- **Points of interest (POIs)** Potential charging locations are based on a dataset of motorway service areas and truck parking facilities in the Netherlands gathered from Speth and Plötz, 2021 and Panteia, 2025. Each location is described by its coordinates and parking capacity. Three types of locations are distinguished:motorway service areas (VZPs), truck parking areas, and dummy nodes representing potential new sites.
- **Speed profiles** Empirical traffic speed tables for A-roads and N-roads are used to vary truck speeds throughout the day. The data was obtained from the Nationaal Dataportaal Wegverkeer (NDW) for the year 2024. Specific road segments are listed in Appendix A, Table 5. Note that the vehicle filter includes all vehicles over 11.5 meters, such as buses, and is therefore not limited to trucks alone..
- **Departure time distribution** An empirical probability distribution of truck departures across the week is used to assign spawn times to the first trip of each tour. This dataset was also obtained from the NDW.
- **Regulations** European driving and rest rules are encoded directly in the model (maximum 4.5 hours of driving before a 45-minute break, daily driving limits, and required overnight rest). These rules govern when trucks must stop and therefore strongly shape charging demand patterns.

4.5 Submodels

4.5.1 Station Searching Algorithm

A truck uses a heuristic partly deterministic approach to find the best station to charge when the charging criteria are hit. The following variables are used in this approach: distance, waiting time, direction and type of location. The distance is calculated based on the shortest path to the station in the network and is valued as 1 per meter.

The waiting time is based on the queue time at the station at the moment of the calculation. Each minute waiting time is valued at the same as the distance that could have been driven within this minute. To ensure the queue length does not become longer than is possible at the location, a maximum queue threshold is set at 20% of the maximum truck parking capacity of that location. If this threshold gets triggered the waiting penalty becomes so high the location becomes less desirable than a dummy location.

For direction the vector of the current location and the end location is used in combination of the vector of current location to the charging station. If the direction is determined to be roughly the same direction (60 degree margin) the weight is set at 1, otherwise the weight is set as 3. This makes, ceteris paribus ,a charging station 30km in the right direction just as attractive as a charging station 10km in the wrong direction.

A location can be categorized in 3 types of location, either a VZP (Verzorgingsplaats), TP (Truck Parking) or DUM (Dummy location). VZP are small locations often close to the main road that provide few locations for trucks to park. TP are large truck parkings, often more secluded and with facilities to provide truckers a more comfortable resting experience. Dummy locations are non-existent locations which are used whenever existent locations have reached their max capacity, these are required to determine if their is a lack in capacity at current locations. The weight put on these dummy locations is 5, making the unappealing unless no other location is available. These variables result in the following mathematical formula:

$$
\begin{aligned}
d_i &= \text{shortest path distance to station in meter } i \\
w_i &= \text{estimated waiting time at station minutes } i \\
\theta_i &= \text{directional alignment factor (1 if in correct direction, 3 otherwise)} \\
t_i &= \text{type penalty for station } i \text{ (1 for real, 100 for dummy)} \\
v &= \text{truck speed in meter/min}
\end{aligned}
$$

Then the station score S_i is calculated as:

$$S_i = (d_i + (w_i \cdot v)) \cdot \theta_i \cdot t_i$$

The best station i^* is chosen by minimizing this score:

$$i^* = \arg\min_i S_i$$

The function for direction uses the dot product of normalized direction vectors to determine if a candidate station lies in roughly the same direction as the destination:

$$\cos(\theta) = \vec{u}_{\text{dest}} \cdot \vec{u}_{\text{candidate}} \geq 0.5$$

The threshold of 0.5 results in a 60 degree threshold between the two vectors to determine whether the direction is roughly in line with the end destination.

4.5.2 Truck Spawn Distribution

Truck spawn events are scheduled at a one-minute interval and depend on both the day of the week and the time of day. To model this temporal distribution, road intensity data from the Nationaal Dataportaal Wegverkeer (NDW) was used. Specifically, data was extracted from the monitoring point `RWS01_MONIBAS_0151hrr0551ra_1`, located at a key exit route from the Port of Rotterdam. This location was selected because it directly captures the outbound truck flow from the port, one of the busiest logistics hubs in the Netherlands.

The data consisted of hourly truck intensity counts for the entire year of 2024. These observed flows were then used to construct a temporal distribution representing the likelihood of a truck starting its tour at any given hour and day of the week. This distribution was generalized and applied to all load/unload locations in the model. While this introduces a simplification, the Port of Rotterdam was chosen as a reference point due to its high truck traffic volume and its central role in the national freight network. As such, it serves as a reasonable generalization for the overall temporal pattern of truck activity in the Netherlands.

Since the tour data only includes five working days, the distribution table for the tour data set is build only for Monday till Friday. This results into the following graph for the truck spawn probability:

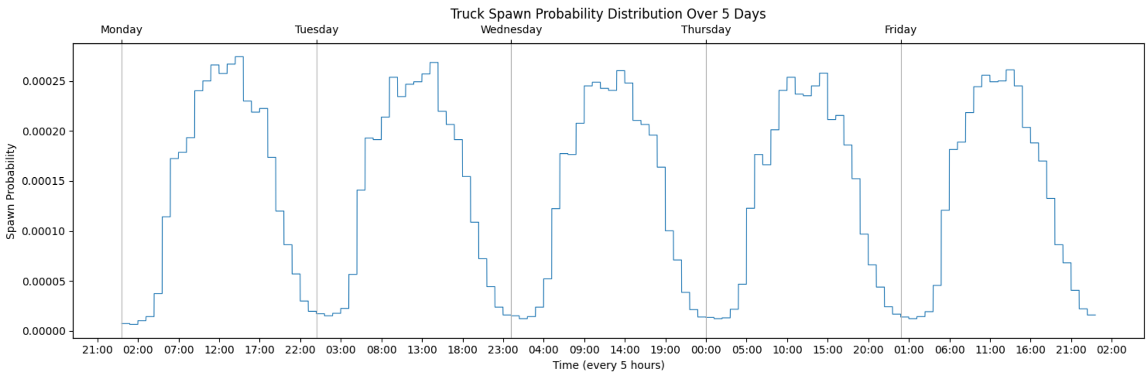


Figure 12: Truck Spawn Distribution Five Days

For the ETIS dataset we also include weekends, the truck spawn distribution for the entire week is this:

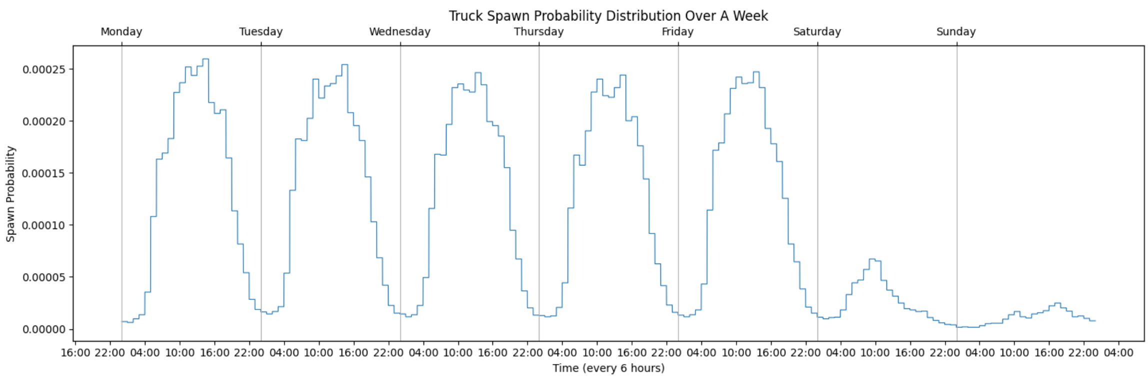


Figure 13: Truck Spawn Distribution One Week

4.5.3 Speed Distribution

The velocity of trucks throughout the day for each road type has been generalized based on the average speed of vehicles longer than 11.5 meters, measured across 15 different segments of A-roads and N-roads. The data was obtained from the Nationaal Dataportaal Wegverkeer (NDW) for the year 2024. Specific road segments are listed in Appendix A, Table 8. Note that the vehicle filter includes all vehicles over 11.5 meters, such as buses, and is therefore not limited to trucks alone.

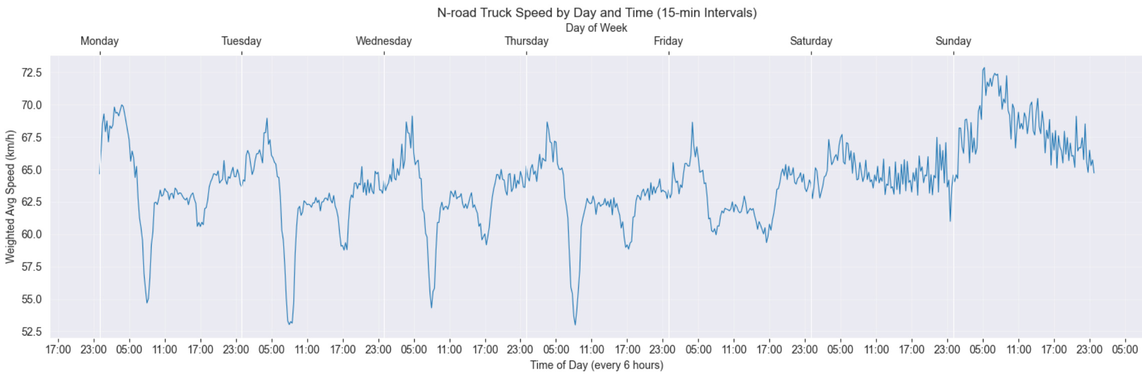


Figure 14: N-road truck speed during the week

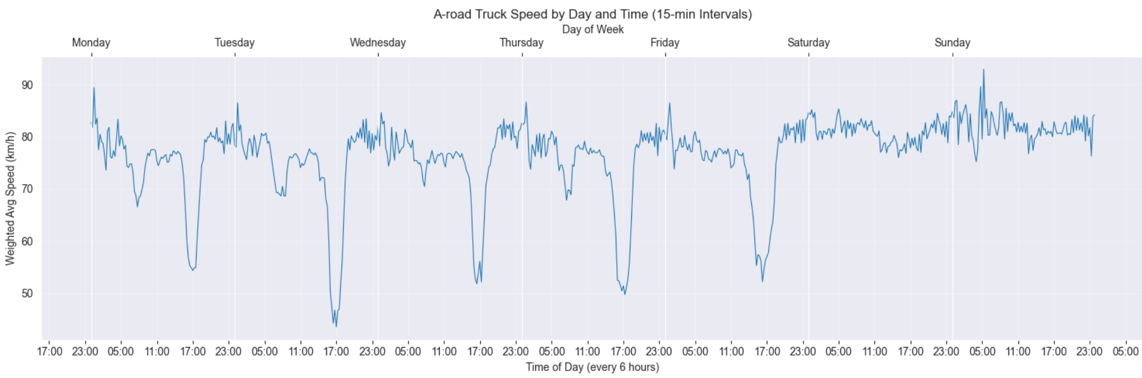


Figure 15: A-road truck speed during the week

The velocity shown reflects the weighted average speed during each 15-minute interval, aggregated across all measured road segments of a given type. Two clear patterns emerge: the morning traffic peak (06:15–09:30) and the afternoon traffic peak (15:30–18:00) lead to noticeable drops in average speed on weekdays. In contrast, weekends display significantly more stable and higher average speeds. Furthermore, the morning peak seems to be the Largest traffic jam for N-roads while the afternoon peak is the largest traffic jam for A-roads.

Interestingly, while A-roads generally allow for higher maximum and average speeds than N-roads, they also experience deeper speed drops during congestion, especially in the morning. For N-roads, the largest reduction in speed typically occurs in the afternoon. This suggests that while A-roads support faster traffic under free-flow conditions, they are more sensitive to peak-hour congestion than N-roads.

Influence of touring cars on the distribution

As previously mentioned the distribution is derived from vehicles longer than 11.5 meters, this therefore includes touring cars. Therefore we need to determine whether this inclusion has a significant impact on the speed distribution. According to Panteia (Panteia, 2024) there were in 2024 about 3578 touring cars in the Netherlands. In comparison, the Netherlands has 170.000 (Centraal Bureau voor de Statistiek (CBS), 2025a) trucks registered and has a large influx of international trucks as well. This means touring cars likely represent 1-2% of the vehicles measured in the distribution. The maximum speed of touring cars is 100km/h instead of the 80km/h of trucks. This means the expected effect of touring cars on the speed distribution is an increase from 80km/h to 80.4km/h and can therefore be neglected.

4.5.4 Battery Consumption

To estimate battery consumption of a truck during operation, we calculate the energy required to overcome resistance forces acting on the vehicle. The total energy consumed during one time step of one minute is given by the following formula (Basso et al., 2019; Mareev et al., 2017):

$$E = \frac{1}{\eta}\left(\alpha \cdot m + \beta\right)$$

where:

- E: total energy consumption (Joules)
- η: drivetrain efficiency (dimensionless)
- m: vehicle mass (kg)
- α: mass-dependent energy coefficient (J/kg)
- β: mass-independent energy consumption (J)

This equation accounts for both forces that scale with vehicle mass (e.g., rolling resistance, gravity, and acceleration) and forces that are independent of mass, primarily air drag. Dividing by η accounts for drivetrain losses, as only a fraction of the battery energy is converted into motion.

Mass-dependent energy (α): This component captures energy required to accelerate the vehicle, overcome gravitational forces due to road inclines, and resist rolling friction. It is calculated as:

$$\alpha = (a + g \cdot \sin(\theta) + g \cdot f_r) \cdot v \cdot \Delta t$$

where:

- a: acceleration (m/s^2)
- g: gravitational acceleration (9.81 m/s^2)
- θ: road slope angle (radians)
- f_r: rolling resistance coefficient
- v: vehicle speed (m/s)
- Δt: duration of time step (s)

The expression inside the parentheses represents the total acceleration load per unit mass, while multiplying by speed and time gives the distance-based energy cost.

Mass-independent energy (β): This term models aerodynamic drag, which depends on the vehicle's shape and speed but not its mass:

$$\beta = \left(\frac{1}{2}\rho C_d A_f v^3\right) \cdot \Delta t$$

where:

- ρ: air density (kg/m^3)
- C_d: drag coefficient
- A_f: frontal area (m^2)

The v^3 term reflects how aerodynamic losses increase rapidly at higher speeds. This makes highway driving particularly energy-intensive for large vehicles with high frontal area and drag coefficients.

Use in model: The model distinguishes between different sources of energy consumption and reflects realistic physical behavior. While all resistance-related parameters are held constant during the model run, velocity and acceleration vary over time. The only exception is during sensitivity analyses, where parameters the resistance parameters are adjusted.

The velocity in the model evolves according to the patterns described in Subsection 4.5.3, incorporating effects such as traffic congestion. While a lower velocity generally reduces energy consumption, traffic jams introduce frequent acceleration and braking phases, which significantly increase energy usage.

To account for this, the model introduces an adaptive acceleration component that responds to deviations from normal traffic flow. When velocity drops below the mean velocity, the acceleration variable is artificially increased to reflect the additional energy required for stop-and-go driving. This acceleration increases linearly as speed drops, reaching a maximum value of 0.4 m/s^2 at the lowest observed velocity. This behavior helps the model replicate the elevated energy consumption observed in congested driving conditions.

Model Parameters

To simulate the battery consumption of a heavy-duty truck, the following physical and vehicle-specific constants are used in the model. These values are chosen to reflect a typical fully loaded long-haul truck driving under average conditions.

- **Vehicle Mass (m): 38,000 kg**
  This represents a fully loaded truck with cargo. It strongly influences both rolling resistance and acceleration energy demand. Legally the maximum weight of a truck in Europe can be 40.000kg with exceptions for some which can be 44.000kg (Mareev et al., 2017)
- **Gravitational Constant (g): 9.81 m/s^2**
  The standard gravitational acceleration used in force calculations related to slopes and rolling resistance.
- **Rolling Resistance Coefficient (f_r): 0.004**
  A typical value for truck tires on asphalt. Rolling resistance accounts for deformation of the tires and the road surface. (Basso et al., 2019)
- **Road Slope Angle (θ): 0.0 radians**
  The road is assumed to be flat throughout the simulation. Sloped roads could be included by changing this value.
- **Air Density (ρ): 1.225 kg/m^3**
  Represents standard atmospheric conditions at sea level. This parameter affects aerodynamic drag. (Basso et al., 2019; Mareev et al., 2017)
- **Drag Coefficient (C_d): 0.48**
  This is a realistic value for a streamlined truck with a trailer. It determines the extent of aerodynamic drag experienced by the vehicle. (Mareev et al., 2017)
- **Frontal Area (A_f): 10 m^2**
  An estimated average frontal cross-sectional area for a heavy-duty truck, used in calculating air resistance. Basso et al., 2019
- **Drivetrain Efficiency (η): 0.88**
  Assumes that 88% of the energy delivered by the battery is converted into mechanical energy at the wheels, while 12% is lost to inefficiencies in the drivetrain (Åkerblom et al., 2020).
- **Time Step Duration (Δt): 60 seconds**
  Energy calculations are performed per minute, corresponding to a time resolution of 60 seconds across the entire model.

These constants form the basis for computing both the mass-dependent and mass-independent components of energy consumption, as described in the previous subsection. All values are drawn from existing literature.

Energy Consumption Curve

The energy consumption curve that is created by using the parameters and formula above with the dynamic application in velocity and acceleration result in the following energy consumption curve for A-roads and N-roads. The form of the graph has been cross-validated by comparing it to literature on energy consumption of battery electric vehicles (non-trucks) (Mamarikas et al., 2022).

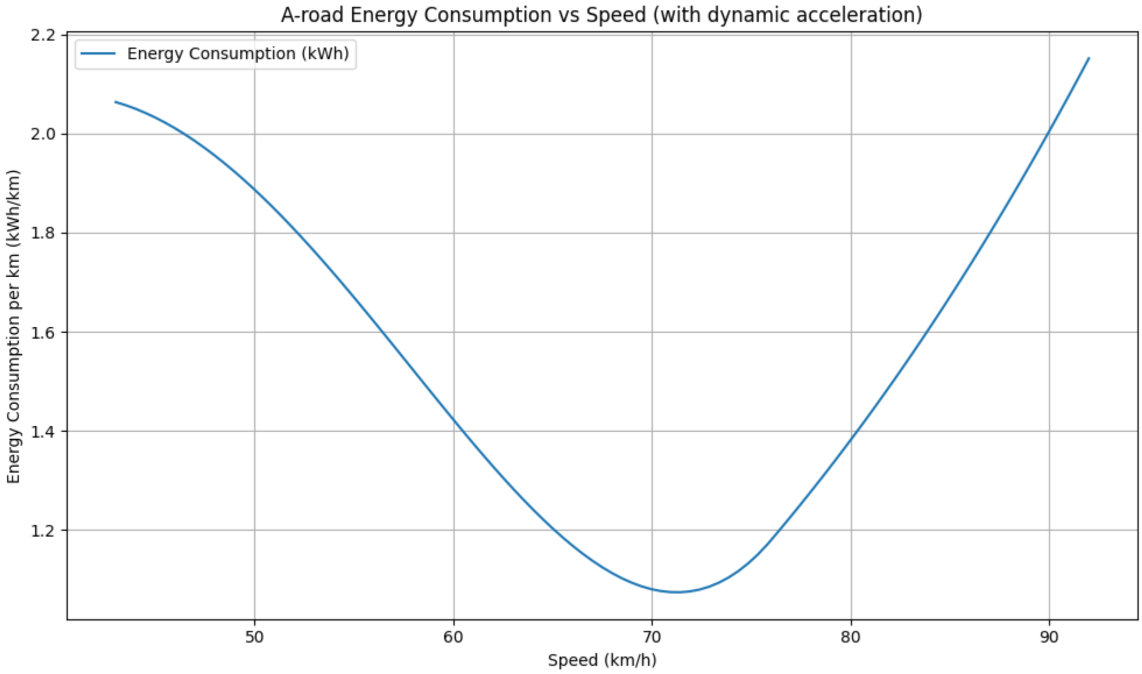


Figure 16: A-road Energy Consumption Curve

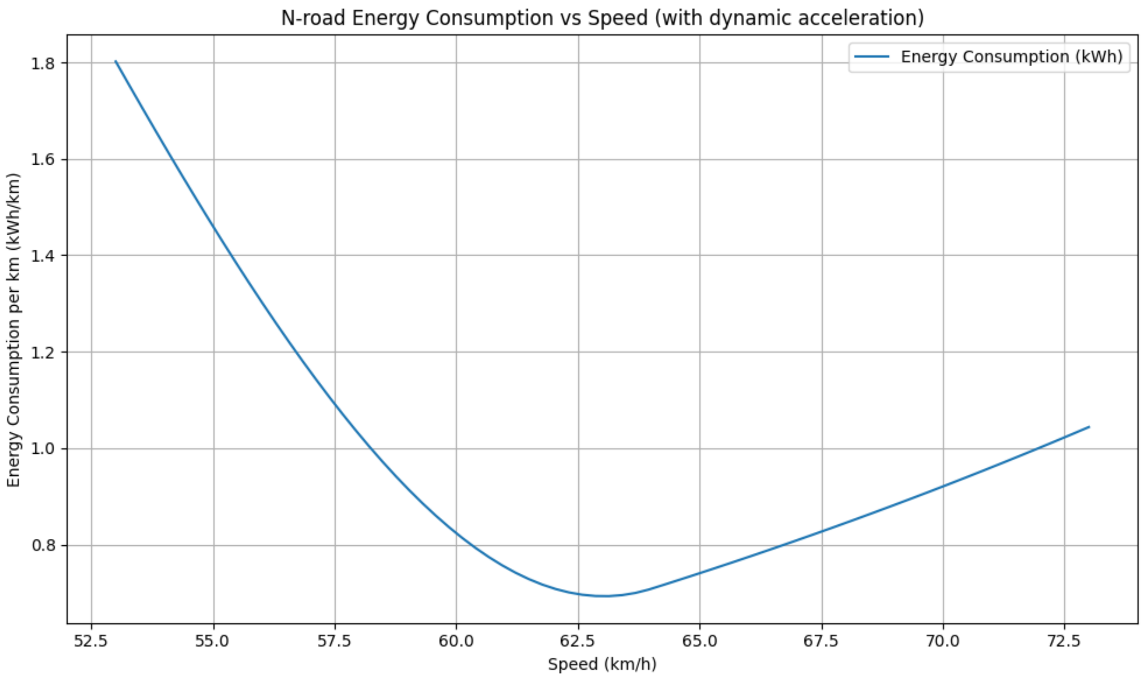


Figure 17: N-road Energy Consumption Curve

The energy consumption curve accounts for additional energy use during stop-and-go traffic. When a truck's velocity drops below the road's mean speed, congestion is assumed, and an acceleration factor is added to reflect increased energy demand. The acceleration is added in a quadratic form going from mean velocity towards the minimum velocity. Unfortunately, there is no literature on the effect of congestion on electric truck battery consumption. therefore, there is not reference material for the acceleration curve for truck. However, Mamarikas et al., 2022 researched the energy consumption for regular electric cars, the acceleration follows the same pattern for energy consumption for trucks as this research. This behavior is embedded in the curve: for example, energy consumption is higher at 50 km/h than at 80 km/h, capturing the inefficiencies associated with lower-speed driving and frequent acceleration.

4.5.5 Network Creation

The road network forms the spatial environment in which truck agents move and interact with charging infrastructure. Dutch A-roads and a selection of freight-relevant N-roads were extracted from the Nationaal Wegenbestand (NWB) and projected to EPSG:3035. Each road segment was represented as an edge in a graph with attributes for length and road identifier. Only the largest connected component was retained to ensure continuity of the network.

Points of interest were added as nodes to the graph, including motorway service areas (VZPs), truck parkings (TPs), dummy nodes, and load/unload locations. Each of these points was connected to the nearest road node using a spatial index (KD-tree), ensuring that facilities are accessible within the road network.

For international tours, special connections were required to allow trucks to enter and leave the Dutch network. Border nodes were defined along the major eastern and southern highways, and each long-distance load/unload node was connected to one of these border nodes. The selection of the most appropriate border node was based on a cost function that balances geometric distance with the relative traffic intensity of the corridor. Specifically, for a load/unload node p and a candidate border node b, the cost is calculated as:

$$\text{cost}(p,b) = \frac{d(p,b)}{1+\frac{1}{2}\,I_b}$$

where:

- $d(p,b)$ = Euclidean distance between p and b,
- I_b = normalized intensity value of the corridor at border node b, derived from NDW traffic data.

The denominator ensures that corridors with higher observed intensities are favored, effectively lowering the cost of connecting to busier border roads. The border node b^* with the lowest cost is then selected:

$$b^* = \arg\min_{b\in B} \text{cost}(p,b)$$

and a synthetic edge is added between p and b^*. This approach ensures that international load-/unload locations are not only linked by spatial proximity but also reflect the relative importance of cross-border freight flows.

The result is a directed graph of the Dutch national road network enriched with border nodes, charging candidates, and load/unload points. This network provides the spatial backbone for routing and accessibility analysis within the agent-based simulation. Figures of the results can be found in appendix A.7

5 Experimental Design

5.1 Scenario Analysis

This section presents the simulation scenarios used to analyze spatial charging demand under varying conditions of electric truck adoption, resting behavior, and available charging technologies. The goal is to explore how infrastructure needs evolve across different stages of electrification in the road freight sector, under alternative policy and technology assumptions. To ensure robustness the scenario analysis is run on 4 different seeds: 2,3,4,5

Three scenario dimensions are considered:

1. **Fleet Electrification Level**: Six electrification levels are simulated—5%, 10%, 20%, 40%, 60%, and 100%—to reflect progressive transitions from a predominantly diesel fleet to full electrification.

2. **Resting Policy**: Two resting behavior assumptions are tested:

   - **Truck Parking only (TP)**: Drivers are permitted to sleep only at designated truck parking locations.
   - **Truck Parking and Public Service Areas (TP+VZP)**: Drivers may also sleep at public service areas (VZPs), increasing spatial flexibility.

   These scenarios reflect uncertainty about future regulatory restrictions on overnight stays at public service areas. Comparing them highlights how such policies may influence spatial charging demand patterns. Government has been thinking about restricting VZP overnight sleep because of the lack of security at these locations.

3. **Charging Technology**: Two infrastructure configurations are considered:

   - **MCS only**: Trucks can charge exclusively at Megawatt Charging System (MCS) stations, simulating a future fast-charging focused network.
   - **CCS + MCS**: Trucks can charge using both Combined Charging System (CCS) and MCS chargers, reflecting a mixed-infrastructure scenario with legacy and future compatibility. CCS chargers would be used for overnight charging.

Combining these dimensions results in a total of 24 scenario combinations.

Table 2: Overview of Scenario Combinations

Scenario	Electrification Level	Resting Policy	Charging Technology
5TM	5%	TP	MCS only
5TC	5%	TP	CCS + MCS
5VM	5%	TP+VZP	MCS only
5VC	5%	TP+VZP	CCS + MCS
10TM	10%	TP	MCS only
10TC	10%	TP	CCS + MCS
10VM	10%	TP+VZP	MCS only
10VC	10%	TP+VZP	CCS + MCS
20TM	20%	TP	MCS only
20TC	20%	TP	CCS + MCS
20VM	20%	TP+VZP	MCS only
20VC	20%	TP+VZP	CCS + MCS
40TM	40%	TP	MCS only
40TC	40%	TP	CCS + MCS
40VM	40%	TP+VZP	MCS only
40VC	40%	TP+VZP	CCS + MCS
60TM	60%	TP	MCS only
60TC	60%	TP	CCS + MCS
60VM	60%	TP+VZP	MCS only
60VC	60%	TP+VZP	CCS + MCS
100TM	100%	TP	MCS only
100TC	100%	TP	CCS + MCS
100VM	100%	TP+VZP	MCS only
100VC	100%	TP+VZP	CCS + MCS

5.2 Sensitivity Analysis

To evaluate and understand how key assumptions influence the spatial demand for megawatt-scale charging infrastructure, a sensitivity analysis was performed. Furthermore, the sensitivity can be used to check the robustness of the model. This analysis focuses on four key parameters: battery capacity, maximum allowable queue threshold, drivetrain efficiency, and search distance threshold for charging stations. These parameters were selected because of their direct impact on truck charging frequency, rerouting behavior, and charger utilization in the simulation.

5.2.1 Selected Parameters

Parameter	**Description**	**Baseline**	**Variation**
Battery capacity	Battery capacity of the truck (in kWh), influencing driving range and charging frequency.	600	500, 700
Maximum queue threshold	Queue threshold as a percentage of station capacity, above which trucks avoid the station.	20% of capacity	10%, 30%
Drivetrain efficiency (η)	Efficiency of energy conversion in the drivetrain (dimensionless).	0.94	0.9, 0.96
Search distance threshold	Maximum distance (in km) a truck searches for a charging station when rerouting.	30 km	20, 40, 50 km

Table 3: Overview of sensitivity parameters

5.2.2 Methodology

A full factorial sensitivity analysis was conducted, in which all possible combinations of the selected parameter values were simulated. This approach allows interactions between parameters to be captured, rather than varying them one at a time. Each scenario was rerun using identical OD input and a fixed random seed to ensure comparability across the full set of runs. This results in a design with 108 individual runs.

The following performance indicators were analyzed for every run:

- Average distance traveled
- Average tour time
- Utilization share by charger type (VZP, Parking, Dummy)
- Intensity of peak demand locations

5.2.3 Parameter Bounds Justification

The variation bounds were chosen based on literature, technological expectations, and behavioral assumptions:

- The range of battery capacity reflects realistic sizes for medium- and long-haul electric trucks. According to Mareev et al., 2017, a 4.5 hour drive would require a battery between 450 and 650 kWh, therefore a battery of 600 kWh should be able to complete most of the trips with a single stop. Shoman et al., 2023 measures an average requirement between stops of 556 kWh and recommends a battery size of 750 for long haul trucks.

- Maximum queue threshold variations simulate different levels of aversion for queues among drivers and queue possibility at charging locations. Realistically this should be different for every location, with some locations having additional space and others not. For simplification this is static across the model and linked to parking capacity.

- The bounds for drivetrain efficiency represent differences between current truck models, considering both optimistic and conservative scenarios for energy efficiency. According to Mareev et al., 2017, a gearbox efficiency of 0.94 can be considered standard. The values of 0.90 and

0.96 were chosen to represent a conservative approach and an optimistic approach. Since, gaining additional efficiency is harder the more efficient it becomes, an addition of just 0.02 has been chosen instead of an addition of 0.04. During my research a misunderstanding between gearbox and drivetrain efficiency has occurred. This led to the assumption 0.94 is a standard drivetrain efficiency. However, this is the gearbox efficiency, drivetrain efficiency is closer to 0.88 (Åkerblom et al., 2020). This means the sensitivity analysis still shows a correct direction but uses 3 highly optimistic values.

- The search distance threshold affects spatial flexibility: a lower value reflects local-only rerouting, while higher values simulate more aggressive search behavior, which could affect grid load distribution and charger access equity.

Expected Effects

Each parameter is expected to influence the model outcomes in distinct ways:

- **Battery Capacity**: Decreasing battery size is expected to increase the amount of charging events. A smaller battery size might trigger charging events because of low battery instead of time related. This can lead to additional charger events, especially for longer trips. A larger than necessary battery should not influence the model as it should only trigger charging events for time-related reasons and the model does not take mass into account.

- **Queue Threshold**: A lower threshold should lead to more use of dummy locations, but lower waiting times as the queues are shorter. Furthermore, this would lead to a higher number of chargers required as fewer trucks can be in queue for a single charger. A higher threshold allows trucks to tolerate more crowding, potentially reducing travel time but increasing localized charger congestion.

- **Drivetrain Efficiency**: More efficient drivetrains reduce energy consumption, thereby lowering charging demand. Less efficient drivetrains are expected to amplify charging duration and needs.

- **Search Distance Threshold**: Expanding the search radius allows trucks to distribute more evenly across the network and may reduce queuing. However, longer detours may increase travel time and shift demand to previously underutilized stations. A lower threshold could concentrate demand locally and increase queue times and dummy location usage.

These expectations serve as hypotheses against which the sensitivity results will be interpreted in the discussion section.

6 Verification and Validation

6.1 Import & Export validation

This subsection validates the total import and export numbers of multiple datasets that have been considered for this project.

6.1.1 ETISplus dataset

The ETISplus dataset is a comprehensive resource that models freight transport flows across Europe. Originally developed in 2012 under the European Commission's 7th Framework Programme and based upon data from Eurostat, it provides detailed origin-destination (O-D) matrices for various transport modes, including road freight for 2010. These matrices are structured at the NUTS-3 regional level, covering 1,675 regions across Europe (ETISplus, 2012).

Fraunhofer institute updated this dataset in 2022 to fit Eurostat data from 2019 (Speth, Sauter, Plötz, & Signer, 2022). This is the dataset that has been put through the validation testing. This dataset also includes a road network of the E-road but this will not be used as we use a bigger road network in the Netherlands. Speth, Sauter, Plötz, and Signer, 2022 also created a forecast for freight road traffic for 2030 which is also being considered for usage depending on the quality of the 2019 set.

6.1.2 Recreated ETISplus dataset

After validation it became clear the original ETISplus dataset and the updated version from Fraunhofer did not meet the expected values for import or export in the Netherlands. Therefore, the decision was made to recreate the ETIS model following the same methodology and using the data from CBS and Eurostat. This new dataset is also taken through the validation process. The process of creating this dataset can be found in appendix A.6

6.1.3 Tour data

A non-public data set has been acquired for potential use in this research. This is a synthetic dataset from Logistic Road Freight module from BasGoed 6 used by the Ministry of Infrastructure and Water Management. This file contains tour data from trucks in the Netherlands and was simulated for 5 work days 2022 based on real tour data. The dataset contains 1040 unique carriers and their tours made during 5 days. According to the Ministry of Infrastructure and Water Management a year consists out of roughly 256 of these 5 working days. The data includes all provinces in the Netherlands, Luxembourg, Belgium, Germany and France. In total this data includes 6928 locations and 4 million trips.

6.1.4 Comparison between CBS and Eurostat Data

Both CBS (Centraal Bureau voor de Statistiek (CBS), 2025b) and Eurostat (Eurostat, 2024a, 2024b, 2024g) provide data on the total volume of freight transport in the Netherlands. However, several of these sources are limited in scope, as they report only freight movements by vehicles with a Dutch license plate. Since the aim of this study is to capture the full extent of freight transport—regardless of vehicle nationality—such sources do not offer a comprehensive representation of the flows under investigation.

Fortunately, both CBS and Eurostat also publish statistics on bilateral transport flows between countries, which provide a more complete picture of cross-border freight movements (Centraal Bureau voor de Statistiek (CBS), 2025c; Eurostat, 2024f). These datasets formed the basis for validating the alternative data sources used in this study, namely the Tours and ETISplus datasets. The initial step in this validation involved comparing total import and export volumes from these datasets with the official figures reported by CBS and Eurostat. The results of this comparison are presented in the table below.

Source	CBS	Eurostat 2023	ETIS 2019 Fraunhofer	Tours data BasGoed 6	Recreated ETIS (2019)
National	558 million tonne	525 million tonne	351 million tonne	13.1 million tonne	557 million tonne
Int. Unloading	94 million tonne	92 million tonne	124 million tonne	4.4 million tonne	102 million tonne
Int. Loading	102 million tonne	103 million tonne	123 million tonne		107 million tonne
Total	754 million tonne	720 million tonne	598 million tonne	17.6 million tonne	766 million tonne

Table 4: Comparison of import/export data

The CBS data contains the freight transport flow from European countries to other European countries (Centraal Bureau voor de Statistiek (CBS), 2025c). With this information the total international and national freight transport could be calculated. These statistics should not be confused with other CBS sources as these other CBS sources only look at Trucks that are registered in the Netherlands (Centraal Bureau voor de Statistiek (CBS), 2025a, 2025b).

Eurostat is gathered from (Eurostat, 2024f), this data is from 2023 but matches the CBS data closely and does differentiate between loading and unloading. Just like CBS, Eurostat also has numbers which only represent trucks registered in the Netherlands, this data is not used in this research (Eurostat, 2024a, 2024b, 2024g).

The international and national transport amount for the ETISplus data has been calculated by filtering the dataset on dutch destination to dutch origin, Dutch origin to international destination and international origin to Dutch destination. The national amount turned out to be 351 million tonne, which is significant less than CBS and Eurostat suggest. International it is 122million loading and the same for unloading, this is closer to the numbers published by CBS and Eurostat but still 20% off.

Surprisingly, when comparing the Fraunhofer ETIS dataset from 2010, which serves as the foundation for their 2019 dataset, Substantial discrepancies were observed between it and the original ETIS 2010 dataset published by the European Commission. These differences are unexpected, given that the 2019 dataset is explicitly based on the earlier version. This inconsistency raises further concerns about the validity and reliability of the 2019 ETIS dataset.

Filtering the Tours data proved to be more complex, as it consists of tours composed of multiple trips, some of which take place within the Netherlands while others extend beyond its borders. A further complication arises from partial deliveries, where trucks may distribute their cargo across multiple destinations rather than delivering it all in a single trip. To address the issue of trip nationality, filtering was applied at the individual trip level: any trip involving kilometers outside the Netherlands was classified as international. To account for partial deliveries, the weight recorded for the subsequent trip in the same tour was also considered. Additionally, the classification was cross-validated using the total weight transported by the end of each tour, ensuring consistency in the treatment of multi-stop deliveries.

The Tours dataset represents a simulation of five working days, out of a total of approximately 256 working days in a year. As such, the focus lies primarily on the distribution of transport flows, rather than absolute volumes. When comparing the Tours data to official CBS figures, national transport volumes amounted to approximately 1/42, and international transport to 1/44, of the annual totals reported by CBS. Given that the dataset covers 5 out of 256 working days, the expected proportion would be around 1/51. While the Tours dataset slightly overestimates total flows, the deviation remains relatively small and within a reasonable margin for a synthetic dataset of this nature. Furthermore, the tour data also takes the weight of the container into consideration, this would very well explain the overshoot of weight in this dataset.

6.2 Verification of Directional Threshold and Station Reachability

To validate the choice of angular thresholds for determining whether a charging station is considered to be "along the route", an experiment was designed using the Dutch road network $G = (V, E)$, where nodes V correspond to coordinates (x, y) and edges E are weighted by road length in meters. A subset of nodes $V_c \subset V$ was labeled as charging stations based on their node attribute.

We performed the following steps:

1. Select $N = 1000$ random origin nodes $o \in V$.

2. For each origin, sample a random destination $d \in V, d \neq o$.

3. Compute the baseline shortest path distance between origin and destination:

$$D_{od} = \min_{p \in P(o,d)} \sum_{e \in p} \ell(e),$$

   where $P(o, d)$ is the set of paths between o and d and $\ell(e)$ is the length of edge e.

4. Compute all reachable charging stations within a cutoff radius $R = 30{,}000\,\mathrm{m}$ along the road network:

$$V_c^R(o) = \{s \in V_c \mid D_{os} \leq R\}.$$

5. For each candidate station $s \in V_c^R(o)$, calculate:

   - The via distance:

$$D_{o \to s \to d} = D_{os} + D_{sd}.$$

   - The detour:

$$\Delta_{osd} = D_{o \to s \to d} - D_{od}.$$

   - The angle ϕ_{osd} between the vectors $\vec{v}_{od}$ and $\vec{v}_{os}$ derived from the node coordinates:

$$\cos(\phi_{osd}) = \frac{\vec{v}_{od} \cdot \vec{v}_{os}}{\|\vec{v}_{od}\| \, \|\vec{v}_{os}\|}.$$

6. For thresholds $\theta \in \{15^\circ, 30^\circ, 45^\circ, 60^\circ, 75^\circ, 90^\circ\}$, select all stations with $\phi_{osd} \leq \theta$. For each threshold and origin we record:

$$\begin{aligned} n_\theta(o) &= \text{number of stations with } \phi_{osd} \leq \theta, \\ f_\theta(o) &= \max_{s:\phi_{osd} \leq \theta} D_{os}, \\ \Delta_\theta^{\max}(o) &= \max_{s:\phi_{osd} \leq \theta} \Delta_{osd}. \end{aligned}$$

The outcome of this procedure is a validation dataset in which each sampled origin node o is associated with metrics $\{n_\theta(o), f_\theta(o), \Delta_\theta^{\max}(o)\}$ for every angular threshold θ. These values allow us to test how sensitive the model results are to the choice of angular cut-off. They provide evidence of how the number of available stations and their associated detour penalties vary as the directional constraint is relaxed from 15° to 90°. The results show that while the number of candidate stations increases steadily with larger thresholds, the detour penalty grows disproportionately beyond 45°. A cut-off at 60° therefore balances coverage (number of reachable stations) with efficiency (moderate detour distance), justifying its use in the station searching heuristic.

Table 5: Validation of angular thresholds for station selection.

Angle threshold (°)	**Mean stations (30 km)**	**Median detour (km)**	**P75 detour (km)**
15	2.2	4.8	9.2
30	4.4	5.9	13.0
45	6.6	9.1	17.2
60	8.4	13.7	21.7
75	10.5	18.1	26.6
90	12.3	22.3	31.3

6.3 Seed Variance Analysis of Station Utilization

To assess the robustness of the simulation outcomes against stochastic effects, the variance in charger utilization across different random seeds was evaluated. For each station and timestep, the number of charging trucks was aligned across 19 seeds (2-20), and the variance was calculated. Figure 18 shows the distribution of these variances across all stations.

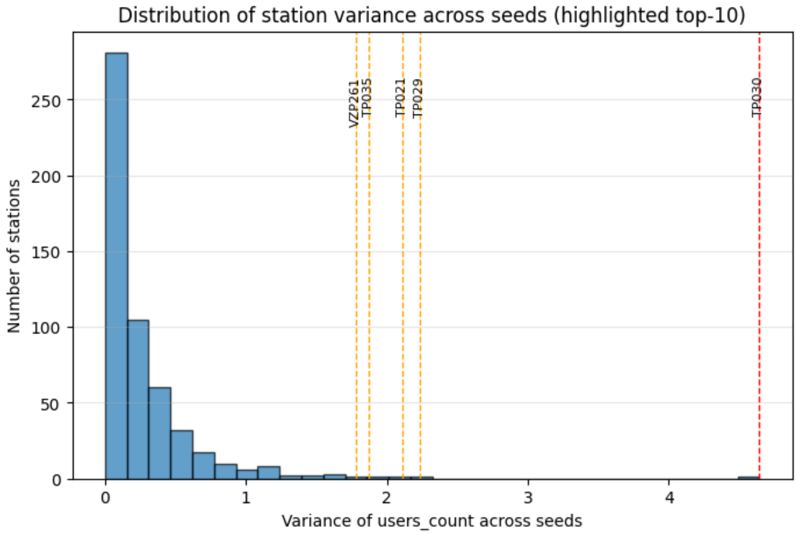


Figure 18: Distribution of variance in station utilization across seeds. The top-5 most variable stations are highlighted, with TP030 in red.

The majority of stations exhibit very low variance values (< 1), meaning their utilization patterns are consistent across seeds. This suggests that most locations in the model are not strongly affected by stochastic differences in routing and timing. However, a few stations stand out as clear outliers. In particular, TP030 shows an average variance of 4.6, far exceeding all other sites. This indicates that TP030's utilization is highly sensitive to the random seed used in the simulation, and therefore less robust than other locations.

Interestingly, when looking only at the long-run mean utilization per seed, TP030 appears remarkably stable: the average number of simultaneous users lies between 3.3 and 3.8 across all seeds. This narrow range suggests that overall throughput is consistent.

To better understand this sensitivity, the distribution of instantaneous truck counts at TP030 across all seeds and timesteps was examined. As shown in Figure 19, the distribution is extremely skewed. Most of the time, TP030 hosts between 0 and 5 charging trucks. Yet, the long right tail reveals rare but very large spikes, with counts occasionally exceeding 60 simultaneous users. These rare peaks inflate the variance and lead to a coefficient of variation of roughly 250%, meaning that the standard deviation of the load at TP030 is more than twice its mean.

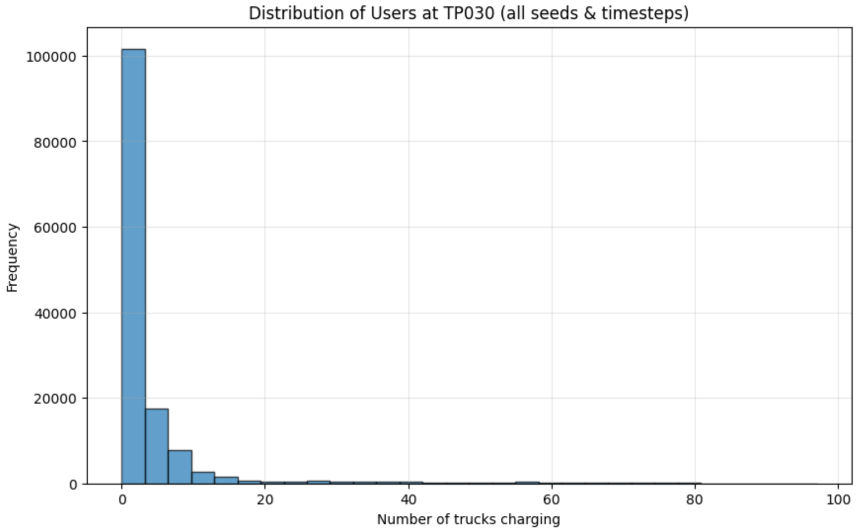


Figure 19: Distribution of instantaneous truck counts at TP030 across seeds and timesteps.

While most stations show stable utilization independent of seed choice, TP030 is a notable exception. Its strategic location (Venlo) and its role as a major corridor hub likely make it especially sensitive to stochastic fluctuations in routing and demand. From a planning perspective, this result highlights the need for cautious interpretation of load forecasts at such border and corridor locations, as their utilization may be less predictable than that of typical service areas.

6.4 Results of the Sensitivity Analysis

To assess how model outcomes respond to changes in input parameters, a sensitivity analysis was performed. The simulation design was a full-factorial experiment covering all combinations of the key parameters: battery capacity, maximum queue length, search threshold, and drive train type. The resulting dataset contains 108 runs with associated key performance indicators (KPIs), such as total energy consumption, peak users, and mean trip duration. The full sensitivity design can be found in section 5.2.

To identify the direction and strength of relationships between parameters and KPIs, ordinary least squares (OLS) regression models were estimated (Wooldridge, 2012). All continuous design variables were standardized to enable direct comparison of effect sizes. Interaction terms were included to capture joint effects between parameters. Since simulation outcomes often have heteroskedasticity, heteroskedasticity-consistent standard errors of type HC3 were applied (White, 1980). This correction ensures valid deduction even when error variances differ across design conditions. The OLS results therefore indicate which factors increase or decrease a KPI, and by how much, while providing reliable significance testing. The results of the OLS can be found below in table 6 in which the significance is indicated by stars *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$.

Table 6: OLS regression results (HC3 robust SE) for selected KPIs. Only significant or dominant factors are reported. Effects are relative to baseline scenario (battery = 600 kWh, max_queue = 0.2, drive_train = 0.94, search_threshold = 30000).

KPI	Factor (Level)	Effect vs. Baseline	95% CI	Significance
Energy (kWh)				
	Battery cap (500)	+496	[486; 505]	***
	Battery cap (700)	–347	[–359; –336]	***
	Max queue (0.1)	+30	[18; 42]	***
	Drive train (0.9)	+269	[257; 280]	***
	Drive train (0.96)	–121	[–131; –111]	***
	Search threshold (20,000)	–32	[–45; –19]	***
	Search threshold (40,000)	+13	[507; 26]	*
	Search threshold (50,000)	+24	[10,709; 38]	***
	Others	negligible (ns)		
Mean distance (m)				
	Battery cap (500)	+164	[98; 230]	***
	Battery cap (700)	–92	[–139; –45]	***
	Max queue (0.1)	+422	[356; 488]	***
	Max queue (0.3)	–123	[–166; –80]	***
	Search threshold (20,000)	–325	[–385; –266]	***
	Search threshold (40,000)	+123	[72; 174]	***
	Search threshold (50,000)	+252	[175; 329]	***
	Others	negligible (ns)		

in addition to OLS regression, an analysis of variance (ANOVA) was conducted to decompose the variance in each KPI across main effects and interactions. Type-II ANOVA was chosen to account for balanced factorial design and to provide interpretable effect sizes (Lakens, 2013). The resulting η^2 statistics quantify the proportion of variance in each KPI explained by a given factor. This allows ranking the relative importance of design variables: large η^2 values indicate dominant drivers of system behavior, while values below 0.01 are considered negligible. The results of this analysis for the total energy consumption output can be found in figure 7

Table 7: Two-way ANOVA on energy_kWh

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	1.296e+13	667080.41	$<$ 1e-16	0.811	1.000
max_queue	2.0	3.011e+10	1550.05	$<$ 1e-16	0.002	0.979
drive_train	2.0	2.878e+12	148133.03	$<$ 1e-16	0.180	1.000
search_threshold	3.0	4.963e+10	1702.99	$<$ 1e-16	0.003	0.987
battery_cap×max_queue	4.0	3.489e+09	89.79	$<$ 1e-16	0.000	0.841
battery_cap×drive	4.0	4.736e+10	1218.81	$<$ 1e-16	0.003	0.986
battery_cap×search_threshold	6.0	2.304e+09	39.54	$<$ 1e-16	0.000	0.777
max_queue×drive_train	4.0	1.314e+08	3.38	1.39e-02	0.000	0.166
max_queue×search_threshold	6.0	4.307e+09	73.90	$<$ 1e-16	0.000	0.867
drive_train×search_threshold	6.0	1.902e+08	3.26	7.04e-03	0.000	0.224
Residual	68.0	6.605e+08			0.000	0.500

The sensitivity analysis revealed that for several KPIs, the majority of variance is explained by a single dominant parameter. as seen in figure 7 battery capacity accounted for over 80% of the variance in total energy consumption ($\eta^2 = 0.81$), while drive-train efficiency explained an additional 18%. All other parameters contributed less than 1% and can be considered marginal. For other KPIs such as mean distance, both max queue and search threshold emerge as the primary drivers, with interaction effects occasionally contributing in specific ranges. The OLS coefficients corroborated these findings, showing strong positive associations for the dominant parameters and statistically insignificant effects for the remainder.

The effects of the variables shown in the sensitivity analysis do follow our predictions. In the model with 600 kWh battery capacity about 15% of the charging events occur because of low batteries, by increasing the battery capacity or drive-train efficiency it is logical the amount of charges required lowers. However, with battery capacity, the consumption remains the same, therefore total energy kWh spend does not decrease in reality. This exposes a flaw in the model, because instead of the truck arriving with a high charge it now arrives with a low charge, making it only look like it used less energy because it charged 1 time less.

Increasing search threshold and decreasing max queue both increase either the likelihood of picking certain stations and therefore influence distance traveled. The full ANOVA and OLS analysis can be found in appendix A.9

7 Results

This section presents and analyzes the results obtained from the agent-based model. It begins with a discussion of the general outcomes, illustrated through spatial maps and figures. The underlying mechanisms are clarified, and where relevant, atypical patterns in the results are addressed. Following this general overview, the section turns to the research questions outlined in Section 1. These questions focus on key aspects of road freight transport, including the logistic behavior and traffic patterns of trucks, the suitability of an agent-based model to represent such dynamics, the potential influence of policy interventions on the placement of charging infrastructure, the energy implications of infrastructure placement, and, finally, the distribution and quantity requirements for truck charging infrastructure within the Netherlands.

Unless stated otherwise the results below are shown with an electrification phase of 20%, motorway service areas (VZPs) can be used as sleeping areas and MCS only.

7.1 Findings from the initial path-based trial

The first iterations used a reconstructed ETISplus origin–destination dataset (see Appendix A, Section A.6). However, the results of these simulations ran into one big issue; In the path-based (single-trip) setup, each agent executes only one origin–destination trip. using a single trip, especially in the Netherlands, leads to trips to short to trigger the charging requirements. This ultimately leads to zero charging moments for all the national truck travel. With the initial investment cost of a charging system being high it is unlikely all national truck travel would resort to depot charging. Therefore, the path-based methodology using a recreated ETISplus dataset is not suited to capture the complexity of truck logistics and the placement of MCS. This has led to conversion of the model to tour-based to better suit the complexity of truck logistics and MCS placement. all results reported below are based on the tour-based dataset.

7.2 The Predicament of Peak Charging Times

Before delving into the results, it is necessary to highlight one of the key limitations of the model that will explain behavior further in the results. The simulation strictly follows European driving regulations, which mandate that truck drivers take a 45-minute break after 4.5 hours of driving and a longer rest period after 9 hours of driving (European Parliament and the Council of the European Union, 2015). When these rules are combined with the departure time distribution described in Section 4.5.2, they produce distinct peak moments during which a large number of trucks simultaneously require charging. This effect is illustrated in Figure 20.

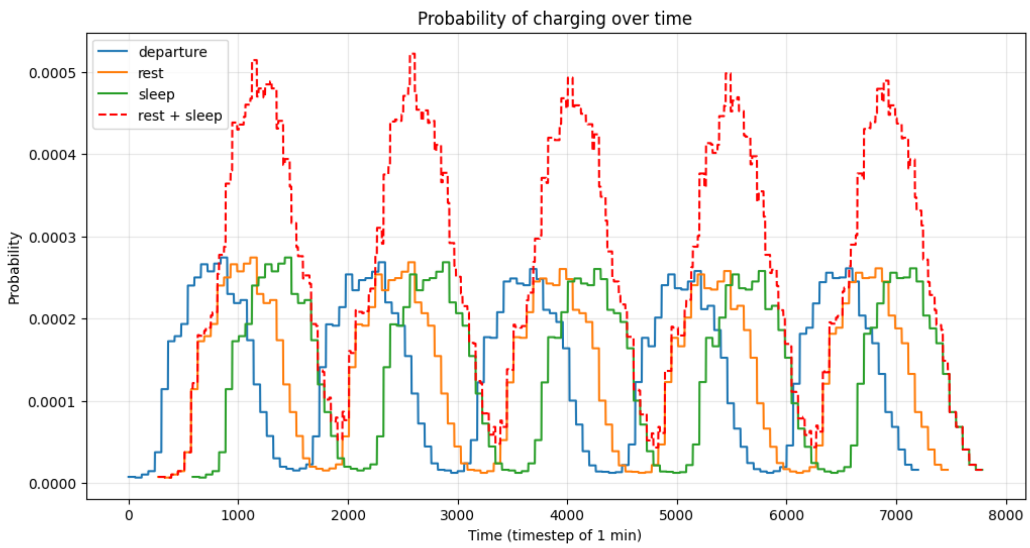


Figure 20: Peak charging moments over time (t=0 -> 00:00 Monday, timestep = 1 minute)

In Figure 20, the blue line illustrates the distribution of truck departures, which subsequently leads to rest and sleep periods, represented by the green and orange lines. Around 18:00, these two schedules overlap, creating a peak surge in charging demand, visualized by the red dashed line. The realism of this pattern will be further discussed in Section 8, the following subsection will show some of the implications of this behavior.

7.3 Charging, resting, and sleeping behavior at a single station

Charging stations serve multiple purposes throughout the day, as they are used not only for recharging but also for resting and overnight sleeping. Each of these activities requires a parking space, meaning that different uses directly compete for the same limited capacity. This competition can result in situations where several hundred trucks occupy a location for rest or sleep without accessing the chargers, thereby preventing other vehicles from making use of available charging points. An example of this phenomenon is illustrated in Figure 21, which depicts the utilization of the truck parking facility "TP030" over a two-day period in the 60VM scenario. TP030, located near Venlo close to the German border, is the largest truck parking facility in the Netherlands with a capacity of approximately 390 vehicles.

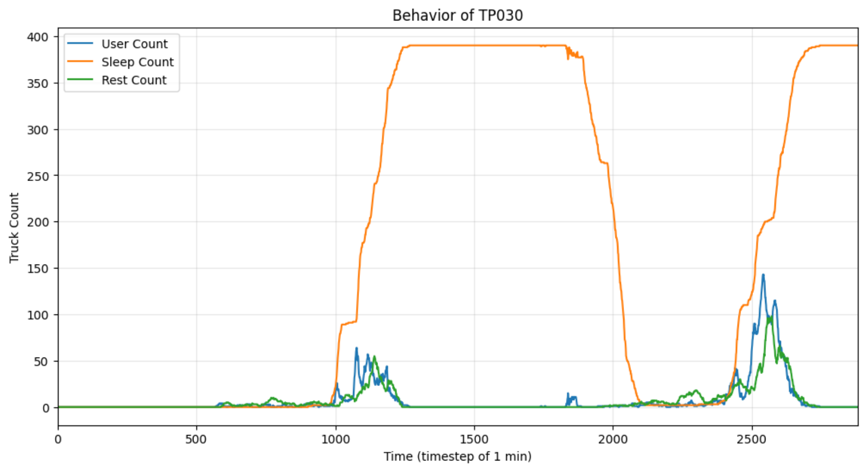


Figure 21: Charging, resting, and sleeping behavior at TP030 in scenario 60VM for 2 days

Figure 21 highlights several operational challenges. First, it confirms the strong peak in charging demand described in the preceding subsection: while the average daytime demand is moderate, short periods of exceptionally high charging activity would require an unrealistically large number of chargers if fully accommodated. Second, the figure shows that following this peak, the site quickly fills with trucks staying overnight, leaving little capacity for vehicles arriving later that require charging. As a result, the charging infrastructure at this site becomes effectively inaccessible, despite the physical presence of unused chargers.

This peak-driven dynamic complicates the interpretation of infrastructure needs. In practice, no operator is likely to install sufficient chargers to satisfy the maximum demand. Instead, more realistic strategies involve accepting some level of queuing and scheduling charging times in the evening for trucks planning to stay overnight, this would better distribute the charging demand over time.

7.4 Map of 95th percentile Charging Demand in the Netherlands

To provide a spatial perspective on charging demand, Figure 22 shows the geographic distribution of the 95th percentile charging demand across the Netherlands. The values represent the peak charging needs observed at each location during five working days. Blue circles represent dummy locations and red circles represent real truck parking or rest locations. The visualization highlights distinct spatial patterns, high-demand sites are concentrated along the country's major freight corridors, particularly the A15 (Rotterdam–Germany), the A67 (Eindhoven–Venlo), and the north–south axis through Arnhem and Nijmegen. These are corridors with heavy international transit flows, consistent with their role in connecting the Dutch hinterland to the German Ruhr area and further into

Central Europe.

In contrast, stations located in the northern provinces (Friesland, Drenthe, and Groningen) generally show lower peak requirements. This reflects the comparatively smaller freight volumes routed through these regions, as well as fewer cross-border connections relative to the southern and eastern borders. Notably, several inland hubs such as around Utrecht and Breda also emerge as local hotspots, underlining their strategic role as intersections of national transport flows.

The 95th percentile approach emphasizes the infrastructure requirements at near-peak conditions without being overly sensitive to extreme outliers. From a planning perspective, this provides a more robust indication of long-term grid and charging capacity needs than average utilization. It also underscores the importance of corridor-level coordination: while many sites individually show moderate demand, their collective alignment along freight corridors implies a concentrated strain on both parking facilities and the electricity grid.

Figure 22: Geospatial distribution of 95th percentile charging demand across the Netherlands for scenario 20VM

The appendix contains multiple maps for different electrification phases. All the maps can be also be found in the html file attached to this project.

7.5 Policy scenario: sleeping at VZP or not?

An important policy question is whether long overnight rest should take place at regular resting areas (VZP) along the motorway, or whether trucks should be directed towards dedicated truck parking facilities. Figure 23 shows the number of stations that became fully blocked when trucks were allowed to sleep at VZPs compared with a scenario where sleeping at VZPs was not permitted.

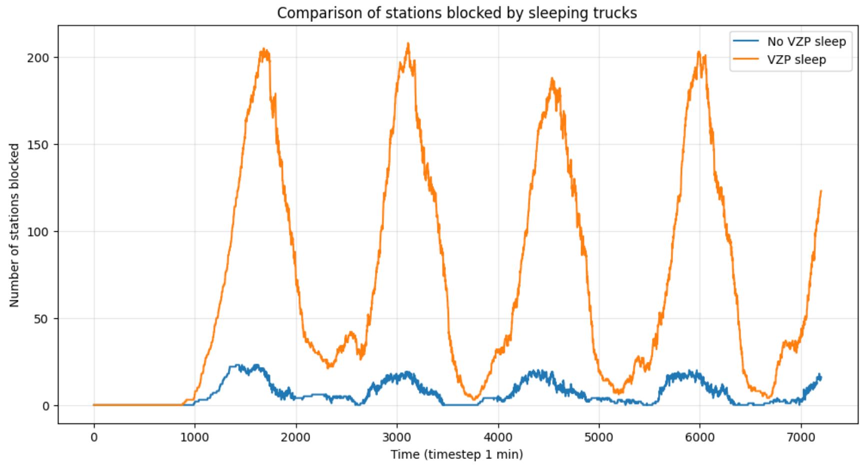


Figure 23: Comparison of blocked stations with and without sleeping at VZPs (60TM & 60VM)

In the baseline case where drivers sleep at VZPs, more than 200 stations can become completely occupied during the night, leaving no space for passing trucks to access the chargers. In contrast, when sleeping is shifted away from VZPs, the number of blocked stations is reduced by an order of magnitude. This shows that overnight parking behavior is a major driver of accessibility problems. From an infrastructure perspective, this means that simply installing more chargers at VZPs is not sufficient. As long as the parking spaces are filled with sleeping trucks, chargers remain inaccessible.

However, this restriction does not eliminate the problem. instead, it shifts the pressure. As Figure 24 shows, trucks that can no longer park overnight at VZPs redistribute to TPs and DUMs. Since DUM locations are no realised location this shift highlights a structural shortage of designated overnight truck parking in the Netherlands. Without sufficient secure long-stay facilities, measures that prohibit sleeping at VZPs may lead to truckers resorting to sleeping at illegal and unsecure locations.

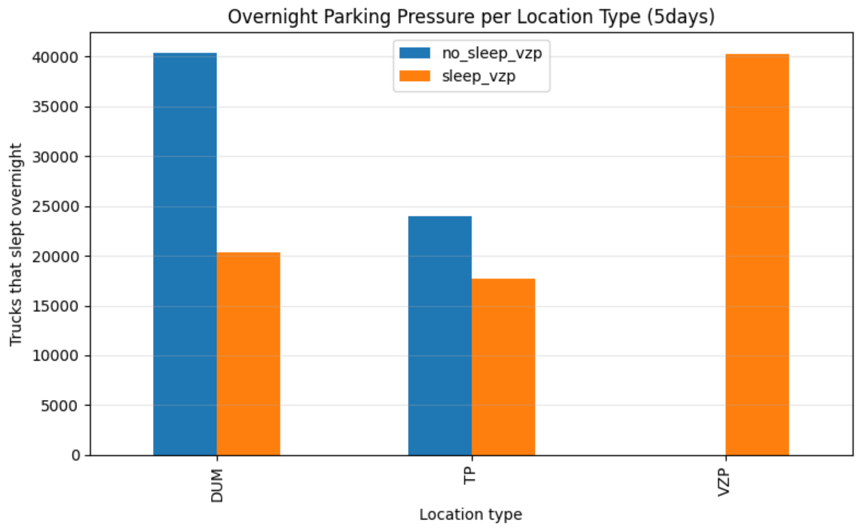


Figure 24: Sleep Pressure per location type for scenario 60VM and 60TM

Whether overnight sleeping is allowed at VZPs or not, policymakers face a clear choice: either expand VZPs so that sleeping and charging can take place separately, or redirect overnight stays to alternative facilities. In the last case, new dedicated parking areas would need to be built to accommodate the actual sleeping demand.

7.6 Impact of combining CCS with MCS

To assess whether allowing slower CCS charging before overnight rest could reduce peak loads at charging stations, we compared two scenarios: one with MCS-only and one where trucks could use both MCS and CCS.

At the network level, the difference is marginal. The average maximum number of simultaneous MCS users per station is 5.24 in the MCS-only case and 4.94 in the MCS+CCS case. Only about 12% of station–seed combinations experience lower peaks under MCS+CCS, for the others peak MCS users are the same.

The effect is highly uneven. The largest truck parkings see the strongest relief: TP030 (Venlo) and TP029 (Roosendaal) show average peak reductions of 6.4 and 4.6 trucks respectively. A handful of other TPs and DUMs also benefit slightly. In contrast, most VZPs see little change, and some even show small increases in peak demand. Figure 25 illustrates this by focusing on the busiest 10% of stations: MCS-only stations show a higher median and a longer upper tail, whereas MCS+CCS flattens the distribution modestly.

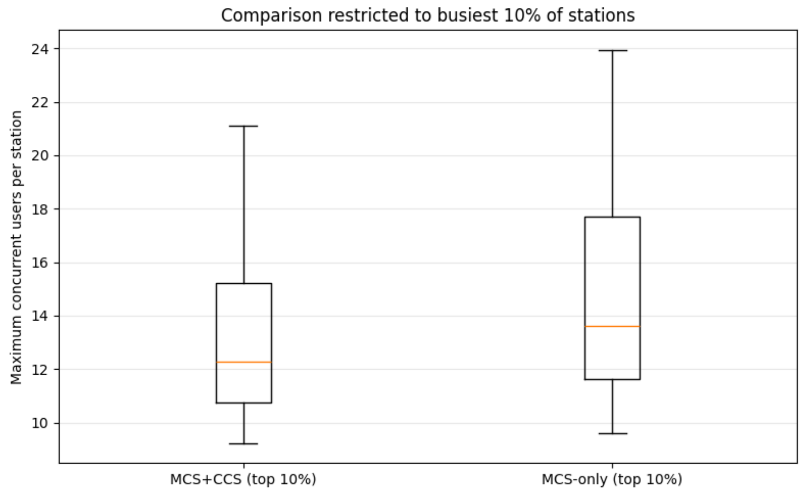


Figure 25: Peak demand at the busiest 10% of stations under MCS-only vs MCS+CCS.

In terms of charging sessions, the totals are nearly identical: 168,517 in the MCS-only case and 168,500 in MCS+CCS. However, in the combined scenario about 18% of sessions (29,844) shift to CCS while the remainder (138,656) still rely on MCS. This shows that CCS is actively used when available, but it does not significantly reduce MCS dependency.

Finally, the infrastructure requirements under the 60% electrification scenario show a clear outcome. In the MCS+CCS case, about 5,164 MCS chargers and 2,802 CCS chargers are required, whereas the MCS-only case requires 5,615 MCS chargers and no CCS. In other words, 2,802 CCS chargers replace only 451 MCS units. Looking at the 95th percentile distribution, the ratio is similar: roughly 1,551 CCS chargers substitute for just 170 MCS, meaning that between six and nine CCS chargers are needed to replace a single MCS. This substitution rate is both space-inefficient and costly. The main reason for this poor replacement rate lies in the 45 minute resting period, which drives the peaks. CCS chargers cannot effectively substitute for MCS at these times, and therefore fail to achieve the intended reduction in peak demand.

7.7 Growth per electrification phase

The staged electrification scenarios reveal a near-linear relationship between the number of battery-electric trucks (BETs) and the required charging infrastructure. Across all simulated penetration levels (5%, 10%, 20%, 40%, 60%, and 100%), the ratio of trucks to Megawatt Charging System (MCS) chargers stabilizes at approximately 40 trucks per charger as can be seen in figure 26.

The proportional growth suggests that infrastructure demand scale predictably with fleet electrification rather than exhibiting threshold effects. While this outcome simplifies planning, it also shows that no efficiency gains are realized when moving to higher electrification levels.

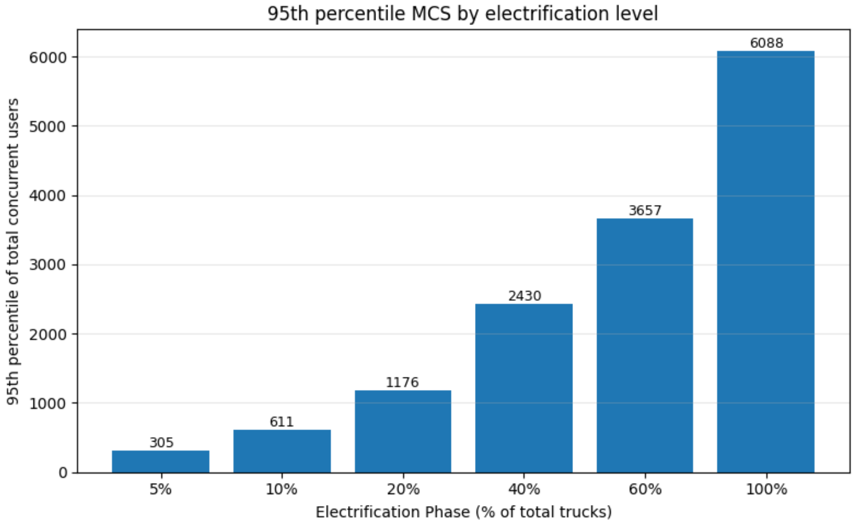


Figure 26: MCS chargers per electrification

7.8 MCS Locations with Power Grid Restrictions

To assess the influence of regional grid capacity on the deployment of MCS, a simulation was performed in which all points of interest (POIs) located in zones with insufficient medium-voltage supply were excluded (based on the congestion map in Figure 3). This reduction lowers the potential number of charging locations from 557 to 325 (or 203 when excluding DUM stations).

The results indicate a clear redistribution of charging demand. Stations in unconstrained zones absorb the traffic that would otherwise have been served by excluded sites, leading to increase in regional energy demand. As shown in figure 27 the absence of grid connections is especially present in the Randstad region: around Amsterdam and Utrecht the absence of available grid supply concentrates all the charging activity at the nearest available hubs. The truck parking facility near Gorinchem (TP014) emerges as a major pressure point in this scenario. Furthermore, The shortest distance between viable stations in the empty area is 80 km, and vehicles diverting towards the Port of Rotterdam face detours of roughly 30 km. Surprisingly, the detour does not seem to influence the mean distance driven or mean driving time significantly.

Figure 27: Geospatial distribution of 95th percentile charging demand under grid restrictions, scenario 20VM.

Figure 28 highlights the five stations with the largest increase in electricity demand compared to the unrestricted scenario. TP014 shows a ten-fold rise in energy use, underlining the absence of grid connections in the area. This concentrated demand not only raises the risk of local congestion but also increases the importance of coordinated planning between transport infrastructure and grid operators.

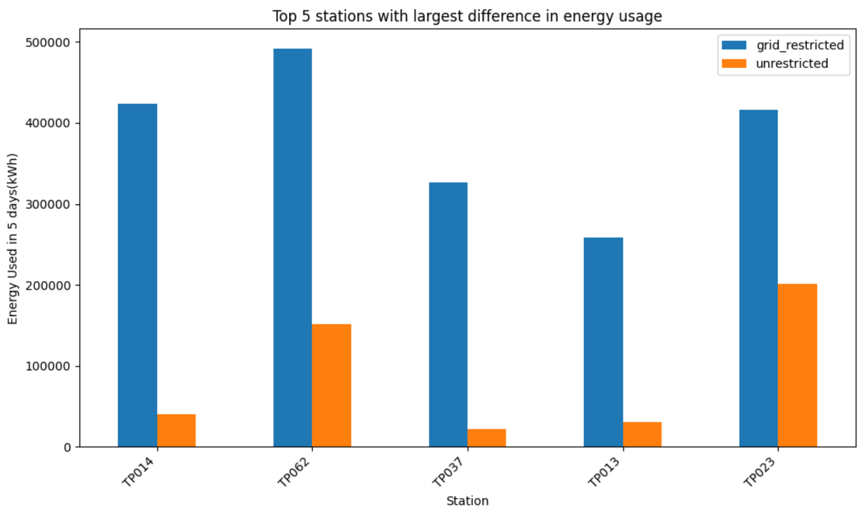


Figure 28: Top 5 stations with highest increase in energy demand under grid restrictions.

This analysis suggests that grid availability is likely to become a key driver of MCS siting in the near term, potentially overriding purely traffic-based optimization approaches. Concentration of demand at fewer sites may worsen local queuing, increase the need for large-scale grid reinforcements, and reduce network resilience. This highlights the importance of grid availability for the roll-out of BETs. An optimal network expansion requires not only identifying corridors of high truck flow but also aligning with regional grid upgrade programs. However, with 20% electrification estimated to be achieved between 2030 and 2035 there is still time for grid improvement (ElaadNL, 2025).

Furthermore, the results raise a compliance concern with the EU Alternative Fuels Infrastructure Regulation (AFIR), which requires high-power charging pools every 60 km on the TEN-T core network and every 100 km on the comprehensive network by 2030. In the restricted scenario, the A12 corridor does not meet this requirement in the simulation, as the gap between viable MCS locations exceeds 60 km. In practice, however, several CCS chargers of up to 350 kW are already installed along the A12. While these do not have full MCS capacity and are not suitable for long-haul movements, they ensure that the corridor formally complies with AFIR's minimum requirements.

7.9 Energy Demand per Region

Figures 29a and 29b present the estimated daily energy demand of BETs, aggregated at two different spatial levels for the electrification phase of 20%. The first map displays the distribution per province, while the second provides a more detailed breakdown per medium-voltage energy distribution zone.

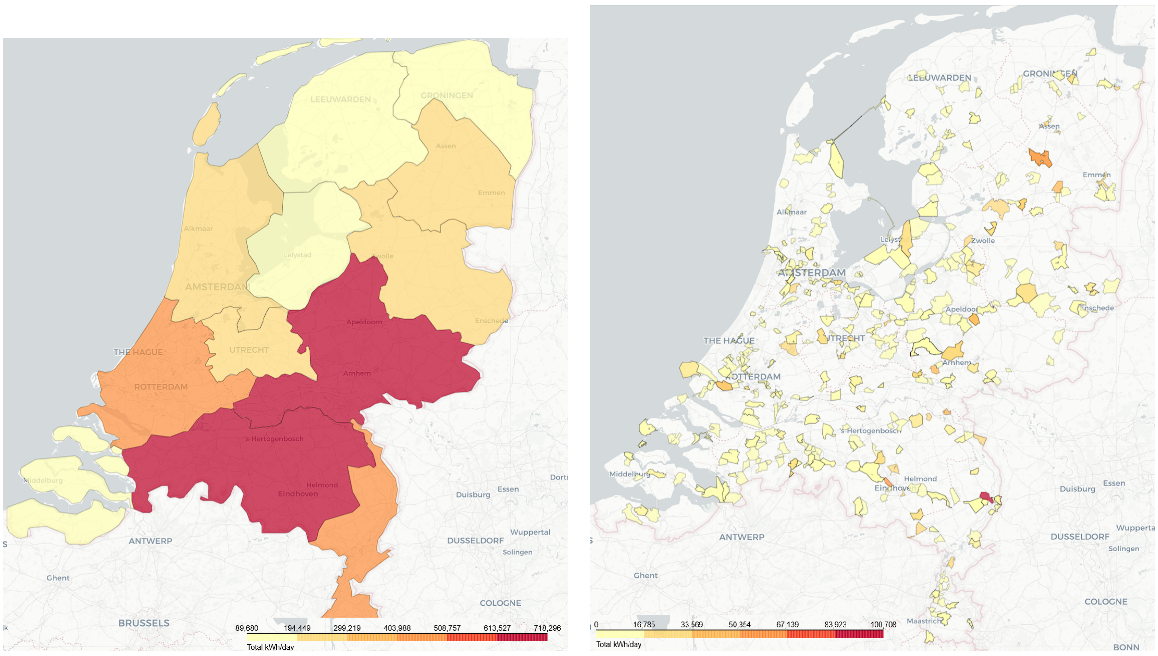
The provincial level provides a broad overview and shows which provinces contribute most to national energy demand. This scale is relevant for policy discussions and the allocation energy targets. However, the energy distribution zones reveal a much more heterogeneous picture. Within the provinces are local hotspots which require more attention. These hotspots emerge around ports, industrial areas, and along major freight corridors. These finer-grained results underline that even within provinces the energy demand for charging infrastructure is spatial divided.

On the provincial map, Gelderland and Noord-Brabant stand out as the regions with the highest expected charging demand, followed by Limburg and Zuid-Holland. Together, these provinces account for the bulk of projected energy use, which is unsurprising given their concentration of industrial activity, port access, and their role as transit corridors for international freight. By contrast, Friesland, Groningen, and Zeeland show relatively low demand. These more rural provinces are less directly connected to major ports or industrial hubs, and therefore play a smaller role in the overall charging load.

The finer-grained map of medium-voltage distribution zones reveals the spatial variation within provinces more clearly. It highlights localized hotspots such as the area around Venlo, which shows particularly high demand, as well as the dense clustering in the Randstad compared to the more dispersed pattern in the northern regions. This contrast underlines the importance of moving beyond provincial aggregates when planning charging infrastructure, as grid pressures emerge very locally.

From a grid planning perspective, the distribution network representation is more actionable. Bottlenecks and reinforcement needs occur locally in the electricity grid and are therefore best captured at the level of technical grid zones. Provincial totals remain useful for planning of the high-voltage network on which the medium-voltage network relies. The network planning for the medium-voltage network requires attention to the distribution of demand within provinces for which the smaller zones are more suitable. The observed concentrations in energy distribution zones are consistent with earlier findings that truck charging demand is highly clustered around the TEN-T corridors and logistics hubs (Lange et al., 2024).

To summarize, the energy demand distribution across provinces gives an overview of which provinces will need to increase their high-voltage network to allow for the increase in supply for the medium-voltage network. The more granular map of the energy distribution zones points out which specific medium-network connections need to increase their energy supply to provide energy for charging infrastructure.



(a) Per province

(b) Per middle-voltage distribution zone

Figure 29: Estimated daily charging demand of battery-electric trucks at two spatial aggregation levels.

8 Discussion

This section consists out of the discussion of the results (section 7 and the methods used (section 3 & 4) to gain these results. The discussion compares the model to the expected reality.

The Lack of Depot Charging

In the current model, depot charging was only represented in a very limited way. Trucks begin their tours with a full battery and end their tours by disappearing from the simulation without recharging. This approach overlooks the significant role depot charging is expected to play in practice. For many operators, particularly for national short distance tours, the depot will likely be the primary charging location (Herlt & Hildebrandt, 2023; Raoofi, 2025). While this would require considerable private investment, it could reduce exposure to higher public charging rates and lower the demand for public charging infrastructure. By not accounting for depot charging, the model also underestimates total daily energy consumption, since the residual state of charge upon returning to the depot is not included in the energy balance. Furthermore, in the model around 15% of charging events occur when the battery falls below the 20% threshold. If trucks were able to recharge during loading and unloading at depots, many of these events would not take place, thereby reducing the number of en-route charging stops. At present, the only case where such opportunity charging is included is at the Port of Rotterdam and Schiphol, where strict time slots already create a natural window for charging if the truck's state of charge drops below 20%.

Risk of Self Created Spawn Distribution

The reliability of the model results is closely tied to the assumptions made about truck departure times. In this study, departure patterns were derived from NDW data near the Port of Rotterdam. While this dataset provides a reasonable basis, it does not guarantee that the simulated distribution fully reflects reality. Any deviation between assumed and actual departure times directly affects the temporal profile of charging demand. For instance, if real-world departures are more evenly spread across the day, peak charging loads would likely be lower. Contrarily, a more concentrated distribution of departures could increase peak demand. But it is more likely that the main effect of such deviations would be a shift in the timing of the peak without really altering overall demand levels.

Standardized Speed for Each Timestep

In the model truck speeds are simplified by assigning a fixed average speed to each road type for every timestep of the day. This method strongly differs from real-world conditions, where congestion patterns are highly variable. Realistically some days experience severe congestion that may even force trucks to reroute, while on other days traffic is relatively smooth. Moreover, congestion is often localized, affecting only certain roads of the Netherlands rather than the entire network like in the model. By applying a global speed assumption, the model removes this spatial variability of road congestion, which leads to overly simplified routing behavior. Traffic jams are not explicitly represented in the model. Instead, congestion is approximated by lowering average speeds and increasing energy consumption. At its most extreme, the model reduces average speeds to around 50 km/h, whereas in practice trucks can experience complete standstills for extended periods or have days without major delays. As a result, the model under represents the diversity of traffic conditions and having a global speed oversimplifies route choices.

Competition with Sleepers and Resters

In the Netherlands there is already a structural shortage of truck parking capacity. According to TLN, the deficit amounts to approximately 4,000 spaces (NOS, 2025). As a result, truck parking (TP) facilities are frequently at or near max capacity, forcing operators to make difficult choices about how to allocate their limited space. One option is to reserve a portion of spaces exclusively for charging, which would further reduce the already insufficient number of sleeping spots. Alternatively, operators may allow all spaces to be used by both sleepers and resters, in which case trucks may be unable to access chargers when the lot is full, even if charging points remain idle. In these situations, the physical availability of chargers is irrelevant if parking capacity is fully occupied. In the end, these choices are shaped by the business model of TP operators, who earn revenues from overnight stays, food and beverage services, but also charging fees. In the model, the decision was made for competition by assuming that when a parking facility is full of resting or sleeping trucks, no additional vehicles can enter to charge. This assumption may lead to an overestimation of the number of chargers required, since in reality some charging points would be available but inaccessible due to lack of parking capacity. Trucks that encounter this situation in the model divert to nearby charging stations, thereby inflating demand at neighboring stations.

Perfect Information in the Searching Algorithm

In the searching algorithm trucks had perfect information and were aware of the queue length and capacity at each charging station. This allowed them to select the optimal station at any point in time. In reality, especially during the early stages of adoption, such information will rarely be available to drivers. Instead, drivers are more likely to head to the nearest station, only to encounter a full lot or long queues. Over time, as the charging ecosystem matures, systems that display real-time availability or even allow reservations may emerge, but this remains unlikely in the initial phases of deployment. By granting trucks perfect information from the start, the model likely underestimates average waiting times and simplifies the spatial distribution of charging demand.

Peak Charging Moments

Charging peaks are one of the most notable outcomes of the model. As shown in Section 7.2, the simulated peaks are very high. In practice it is unlikely that truck parking (TP) operators would size their charging infrastructure to fully cover such a short period of extreme demand, since this would leave most chargers underused during the rest of the day. More realistically, operators would install a smaller number of chargers and accept some waiting during peaks to avoid unnecessary costs. It is also possible that the peaks in reality are much lower than in the model. Truck traffic is often more spread out, and drivers do not always follow rest-time rules to the exact minute. Some may continue driving a little longer or stop earlier, which naturally spreads charging demand. For overnight stops, the timing of charging is also more flexible, whether a truck charges directly on arrival or a few hours later makes little difference if it will remain idle until morning. The model however assumes that trucks always start charging immediately after stopping, which concentrates demand and exaggerates the height of the peaks compared to real-world behavior.

Lack of International Roads and Connections

The road network used in the model is limited to the Netherlands and does not include most of the surrounding European network. Trips originating outside the country are linked to Dutch border nodes based on NDW intensity data and euclidean distance. While this provides a simplified connection, it also introduces distortions in route choice. Some border crossings may be overestimated, while others are underestimated, depending on how flows are assigned.

An additional drawback is that trucks from a given region abroad always enter the Netherlands through the same border location. For example, a truck starting in the southern Ruhr area is routed through Venlo regardless of its final destination. In reality, a truck heading to the northern Netherlands would be more likely to cross at Arnhem. This simplification reduces the realism of cross-border traffic patterns and may misrepresent the distribution of charging demand near border areas.

Energy Consumption Battery

The consumption of energy is highly variable and dependent on a lot of different variables as explained in section 4.5.4. In this model we take all variables as constant except speed and acceleration, acceleration in the model is dependent on speed. Lower speeds are a sign of traffic jams which are paired with stop-and-go traffic and therefore higher acceleration. Previous research suggests that a BET has a consumption between 1.23 kWh/km and 1.94 kWh/km (Mareev et al., 2017). Our model consumes between 1.1 and 2.4 in extreme cases. In reality this behavior is much more complex and different for every truck, weight being the variable with the most impact. Our calculations are done with trucks weighting 38.000 kg, this is close to full but This means that in reality there would be a lot of trucks with less weight, therefore requiring less energy. Therefore this research may overestimate the energy consumed by BET.

Strictness of Following Regulations

Truckers are assumed to follow EU driving and rest-time regulations to the letter. Every truck takes its mandatory breaks at the exact prescribed intervals, which creates strong synchronization in stopping patterns and highly concentrated charging peaks.

In reality compliance with regulations is less strict. Truckers often have some flexibility in when to stop. A driver may decide to continue a little longer to reach a preferred rest area, to stop earlier to avoid congestion or to secure a parking space. These small variations could help spread charging demand more evenly across the day and reduce the height of peaks that appear in the model. The model likely overestimates the peaks of charging behavior. Real-world patterns would likely be more spread out, this would lead to smoother demand curves and potentially lower peak loads at individual locations. However, it should be noted that new trucks from 2025 must be equipped with a tachograph to monitor and enforce rest regulations, this would make truckers adhere more strictly to the regulations.

An experiment were the resting time variable was change from 4.5 hours to a stochastic variable between 3.5 and 5.5 with a normal distribution led to the results in which the peak demand declined by 2.5%

No Growth or Decrease in Tours in Later Electrification Phases

The model assumes that the number of tours remains constant across all electrification phases. This simplification means that freight demand is treated as static over time. In reality transport volumes are dynamic and influenced by a range of variables such as economic growth, trade patterns, and logistics development. Over time, total freight activity in the Netherlands and Europe is expected to change, although the pace of change will depend on macroeconomic conditions and structural shifts in the logistics sector. Whether road freight demand will increase, decrease or change in spatial distribution is uncertain but ignoring this dynamic may lead to an incorrect estimation of future charging and infrastructure needs. The current model provides a snapshot of infrastructure needs under current conditions, but the actual requirements in later phases of electrification could differ substantially, depending on how the freight sector evolves.

Short-Sighted Charging Plans

Charging decisions in the model are made very short-sighted. Trucks select where to charge based only on their immediate situation, without considering longer-term route planning or future constraints. This behavior simplifies the decision-making process but does not reflect how logistics operators are likely to organize charging in practice. Companies running large fleets have strong incentives to minimize downtime and costs, which encourages more strategic planning of charging stops.

As a result, the model likely misrepresent the way trucks decide on where to charge. It is more likely that charging would be coordinated with logistics planning tools. This way operators can avoid congestion and take advantage of lower electricity prices. They could also schedule charging during loading and unloading. Recent studies suggest that optimized charging strategies not only reduce operational costs but can also significantly lower peak loads on the grid (Bertucci et al., 2024). Incorporating strategic behavior would therefore provide a more realistic picture of both infrastructure use and grid impact.

No Competition with Non-Electric Trucks

The model only exists out of BETs, other trucks are not present in the model. This means that competition with conventional diesel trucks for parking space is not included. While in reality both types of trucks will share the same facilities for many years during the transition to zero-emission transport. As long as diesel trucks remain in significant numbers, they will continue to occupy a large share of rest-area capacity, leaving fewer spaces available for electric trucks to park and charge. Especially with the lack of parking spaces in the Netherlands already (NOS, 2025). This competition could increase congestion and waiting times far beyond what the model currently shows. By excluding non-electric trucks, the model therefore underestimates the practical challenges of allocating scarce parking and charging resources.

No Heterogeneity in Truck Specifications

All trucks in the model are created with no variation in weight, battery capacity, drive-train efficiency or other variables that would influence their energy consumption and charging behavior. This assumption has simplified the analysis but does not reflect the diversity that will exist in real fleets. It is more likely that operators will deploy a mix of vehicles with different battery sizes, drivetrain efficiencies, and payload requirements (Link, Stephan, et al., 2024; Schneider et al., 2023).

Ignoring the heterogeneity of trucks conceals the important variation in charging behavior. Smaller trucks with lighter load may require less charging sessions, or use less energy per session. By treating all trucks the same, the charging behavior is oversimplified, this will most likely lead to an overestimation of charging demand since the weight used in the model is close to full.

No Inclusion of Charging and Placement Costs

One of the major simplifications in the model used in the lack of the cost variable. There are two sorts of costs that play a big role in the placement of MCS and the behavior of trucks. The first is all the costs for the operator of the location, in the Netherlands there are 3 costs involved with this. Placement costs, network costs and energy supplier costs. The Netherlands specifically has a very high network costs, this is a cost you pay on the max capacity you can utilize. The network cost in the Netherlands is independent of your utilization, this results in very high costs during low utilization. For instance, in the Dutch region of Venlo, network costs for operating charging stations with low utilization rates are extremely high, at more than 14 euro cents/kWh (Hildermeier & Jahn, 2024). Use of the power network in the neighboring Germany's lower Rhine area is significantly cheaper, at only 6 euro cents/kWh (Hildermeier & Jahn, 2024). However, unlike the Netherlands, Germany's DSO also price utilization, this results in Germany being more expensive in high utilization. With the costs of low utilization being so high in the Netherlands it is not attractive to place low utilization charging infrastructure, this has not been taken into account in the model.

The second sort of costs that is not taken into account is the price to charge per location from the truckers perspective. One of the variables that logistics operators take into account in creating their routes is the price to charge. In some cases it might be worth taking a detour as prices in rural areas might be less expensive than prices along the busy corridors. This is an important variable that can significantly change the demand per location but has not been taken into account in this research.

The Effect of Weather

Lithium-ion batteries as often used in BETs are sensitive for influences of the weather. To be more specific, the efficiency of the battery drops in colder climates (Lv et al., 2021). The Figure below from Lv et al., 2021 shows the effect of temperature on the efficiency of a lithium-ion battery.

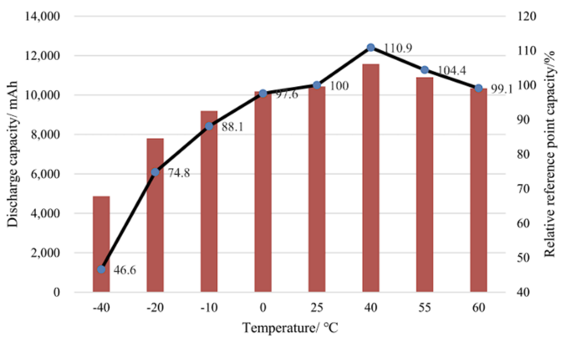


Figure 30: Effect of Temperature on Lithium-ion Batteries (Lv et al., 2021)

Noticeable in this graph is that the efficiency drop from starts to increase from 0 degree Celsius and lower. The drop from 25 degree to 0 degree is only a 2.4% efficiency drop. In the Netherlands our winters have an average temperature of 3.9 degree Celsius (KNMI, 2025), this means lithium-ion batteries should not have a large efficiency decrease in the Dutch Climate. The same study was performed on lithium cobalt oxide batteries, these had an efficiency drop of 6.6% in an environment of 0 degree Celsius (Lv et al., 2021). This model does not take into account this effect of the weather on energy consumption, however the energy consumption used in the model is on the conservative side, therefore the expected impact is minimum.

Limited in the Exploration of Policies

There are many approaches governmental bodies can take to impact or stimulate the placement of MCS infrastructure. This research has only analyzed two of these potential policies, the restriction of overnight stay at VZP, and the operational decision between MCS and CCS. However, there are much more options for the government to support deployment. They could subsidize the placement of MCS, they could prioritize connection to the grid or they could place tariffs on the use of non zero emission trucks. These policies all would have a positive effect on the timeline for MCS deployment. Since this research calculated spatial demand per electrification phase, these policies would likely not effect the results, they would just alter the expected timeline.

Comparison to the Panteia Corridor Model (Panteia, 2025)

The Panteia model is not publicly available, therefore I cannot go into details of this model. However I will still make a comparison with the limited information that can be discussed. Their method of estimating charger requirements resembles the node-based approach described in Section 2.2. In this approach, charger needs are derived primarily from the traffic intensity of the corridor near which a charging location is located. This creates a strong bias toward facilities that are directly adjacent to high-volume corridors. However many truck parking areas (TP) are located several kilometres away from the main highway, where there is more available space. As a result, the Panteia model tends to underestimate demand at these larger, off-corridor locations, while overstating demand at motorway service areas positioned directly along the highway. These smaller sites often only have capacity for a handful of trucks, yet in their results they appear as the locations requiring the largest charging capacity.

Although Panteia includes scenarios where VZPs cannot host sleeping trucks, even under this assumption the estimated charging needs at truck parking areas remain far below what would realistically be required. To illustrate, their model projects that by 2050 the maximum load at a single TP would be around 2.3 MVA, that is roughly equivalent to just two MCS chargers, despite such facilities accommodating more than 300 electric trucks. In comparison, at the 100% electrification phase this study estimates a range of 5–30 MCS per location. Another difference is that Panteia does not consider peak hours in its estimates. By relying only on average traffic intensity, their results underestimate the charging demand that occurs during busy periods.

Despite these differences, one conclusion of both models is the same. The current level of truck parking capacity is insufficient. Additional rest and charging infrastructure will be required. The main divergence in the models lies in how strongly corridor intensity is used as a proxy for demand. The Panteia model therefore tends to underestimate charging needs at larger parking areas, while our model may lean in the opposite direction by overestimating demand because of the influence of peak hours.

9 Conclusion and Recommendations

This section conclude the research by answering the research questions introduced in Section 1. Furthermore, this section will recommend steps for further research.

9.1 Conclusion

This research presented an ABM model to answer a series of research questions with the main question (MQ) being:

Where should megawatt-scale charging infrastructure be placed in the Netherlands to best support battery electric truck transport, based on dynamic agent-based modeling, while minimizing logistics disruptions, balancing charging demand, and ensuring accessibility along key freight corridors?

The sub questions (SQ) were formulated in order to simplify answering the complicated main question. Therefore, we will first answer the sub questions before we ultimately answer the main question.

SQ1: What are the key logistics and travel patterns of road freight trucks in the Netherlands?

The results show that freight flows are strongly concentrated along the main southern and eastern corridors, with the Port of Rotterdam functioning as the most dominant hub. The northern region of the Netherlands has a lower freight demand, which reflects the lower population density in this region. 24% of all trips are international of which most is coming from Germany, especially the Ruhr area provides a lot of road freight through the border at Venlo and Arnhem. Belgium provides the second-largest share of road freight, with most coming in at Noord-Brabant towards the Port of Rotterdam. With an average tour duration of 249 minutes in the Netherlands, most tours fall just short of the 4.5 hour rest threshold. As a result, many tours do not require en-route public charging and can instead rely on depot charging. The average distance traveled on a tour in the Netherlands is 203 km. This is consistent with expectations for a country the size of the Netherlands, especially since only 24% of the trucks in the Netherlands are traveling international routes.

The second research question is focused around national and international policy interventions and regulatory frameworks.

SQ2: How can policy interventions and regulatory frameworks impact the placement and utilization of charging infrastructure?

The European union is trying to advance the deployment of charging infrastructure with the Alternative Fuel Infrastructure Regulation (AFIR). This regulation contains some goals for each country to achieve a certain amount of charging infrastructure on the TEN-T network in Europe (European Parliament and the Council of the European Union, 2023). However, these regulations are relatively modest requirements, requiring only a small amount of charging power per location. Furthermore, AFIR accepts CCS as sufficient, but CCS cannot provide the charging speeds required for long-haul freight. Furthermore, one MCS replaces about 6 to 9 CCS chargers at night. Without mandating MCS, AFIR is unlikely to drive deployment that meets long-haul needs.

However, a different European regulation does significantly influence the behavior of all trucks. The European resting and sleep requirements for truckers decides when truckers take their mandatory breaks. This gives BETs the opportunity to charge as well. To be more specific, this gives BETs 45 minutes the time to charge during their rest break and at least 11 hours during their sleep break. Based on this regulation the minimum charging capacity of a single charger can be calculated. With a long-haul BET requiring approximately 600 kWh battery capacity this would require a charger of 800 kWh in an optimal situation, assuming efficiency loss and small waiting times a charging capacity of 1 MW would be safer (Galassi & Rapone, 2021; Osieczko et al., 2021).

Furthermore, European regulation from 2019 requires new trucks to be more emission friendly starting from 2025 and 2030 (European Parliament and the Council of the European Union, 2019).

This regulation strengthens the case for BET adoption.

One of the major policies in the Netherlands that would influence the placement of charging infrastructure is the prohibition of trucks to sleep at VZP. The expectation is that this would shift away the charging demand from VZP to TP locations. The results in section 7.5 show that this is indeed the case. This policy leads to a shift in charging demand to TPs. 40.000 trucks would need to switch from sleeping at VZPs to TPs. However, It does keep the charging locations at the VZP free from sleeping trucks and with that ensures the availability of charging at these locations.

Another major policy is introduction of Zero Emission Zones (ZEZ) in urban areas. This policies requires vehicles which wish to enter these zones to be zero-emission. This policy would make the use of BETs in some areas mandatory.

SQ3: What are the energy demand implications of large-scale electric truck adoption?

The results depicted in Section 7.9 show that large-scale adoption of battery-electric trucks would generate a substantial new source of electricity demand in the Netherlands. At just 20% electrification the estimated daily energy consumption would be 3.345.696 kWh/day with demand peaks of potentially up to 1200 MW at single moment.While the average daily consumption is significant in itself, the more important implication lies in the spatial distribution of this demand.

Charging demand is concentrated along the busiest freight corridors and concentrated around TPs, creating strong local hotspots. Noord-Brabant for instance requires up to 720.000 kWh/day while Flevoland only requires 89.000 kWh/day at 20% electrification. Moreover, the pronounced peaks that occur in at the busiest moments, create short windows of very high power draw. At certain locations, the model estimates demand so high it would require a connection to the high-voltage net instead of the medium-voltage. This illustrates that the challenge is not only to generate enough electricity, but also to provide sufficient grid capacity and flexibility where and when trucks require it.

This leads to the energy demand creating two implications. First, large-scale electrification of freight will require close coordination between infrastructure deployment and grid reinforcement, especially at motorway service areas and border crossings. Second, depot charging could improve the distribution of the energy demand to lower the stress around TPs. However, it is guaranteed that large-scale truck electrification will put a significant strain on both local grids and national electricity planning.

MQ: Where should megawatt-scale charging infrastructure be placed in the Netherlands to best support battery electric truck transport, based on dynamic agent-based modeling, while minimizing logistics disruptions, balancing charging demand, and ensuring accessibility along key freight corridors?

The clearest way of conveying the answer to the main question is through spatial maps. Spatial maps provide an intuitive overview of clustering and distribution in the Netherlands, making the network easy to interpret. Appendix A.10 presents the full set of maps for each electrification phase. As an example, figure

Figure 31: Spatial Distribution Map for MCS chargers scenario 20VM

The results of the agent-based model show that megawatt charging demand is concentrated along the busiest freight corridors. Especially some of the major corridors such as the A16 corridor connecting the Port of Rotterdam to Belgium, the A67 corridor toward Venlo, and the A1/A15 connection towards Germany. These routes account for the majority of long-haul traffic and therefore represent the most critical locations for charging infrastructure. Larger charging locations are not located directly next to these corridors but in the approximate area.

Border crossings are another priority: Venlo and Arnhem stand out as the main entry points for international freight from the Ruhr area, while the southern corridors through Noord-Brabant accommodate significant flows from Belgium. Charging hubs near these crossings will be essential to ensure accessibility for international transport.

The Port of Rotterdam functions as a unique hotspot, with intense daily traffic and strict time-slot operations that already encourage charging during loading and unloading. This makes the port a natural candidate for large-scale megawatt charging deployment.

The amount of chargers per location depends on whether TP operators are willing to accommodate to the peak demand. The large truck parking areas along the A15 and A67 should be equipped with the highest number of chargers, while motorway service areas on less intensive corridors may require only a few. Overall the spatial distribution between charging locations seems to be good. No regions have large spaces without any chargers, some regions do need the creation of new locations as their is currently no parking station available.

Logistic disruptions are minimized by aligning charging with the mandatory 45-minute driver rest break. Nevertheless, approximately 15% of charging events in the model occur unplanned due to a low state of charge. To remain conservative, the model assumes relatively high energy consumption, which increases the likelihood of such events. These unplanned charges cause limited disruptions but could become more significant if truck parking (TP) operators fail to provide sufficient capacity during peak demand. In that case, longer waiting times and higher levels of logistic disruption are likely.

Taken together, this indicates that megawatt charging infrastructure should not be evenly distributed across the network. Instead, deployment should focus on: major freight corridors (A15, A16, A67, A1), border crossings at Venlo, Arnhem, and Noord-Brabant, and lastly the Port of Rotterdam. The remaining part of the Netherlands still requires a significant sum of MCS. However, the bulk of MCS needs to be appointed at the major freight corridors.

9.2 Recommendations

This section will provide recommendations to policy makers, researchers and recommendations for the other stakeholders identified in section 2.9. The recommendation for policy makers are focused on enabling the transition to BETs by supporting the deployment of MCS locations. The recommendation for researchers is focused on improving the existing model and filling in knowledge gaps.

Recommendations for policy makers

Policymakers must recognize that charging infrastructure cannot be considered in isolation from logistics and energy system needs. A priority is to address the chronic shortage of truck parking capacity in the Netherlands. Without sufficient overnight facilities, unnecessary competition is created between sleeping and charging. which results in a higher demand of MCS due to unreachable charging locations. At the same time, the introduction of sleep restrictions at VZPs could help guarantee that charging infrastructure remains available throughout the day, preventing long-term parking from blocking charger access at smaller VZPs. Such a policy must, however, go hand in hand with the creation of alternative sleep locations so that drivers rest requirements remain protected.

On the energy side, the rapid roll-out of megawatt charging will only be feasible if grid capacity is reinforced. Expansion of the high-voltage transmission network is needed to unlock additional capacity for the medium-voltage network. Targeted upgrades to the medium-voltage distribution grid will ensure that charging hubs can actually deliver the power required. The alignment between national grid reinforcement and charging infrastructure deployment should be considered a priority policy.

When it comes to spatial planning, the logical starting point is the main freight corridors where traffic intensity and charging demand are highest. However, focusing exclusively on these corridors risks leaving smaller but still important routes under served. Areas without charging facilities would be an obstacle for widespread BET adoption. Therefore, a balanced roll-out strategy is needed, prioritizing the corridors connected to Venlo, Arnhem, Rotterdam and Noord-Brabant, without neglecting roll-out in the lesser intensity areas. Finally, policymakers should avoid being drawn to the cheaper CCS solution. CCS is not able to provide the charging capacity required for long-haul BETs. If Europe is serious about electrifying international freight, MCS must be placed at the heart of the infrastructure strategy.

Recommendation for future research

Future research can build upon the current work in several important ways. Firstly, the influence of peak hours could be analyzed in greater detail. Peak hours have a great influence on this model, therefore a better understanding of this behavior could provide useful. This could be done by using empirical data from TPs arrival times or tachograph records. This would provide a stronger link between simulated behavior and actual stopping dynamics, helping to validate peak load assumptions.

Another area of improvement lies in the monetary integration costs. Megawatt Charging Systems (MCS) are expensive compared to their CCS counterpart, their profitability for truck parking operators is uncertain. This also makes TP operator strategies for including MCS ambiguous. Future studies could explore whether revenues from overnight sleeping spots outweigh charging fees.

The representation of the road network could also be improved. Increasing the level of detail by including secondary roads or international road networks. This would yield a more accurate picture of truck movements and therefore infrastructure needs. Furthermore, freight flows, corridor intensities and modal splits are expected to evolve over time. Therefore, using logistic predictions for later years instead of just 2022 could improve accuracy.

The topic of energy consumption of BETs is still underexplored in literature. The reports based on empirical data are published by industrial giants heavily involved in the sector, this introduces the risk of bias. Therefore, more research into energy consumption of BETs could improve the reliability of future predictions. The energy consumption used in this model was simplified. Therefore, including trucks with heterogeneous characteristics would already increase realism. This includes variations in vehicle size, payload, aerodynamics, and driving style, which all influence energy consumption. As many logistics operators are expected to combine depot charging with corridor charging. Driver behavior could also be modeled in greater detail, reflecting preferences for waiting, detouring, or price sensitivity, rather than assuming uniform decision rules.

Another improvement for future research would be the inclusion of all trucks types simultaneously. Rather than modeling just one type of truck, BET in this case, modeling all trucks would also simulate competitive behavior between different types of trucks. Finally, the interaction with the electricity grid deserves deeper analysis. Smart charging and load management strategies could be tested to mitigate grid stress and reduce peak loads at charging hubs.

Together, these recommendations would strengthen the validity of future research by capturing the technical, economic and behavioral complexity in greater detail.

9.3 Recommendations for Other Stakeholders

Logistic Operators should start making cost analysis whether it would be more cost efficient to invest in charging infrastructure at their own depot or use public charging infrastructure. Furthermore, they should create their own timeline when they transition towards a sustainable fleet, as European regulation will force them to either way. Important in this decision is to take into account the price of the BET as the costs of battery is expected to decrease rapidly over time (Link, Stephan, et al., 2024).

CPOs should carefully consider the quantity of charging infrastructure at each location. Demand is very time dependent and the large peaks can result to an overestimation of charging infrastructure required. Since their is a fast expected growth in demand, placing many chargers could be more convenient, but with the structure of network costs being dependent on the maximum capacity in the Netherlands, low utilization rates come with very high costs. Therefore, it would be more cost efficient to gradually develop the charging infrastructure at a location instead of over constructing.

DSOs and TSO should be aware of the large strain MCS infrastructure could have on the grid. This model estimates the national energy consumption per day to be approximately 830.000 kWh/-day in the electrification phase of just 5%. Furthermore, most of this demand is estimated to occur around 17:00. This means the grid should be able to handle such a peak load. The energy consumption scales linearly with the electrification, therefore a fully transitioned road freight sector will demand more than 10 million kWh/day. There is also spatial disparity in this demand, with Brabant and Gelderland having the highest consumption.

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A Appendix A

A.1 Github link for the model

https://github.com/TuDelftSven/MCS_Infrastructure_Model_Thesis/tree/master/Model_netherlands

The current GitHub misses the tour data file as this file is not publicly available.

A.2 Concept model

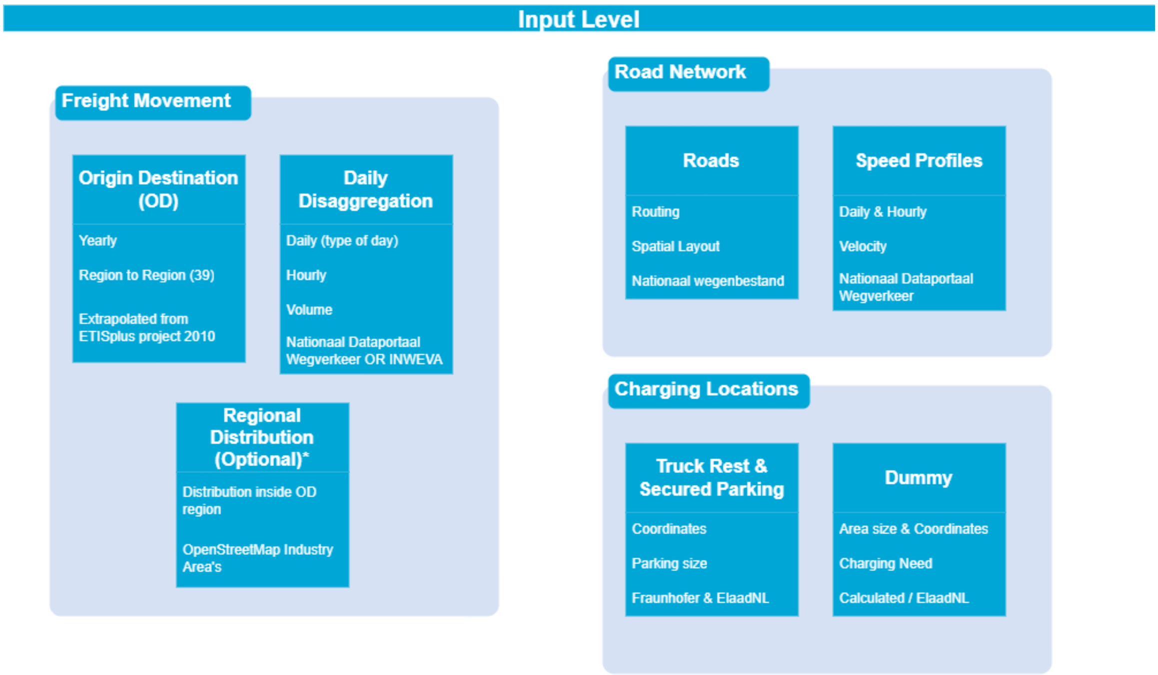

Figure 32: Concept Agent-based model input level

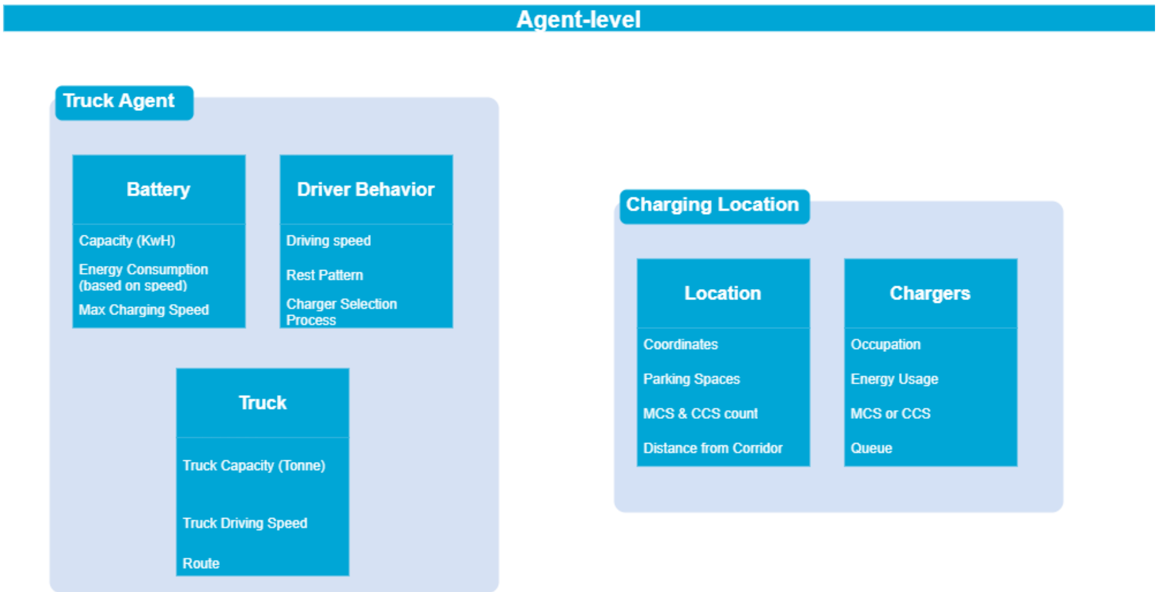

Figure 33: Concept Agent-based model agent level

A.3 N-roads and A-roads Speed distribution

N-roads	**A-roads**
GEO2A_R_RWSTI362065	RWS01_MONIBAS_0730vwd0171ra
PZH01_MST_0057_00	RWS01_MONIBAS_0500vwr2041ra
GEO0C_Z_RWSTI2183	RWS01_MONIBAS_0070vwa1956ra
RWS01_MONIBAS_0151hr0075ra	RWS01_MONIBAS_0040vwa0756ra
GEO8R_RWSTI358092	RWS01_MONIBAS_0280vwc0383ra
GEO8R_RWSTI358439	RWS01_MONIBAS_0160vwx0205ra
red GEO2A_R_RWSTI1100800	RWS01_MONIBAS_0201hr0194rb
GEO2A_R_RWSTI362779	RWS01_MONICA_10D00B0AC4556020000
GEO0C_Z_RWSTI360264	RWS01_MONICA_10D00E0841D0070000F
GE0OK_K_RWSTI362962	RWS01_MONIBAS_0241hr0010ra
GEO0K_Z_RWSTI363482	RWS01_MONIBAS_0090vwa0257ra
PZH01_MST_0653_00	RWS01_MONICA_10D00C09BC2B0220000B
GE0OK_K_RWSTI357974	RWS01_MONIBAS_0150vwf0398ra
RWS01_MONICA_10D00E020062D0070000B	RWS01_MONICA_10D0800A841D0050005
	RWS01_MONICA_10D00A04C00F68200009

Table 8: N-roads and A-roads Mapping

A.4 Included N-roads

The following N-roads were included in the model:

N11, N14, N15, N18, N200, N208, N209, N3, N31, N33, N35, N36, N46, N48, N50, N57, N59, N61, N62, N65, N9, N915, N99, N324, N307, N231.

A.5 Agent States and Actions

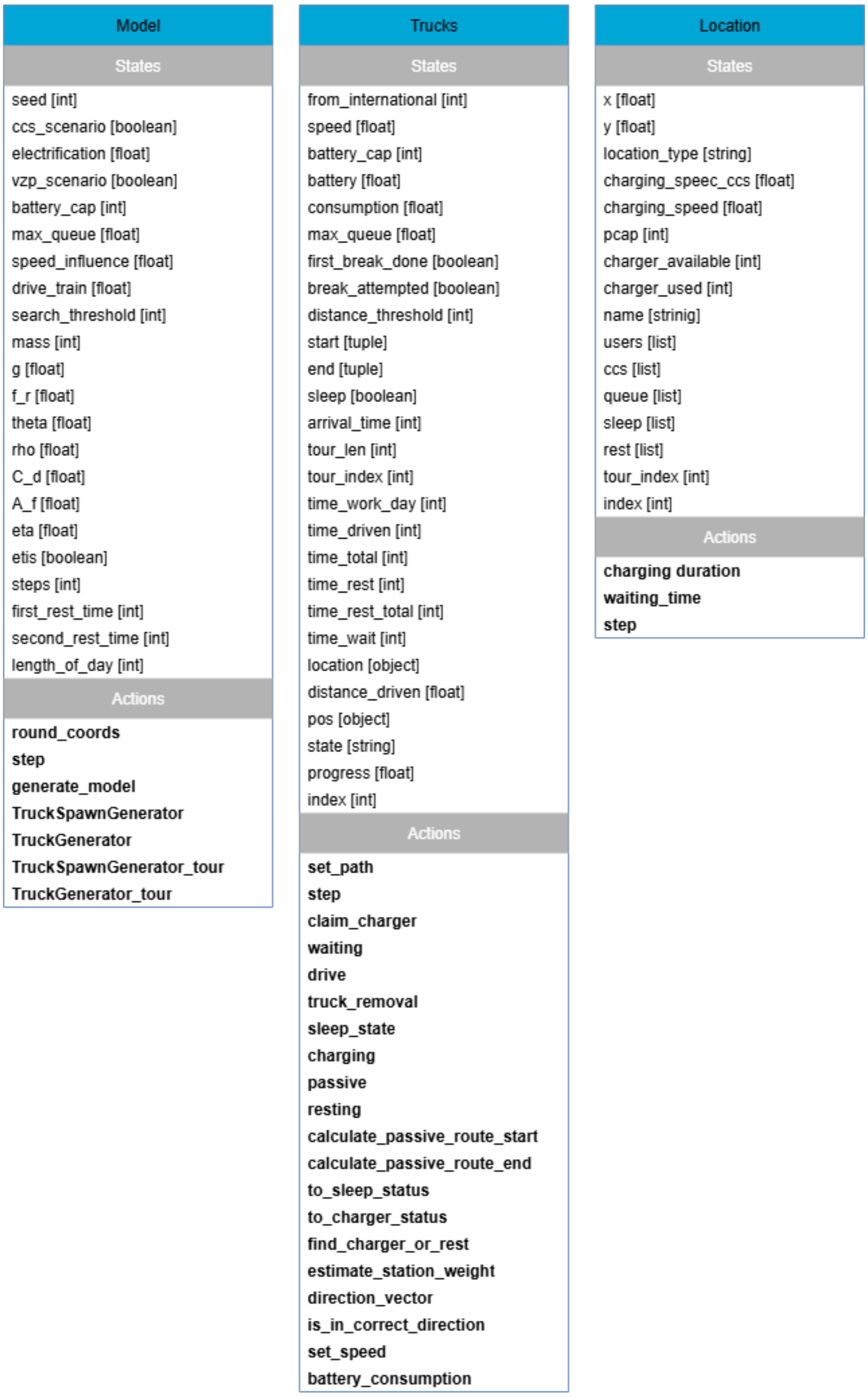

Figure 34: Agents States and their Actions

A.6 Recreating ETIS dataset

A.6.1 Data Creation

During the validation phase, the publicly available ETIS (European Transport policy Information System) and non-public Tours datasets from BasGoed 6 were evaluated for suitability. However, the ETIS data set in particular did not seem very valide after inspection. The national and international traffic flows of the ETIS dataset did not match with the expected numbers gained from CBS and Eurostat. The Tour dataset from BasGoed6 seems more reliable but was only modeled for 5 working days without the inclusion of weekends or international destinations outside of Belgium, France and Germany.

Because of these validation issues in the datasets the decision was made to create an own dataset based on Eurostat data and the ETISplus project methodology described in the manual (ETISplus, 2012).

A.6.2 Data Sources and Preprocessing

The transport flow data used in this analysis was sourced from Eurostat, specifically from their publicly available statistics. Separate datasets were used for loading and unloading activities, as well as for distinguishing between international and national (domestic) transport.

For international loading, data was extracted from:

- road go na rl3g (national transport, by region of loading) (Eurostat, 2024a)
- road go ta rl (total transport, by region of loading). (Eurostat, 2024f)

Similarly, for international unloading, data was retrieved from:

- road go na ru3g (national transport, by region of unloading) (Eurostat, 2024b)
- road go ta ru (total transport, by region of unloading) (Eurostat, 2024g)

International loading volumes per region were obtained by subtracting national values from total values, the same was done for unloading:

$$\text{International Loading} = \text{Total Loading} - \text{National Loading}$$

For domestic (national) transport, separate datasets were used directly:

- road go na rl3g for national loading (Eurostat, 2024d)
- road go na ru3g for national unloading (Eurostat, 2024e)

Notably, the international datasets aggregate transport volumes over all commodity types, while the national datasets provide breakdowns across 21 different commodity categories, offering a more granular and precise view of domestic flows.

A.6.3 Distance Decay Function Using Negative Exponential Distribution

To model the deterrence effect of distance on transport flows between spatial zones, a negative exponential distribution function was applied. This function reflects the empirical observation that flows between zones decrease as the distance between them increases (Oshan, 2016). The general form of the negative exponential decay function is:

$$f(d_{ij}) = e^{-\beta d_{ij}}$$

where:

- $f(d_{ij})$ is the impedance or deterrence factor between origin zone i and destination zone j,
- d_{ij} is the distance between zones i and j,

- β is a positive decay parameter that determines the steepness of the decline.

The function assigns a weight to each zone pair (i, j), which is then used to determine the probability or likelihood of interaction between them in the spatial interaction model. As distance increases, the exponential term decreases rapidly, reflecting the intuition that spatial interactions are more likely over shorter distances.

Calibration

The decay parameter β was calibrated based on domain knowledge and empirical adjustment by iteration, with the goal of reflecting the expected spatial distribution of transport interactions. A higher β value results in a steeper decline, meaning that flows drop off more quickly as distance increases. For the Netherlands the average Kilometer per tonne can be calculated using Eurostat data(Eurostat, 2024h). This results in a domestic average kilometer per tonne of 63 and international of 126. The β is calibrated to match these numbers for the Netherlands resulting in a β of 0.025782 for domestic and β of 0.00595 internationally.

Application in the Model

For each origin–destination pair, the deterrence weight $f(d_{ij})$ was computed and used to proportionally allocate flows or potential flows. This method enables a realistic distribution of flows across the network while ensuring that the total outflow from each origin zone is preserved.

If necessary, the resulting weight matrix W was normalized so that for each origin i, the weights to all destinations j sum to 1:

$$W_{ij} = \frac{f(d_{ij})}{\sum_k f(d_{ik})} \tag{1}$$

This normalization step ensures the correct proportional allocation of total outflows per origin zone.

A.6.4 Balancing Flows Using Iterative Proportional Fitting (IPF)

To ensure that the estimated transport flow matrix between zones aligns with observed marginal totals (i.e., total loading and total unloading per zone), the *Iterative Proportional Fitting (IPF)* procedure was applied. IPF is a widely used algorithm in transport modeling and contingency table adjustment that balances a matrix so that its row and column sums match known marginal constraints (Deming & Stephan, 1940).

Mathematical Description

Given:

- An initial non-negative matrix $M = [m_{ij}]$, representing estimated flows between origin i and destination j (e.g., based on the distance decay function),
- A vector of row targets $R = [r_i]$, representing the total loading from each origin zone i,
- A vector of column targets $C = [c_j]$, representing the total unloading into each destination zone j,

the objective is to adjust M to produce a new matrix $M' = [m'_{ij}]$ such that:

$$\sum_j m'_{ij} = r_i \quad \text{for all } i, \qquad \sum_i m'_{ij} = c_j \quad \text{for all } j \tag{2}$$

The IPF algorithm alternates between scaling rows and scaling columns until the matrix satisfies the marginal constraints within a specified tolerance ε.

At each iteration:

1. **Scale rows**:

$$m_{ij}^{(k+1)} \leftarrow m_{ij}^{(k)} \cdot \frac{r_i}{\sum_j m_{ij}^{(k)}} \tag{3}$$

2. **Scale columns**:

$$m_{ij}^{(k+2)} \leftarrow m_{ij}^{(k+1)} \cdot \frac{c_j}{\sum_i m_{ij}^{(k+1)}} \tag{4}$$

This iterative process is repeated until convergence, meaning the row and column sums match their respective targets within tolerance ε.

Implementation

First an initial origin–destination matrix was generated using a negative exponential distance decay function (as described in section A.6.3). However, this initial matrix aligns only with the distances and not with the observed international loading and unloading totals obtained from Eurostat.

To reconcile the model with observed data, IPF was applied through the following steps:

- Observed loading and unloading totals per zone were extracted from the processed Eurostat datasets.
- Zone labels were harmonized to ensure consistency between the observed totals and the base matrix.
- The IPF algorithm was applied to adjust the base matrix such that:
  - Each row sum matched the total loading from the corresponding origin zone.
  - Each column sum matched the total unloading into the corresponding destination zone.

The algorithm was implemented in Python, with safeguards to ensure convergence (maximum number of iterations and a small tolerance threshold), as well as non-negativity of all matrix entries.

The resulting matrix represents a balanced estimate of international flows between zones that reflects both spatial interaction effects (captured through distance decay) and empirical constraints from observed transport volumes.

The created transport flows in the origin destination matrix were compared to the expected transport flows in Eurostat and matched closely.

A.6.5 Tonne to Truck Conversion

The model requires input in terms of the number of trucks per route, rather than the volume of freight expressed in tonnes. To convert freight volumes into truck counts, data from Eurostat was utilized (Eurostat, 2024c). Since the average payload per truck differs between national and international transport, distinct conversion factors were applied. For national transport, an average of 10.9 tonnes per truck was used, while for international transport, a value of 14.0 tonnes per truck was adopted (Eurostat, 2024c).

A.7 Created Network

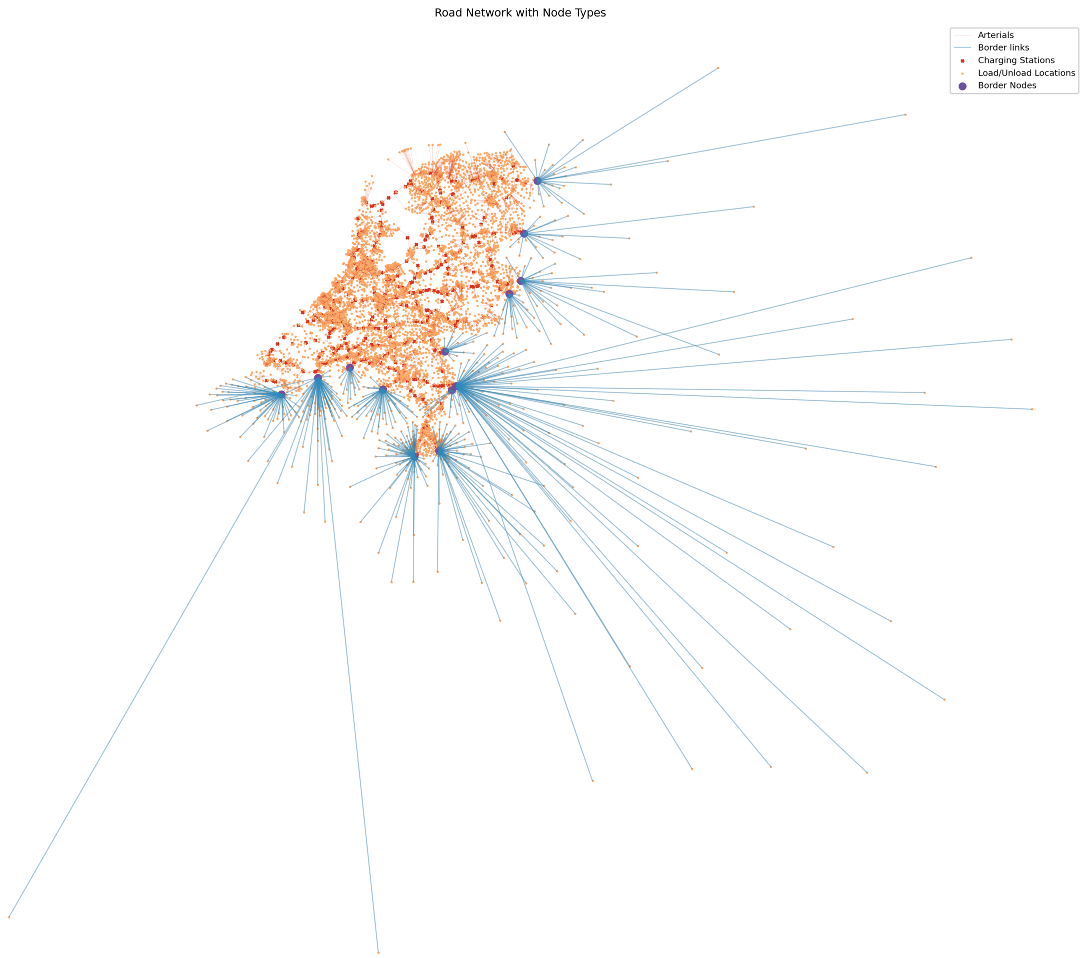

Figure 35: Dutch road network used in the simulation. Roads are shown in blue/red, with POIs (candidate charging sites) and load/unload nodes highlighted in red/orange. Long outside links indicate synthetic connections from international origins/destinations to Dutch border nodes.

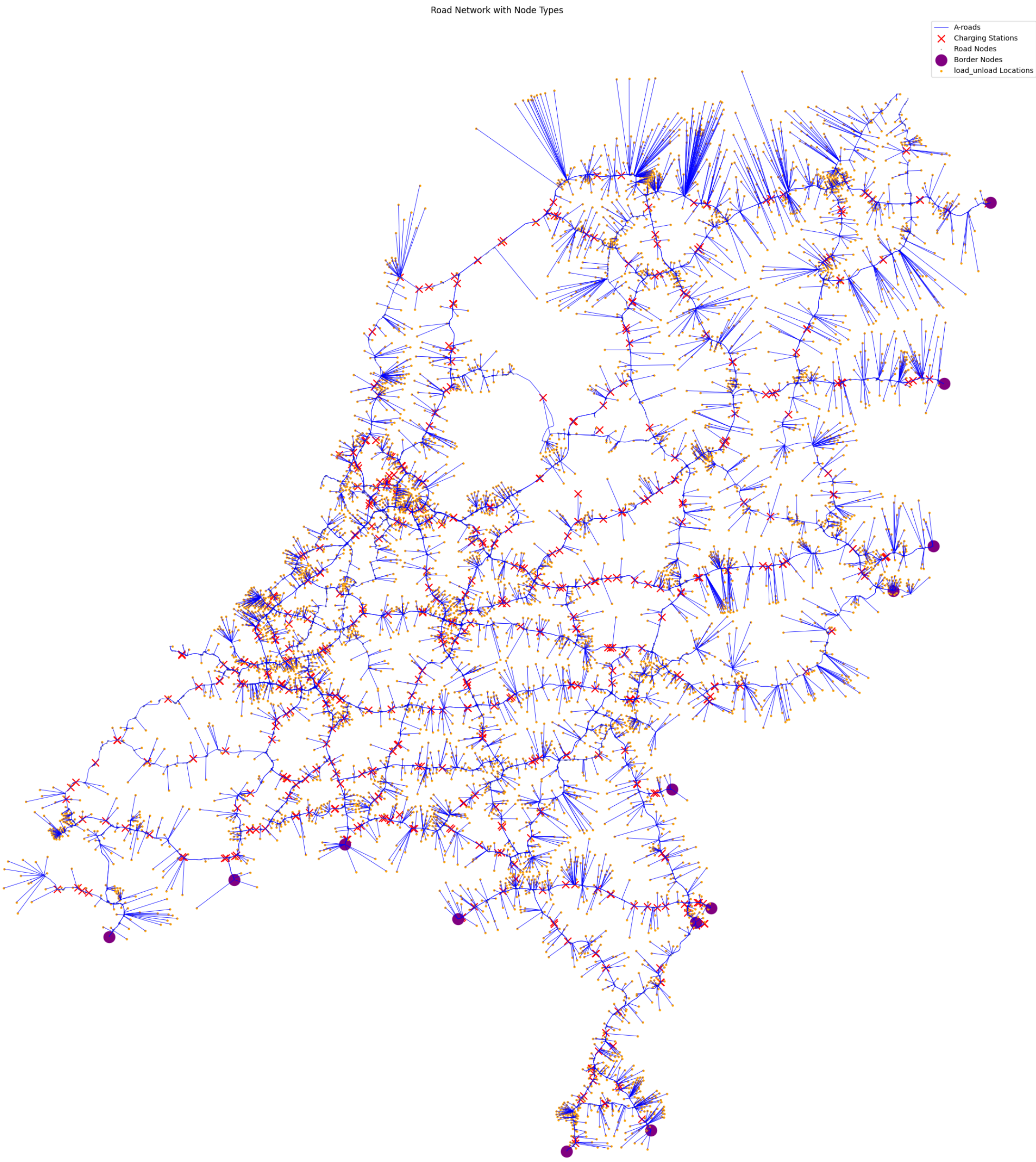

Figure 36: Network detail within the Netherlands. Border nodes (purple), charging candidates, and load/unload locations are visible; synthetic outside connections are omitted for clarity.

A.8 Search Strategy

To establish a solid foundation for this study, a systematic review of existing literature was conducted, focusing on electric truck charging infrastructure, agent-based modeling (ABM), logistics network planning, and Megawatt charging systems. The search was carried out using WorldCat TU Delft Catalogue, Scopus, and Google Scholar, which were selected due to their extensive interdisciplinary coverage and access to high-quality academic sources.

Search Terms
Queries were designed to align with the core problem of strategically planning the placement of electric truck charging infrastructure to balance operational efficiency, grid capacity, and sustainability goals. The search included combinations such as:

- Electric truck charging infrastructure
- Megawatt charging system
- "Electric truck charging infrastructure" AND "network planning
- "Agent-based modeling" AND "electric vehicle charging"
- "Grid capacity" AND "heavy-duty electric vehicles"

These search terms were selected to capture the key themes underlying the research question: How can electric truck charging infrastructure in the Netherlands be strategically planned to ensure efficient logistics operations and support sustainability targets? This approach allowed for abstraction to broader scientific domains, including transportation planning (logistics constraints), energy systems (Grid capacity), and computational modeling (agent-based simulation and electric vehicle charging).

Inclusion Criteria
Studies were included if they:

- Addressed charging infrastructure deployment for electric trucks or heavy-duty electric vehicles.
- Provided empirical or theoretical insights into policy planning for large-scale EV infrastructure deployment.
- Used real-world data to model truck movements, charging patterns, or energy consumption.
- Applied simulation-based methods, such as agent-based modeling, to assess charging station placement, logistics operations, or grid demand.
- Examine technical advancements (e.g., battery chemistry, vehicle range) without considering infrastructure implications.

Exclusion Criteria
Studies were excluded if they:

- Did not address system-wide impacts, such as logistics operations or grid capacity constraints
- Lacked empirical validation or relied purely on theoretical speculation without supporting data.

Selection Process
After compiling an initial list of sources, abstract screening was performed to determine relevance based on the outlined inclusion and exclusion criteria. A full-text review was then conducted for key studies that directly informed the research objectives. Additional papers that provided useful contextual information were archived for potential future reference.

By following this structured approach, the literature review ensures a well-rounded analysis of the technical, economic, and policy dimensions of electric truck charging infrastructure. This process situates the study within broader discussions on logistics, energy systems, and sustainable mobility transitions while identifying gaps that this research aims to address.

A.9 Figures of the Sensitivity Analysis

A.9.1 OLS results

Table 9: OLS regression results (HC3 robust SE) for energy_kWh. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significanc
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	496,199	[486,514; 505,884]	**
battery_cap (700.0)	-347,999	[-359,487; -336,510]	**
drive_train (0.9)	269,237	[257,784; 280,690]	**
drive_train (0.96)	-121,400	[-131,169; -111,630]	**
max_queue (0.1)	30,511	[18,414; 42,608]	**
max_queue (0.3)	-8,336	[-19,505; 2,833]	n
search_threshold (20000.0)	-32,608	[-45,794; -19,421]	**
search_threshold (40000.0)	13,707	[507; 26,908]	
search_threshold (50000.0)	24,381	[10,709; 38,053]	**

Table 10: OLS regression results (HC3 robust SE) for mean_distance. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significance
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	164	[98.1; 230]	***
battery_cap (700.0)	-92.2	[-139; -44.8]	***
drive_train (0.9)	17.3	[-46.3; 81.0]	ns
drive_train (0.96)	-10.8	[-69.8; 48.2]	ns
max_queue (0.1)	422	[356; 488]	***
max_queue (0.3)	-123	[-166; -80.4]	***
search_threshold (20000.0)	-325	[-385; -266]	***
search_threshold (40000.0)	123	[72.4; 174]	***
search_threshold (50000.0)	252	[175; 329]	***

Table 11: OLS regression results (HC3 robust SE) for mean_duration. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significance
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	3.9	[3.8; 4.1]	***
battery_cap (700.0)	-2.2	[-2.3; -2.1]	***
drive_train (0.9)	0.9	[0.8; 1.0]	***
drive_train (0.96)	-0.4	[-0.4; -0.3]	***
max_queue (0.1)	0.2	[0.1; 0.3]	***
max_queue (0.3)	0.0	[-0.1; 0.1]	ns
search_threshold (20000.0)	-0.2	[-0.4; -0.1]	***
search_threshold (40000.0)	0.1	[-0.0; 0.2]	ns
search_threshold (50000.0)	0.2	[0.0; 0.3]	**

Table 12: OLS regression results (HC3 robust SE) for peak_users. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significance
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	182	[163; 201]	***
battery_cap (700.0)	-444	[-465; -423]	***
drive_train (0.9)	123	[102; 145]	***
drive_train (0.96)	-60.9	[-79.0; -42.9]	***
max_queue (0.1)	46.7	[23.2; 70.3]	***
max_queue (0.3)	-26.8	[-46.9; -6.7]	**
search_threshold (20000.0)	-2.4	[-27.0; 22.1]	ns
search_threshold (40000.0)	-24.7	[-48.1; -1.2]	*
search_threshold (50000.0)	-49.3	[-74.8; -23.7]	***

Table 13: OLS regression results (HC3 robust SE) for total_arrivals. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significance
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	-185	[-192; -178]	***
battery_cap (700.0)	87.1	[80.0; 94.1]	***
drive_train (0.9)	-52.0	[-60.4; -43.7]	***
drive_train (0.96)	15.0	[8.9; 21.2]	***
max_queue (0.1)	29.6	[21.7; 37.4]	***
max_queue (0.3)	-18.9	[-27.0; -10.8]	***
search_threshold (20000.0)	-30.5	[-39.9; -21.1]	***
search_threshold (40000.0)	-3.0	[-12.0; 6.0]	ns
search_threshold (50000.0)	-2.0	[-11.7; 7.7]	ns

Table 14: OLS regression results (HC3 robust SE) for total_users. Effects are relative to the stated baseline in the main text.

Factor (Level)	Effect vs. Baseline	95% CI	Significance
Baseline (all refs) (batt=600, q=0.2, dt=0.94, search=30000)	0.0	[0.0; 0.0]	
battery_cap (500.0)	124,050	[121,628; 126,471]	***
battery_cap (700.0)	-87,000	[-89,872; -84,128]	***
drive_train (0.9)	67,309	[64,446; 70,173]	***
drive_train (0.96)	-30,350	[-32,792; -27,907]	***
max_queue (0.1)	7,628	[4,604; 10,652]	***
max_queue (0.3)	-2,084	[-4,876; 708]	ns
search_threshold (20000.0)	-8,152	[-11,449; -4,855]	***
search_threshold (40000.0)	3,427	[127; 6,727]	*
search_threshold (50000.0)	6,095	[2,677; 9,513]	***

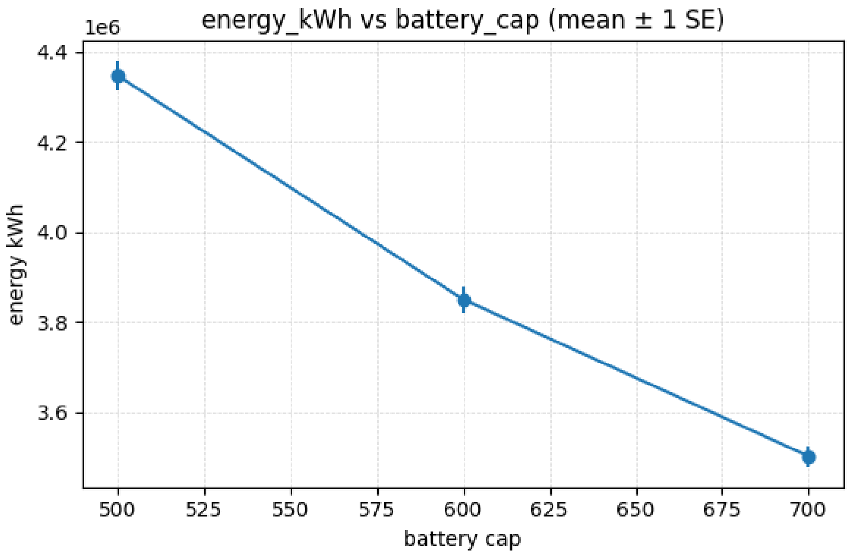

Figure 37: Effect of battery capacity on system energy served (mean ±1 SE); energy decreases with capacity.

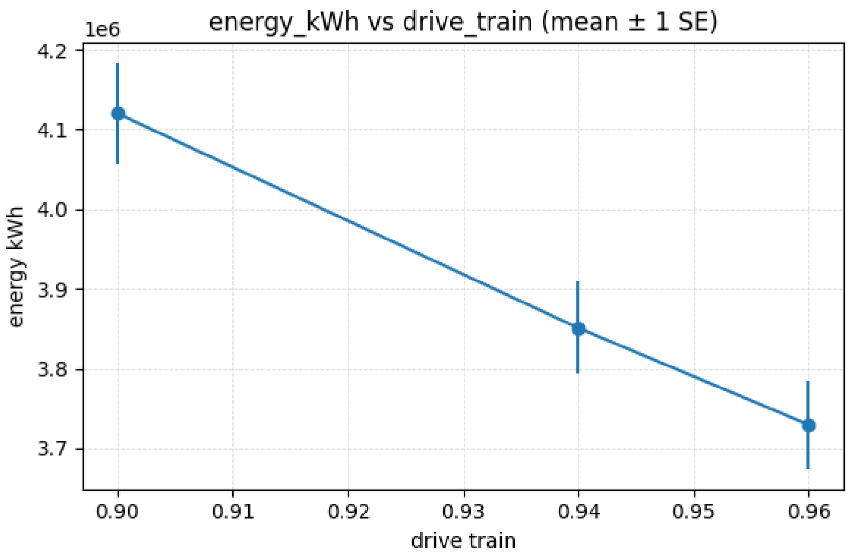

Figure 38: Effect of drivetrain efficiency on system energy served (mean ±1 SE); higher efficiency lowers energy.

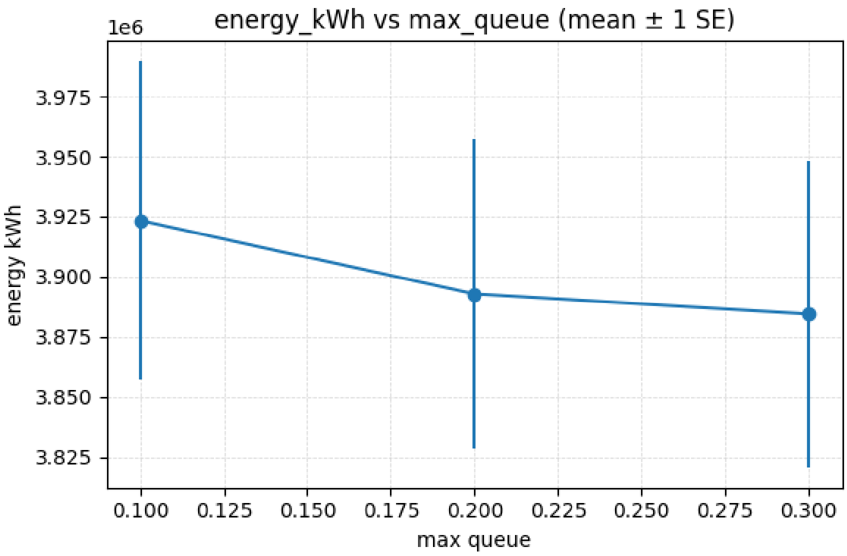

Figure 39: Effect of max acceptable queue on system energy served (mean ± 1 SE); stronger queue aversion raises energy.

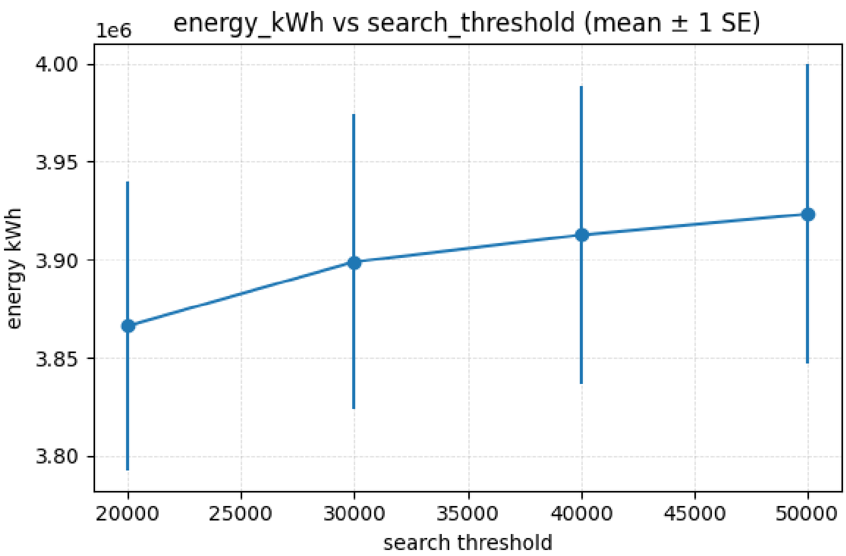

Figure 40: Effect of search radius on system energy served (mean ± 1 SE); larger radii modestly increase energy.

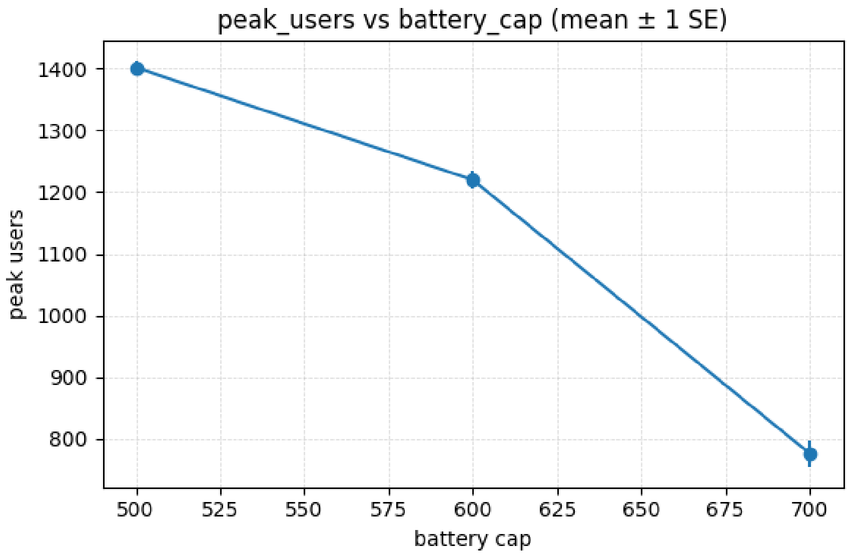

Figure 41: Effect of battery capacity on peak concurrent chargers (mean ±1 SE); capacity reduces peaks.

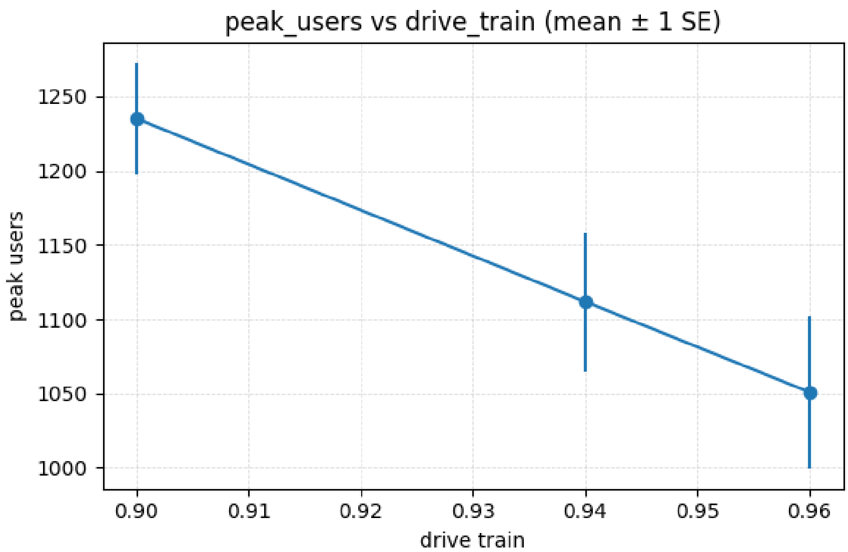

Figure 42: Effect of drivetrain efficiency on peak concurrent chargers (mean ±1 SE); efficiency reduces peaks.

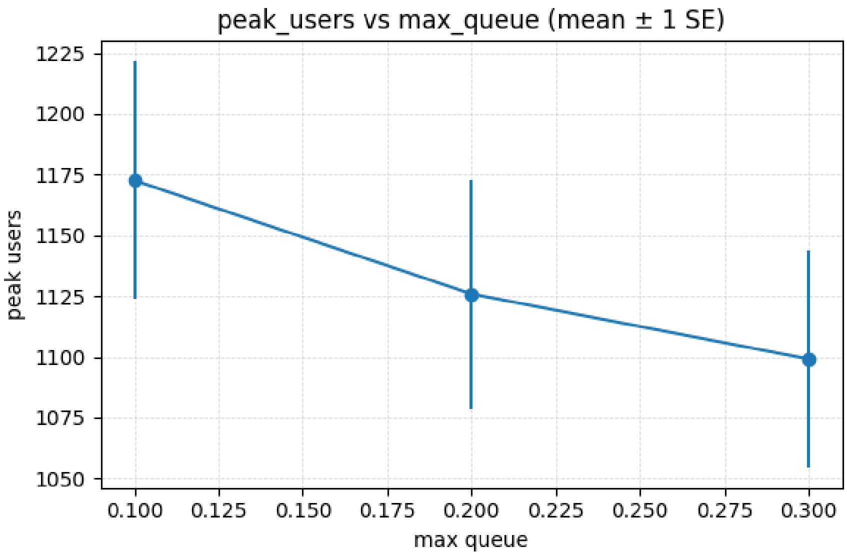

Figure 43: Effect of max acceptable queue on peak concurrent chargers (mean ±1 SE); greater tolerance lowers peaks.

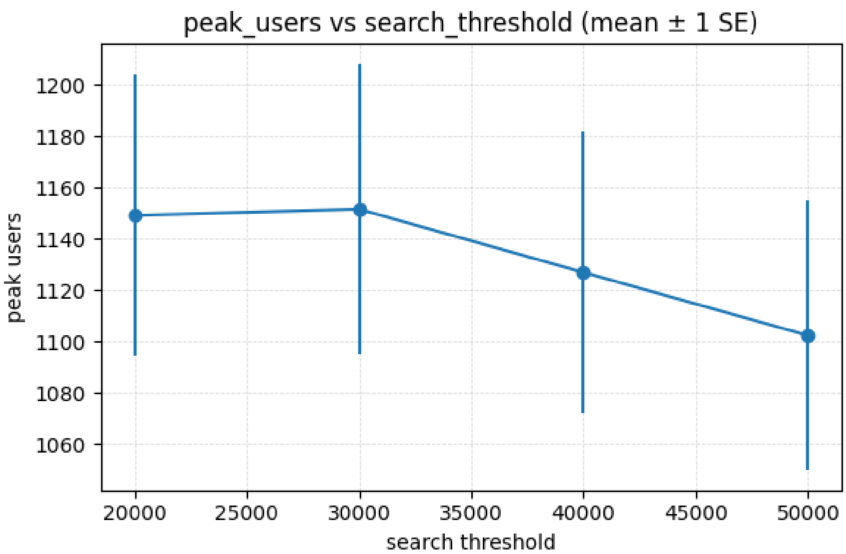

Figure 44: Effect of search radius on peak concurrent chargers (mean ±1 SE); longer searches reduce peaks.

A.9.2 ANOVA results

Table 15: Two-way ANOVA on energy_kWh

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	1.296e+13	667080.41	< 1e-16	0.811	1.000
max_queue	2.0	3.011e+10	1550.05	< 1e-16	0.002	0.979
drive_train	2.0	2.878e+12	148133.03	< 1e-16	0.180	1.000
search_threshold	3.0	4.963e+10	1702.99	< 1e-16	0.003	0.987
battery_cap×max_queue	4.0	3.489e+09	89.79	< 1e-16	0.000	0.841
battery_cap×drive_train	4.0	4.736e+10	1218.81	< 1e-16	0.003	0.986
battery_cap×search_threshold	6.0	2.304e+09	39.54	< 1e-16	0.000	0.777
max_queue×drive_train	4.0	1.314e+08	3.38	1.39e-02	0.000	0.166
max_queue×search_threshold	6.0	4.307e+09	73.90	< 1e-16	0.000	0.867
drive_train×search_threshold	6.0	1.902e+08	3.26	7.04e-03	0.000	0.224
Residual	68.0	6.605e+08			0.000	0.500

Table 16: Two-way ANOVA on peak_users

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	7.461e+06	8541.24	< 1e-16	0.884	0.996
max_queue	2.0	9.963e+04	114.05	< 1e-16	0.012	0.770
drive_train	2.0	6.350e+05	726.92	< 1e-16	0.075	0.955
search_threshold	3.0	4.274e+04	32.61	3.54e-13	0.005	0.590
battery_cap×max_queue	4.0	9.548e+03	5.47	7.10e-04	0.001	0.243
battery_cap×drive_train	4.0	1.386e+05	79.35	< 1e-16	0.016	0.824
battery_cap×search_threshold	6.0	1.403e+04	5.35	1.42e-04	0.002	0.321
max_queue×drive_train	4.0	1.809e+03	1.04	3.95e-01	0.000	0.057
max_queue×search_threshold	6.0	2.450e+03	0.93	4.76e-01	0.000	0.076
drive_train×search_threshold	6.0	9.438e+02	0.36	9.02e-01	0.000	0.031
Residual	68.0	2.970e+04			0.004	0.500

Table 17: Two-way ANOVA on 95th_quantile

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	2.833e+06	59122.20	< 1e-16	0.931	0.999
max_queue	2.0	1.731e+03	36.11	2.06e-11	0.001	0.515
drive_train	2.0	1.475e+05	3078.46	< 1e-16	0.048	0.989
search_threshold	3.0	9.498e+03	132.14	< 1e-16	0.003	0.854
battery_cap×max_queue	4.0	3.784e+02	3.95	6.11e-03	0.000	0.188
battery_cap×drive_train	4.0	4.237e+04	442.03	< 1e-16	0.014	0.963
battery_cap×search_threshold	6.0	3.849e+03	26.77	3.96e-16	0.001	0.703
max_queue×drive_train	4.0	6.229e+01	0.65	6.29e-01	0.000	0.037
max_queue×search_threshold	6.0	1.472e+03	10.24	4.74e-08	0.000	0.475
drive_train×search_threshold	6.0	2.778e+02	1.93	8.80e-02	0.000	0.146
Residual	68.0	1.629e+03			0.001	0.500

Table 18: Two-way ANOVA on total_users

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	8.100e+11	667080.41	$<$ 1e-16	0.811	1.000
max_queue	2.0	1.882e+09	1550.05	$<$ 1e-16	0.002	0.979
drive_train	2.0	1.799e+11	148133.03	$<$ 1e-16	0.180	1.000
search_threshold	3.0	3.102e+09	1702.99	$<$ 1e-16	0.003	0.987
battery_cap×max_queue	4.0	2.180e+08	89.79	$<$ 1e-16	0.000	0.841
battery_cap×drive_train	4.0	2.960e+09	1218.81	$<$ 1e-16	0.003	0.986
battery_cap×search_threshold	6.0	1.440e+08	39.54	$<$ 1e-16	0.000	0.777
max_queue×drive_train	4.0	8.211e+06	3.38	1.39e-02	0.000	0.166
max_queue×search_threshold	6.0	2.692e+08	73.90	$<$ 1e-16	0.000	0.867
drive_train×search_threshold	6.0	1.189e+07	3.26	7.04e-03	0.000	0.224
Residual	68.0	4.128e+07			0.000	0.500

Table 19: Two-way ANOVA on mean_duration

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	6.985e+02	137062.97	$<$ 1e-16	0.949	1.000
max_queue	2.0	1.230e+00	241.33	$<$ 1e-16	0.002	0.877
drive_train	2.0	2.826e+01	5545.89	$<$ 1e-16	0.038	0.994
search_threshold	3.0	2.770e+00	362.40	$<$ 1e-16	0.004	0.941
battery_cap×max_queue	4.0	3.002e-01	29.46	3.22e-14	0.000	0.634
battery_cap×drive_train	4.0	4.325e+00	424.33	$<$ 1e-16	0.006	0.961
battery_cap×search_threshold	6.0	1.574e-01	10.30	4.34e-08	0.000	0.476
max_queue×drive_train	4.0	1.959e-03	0.19	9.42e-01	0.000	0.011
max_queue×search_threshold	6.0	4.036e-01	26.40	5.48e-16	0.001	0.700
drive_train×search_threshold	6.0	1.315e-02	0.86	5.29e-01	0.000	0.071
Residual	68.0	1.733e-01			0.000	0.500

Table 20: Two-way ANOVA on mean_distance

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	1.214e+06	292.29	$<$ 1e-16	0.089	0.896
max_queue	2.0	5.885e+06	1416.83	$<$ 1e-16	0.430	0.977
drive_train	2.0	1.454e+04	3.50	3.57e-02	0.001	0.093
search_threshold	3.0	4.970e+06	797.69	$<$ 1e-16	0.363	0.972
battery_cap×max_queue	4.0	5.249e+05	63.19	$<$ 1e-16	0.038	0.788
battery_cap×drive_train	4.0	6.866e+03	0.83	5.13e-01	0.001	0.046
battery_cap×search_threshold	6.0	2.790e+05	22.39	2.25e-14	0.020	0.664
max_queue×drive_train	4.0	1.941e+04	2.34	6.41e-02	0.001	0.121
max_queue×search_threshold	6.0	6.220e+05	49.91	$<$ 1e-16	0.045	0.815
drive_train×search_threshold	6.0	1.196e+04	0.96	4.59e-01	0.001	0.078
Residual	68.0	1.412e+05			0.010	0.500

Table 21: Two-way ANOVA on total_arrivals

Term	DF	SS	F	p-value	η^2	η^2_{partial}
battery_cap	2.0	1.393e+06	40339.67	$<$ 1e-16	0.888	0.999
max_queue	2.0	4.293e+04	1242.94	$<$ 1e-16	0.027	0.973
drive_train	2.0	8.915e+04	2581.37	$<$ 1e-16	0.057	0.987
search_threshold	3.0	1.694e+04	326.99	$<$ 1e-16	0.011	0.935
battery_cap×max_queue	4.0	8.426e+02	12.20	1.57e-07	0.001	0.418
battery_cap×drive_train	4.0	2.298e+04	332.76	$<$ 1e-16	0.015	0.951
battery_cap×search_threshold	6.0	5.653e+02	5.46	1.18e-04	0.000	0.325
max_queue×drive_train	4.0	2.134e+02	3.09	2.13e-02	0.000	0.154
max_queue×search_threshold	6.0	4.416e+02	4.26	1.06e-03	0.000	0.273
drive_train×search_threshold	6.0	1.422e+02	1.37	2.38e-01	0.000	0.108
Residual	68.0	1.174e+03			0.001	0.500

A.10 The maps of base case, sleep at VZP allowed and no CCS

Figure 45: Spatial distribution of stations — 5% scenario.

Figure 46: Spatial distribution of stations — 10% scenario.

Figure 47: Spatial distribution of stations — 20% scenario.

Figure 48: Spatial distribution of stations — 40% scenario.

Figure 49: Spatial distribution of stations — 60% scenario.

Figure 50: Spatial distribution of stations — 100% scenario.

A.11 Energy Consumption DSO grid size

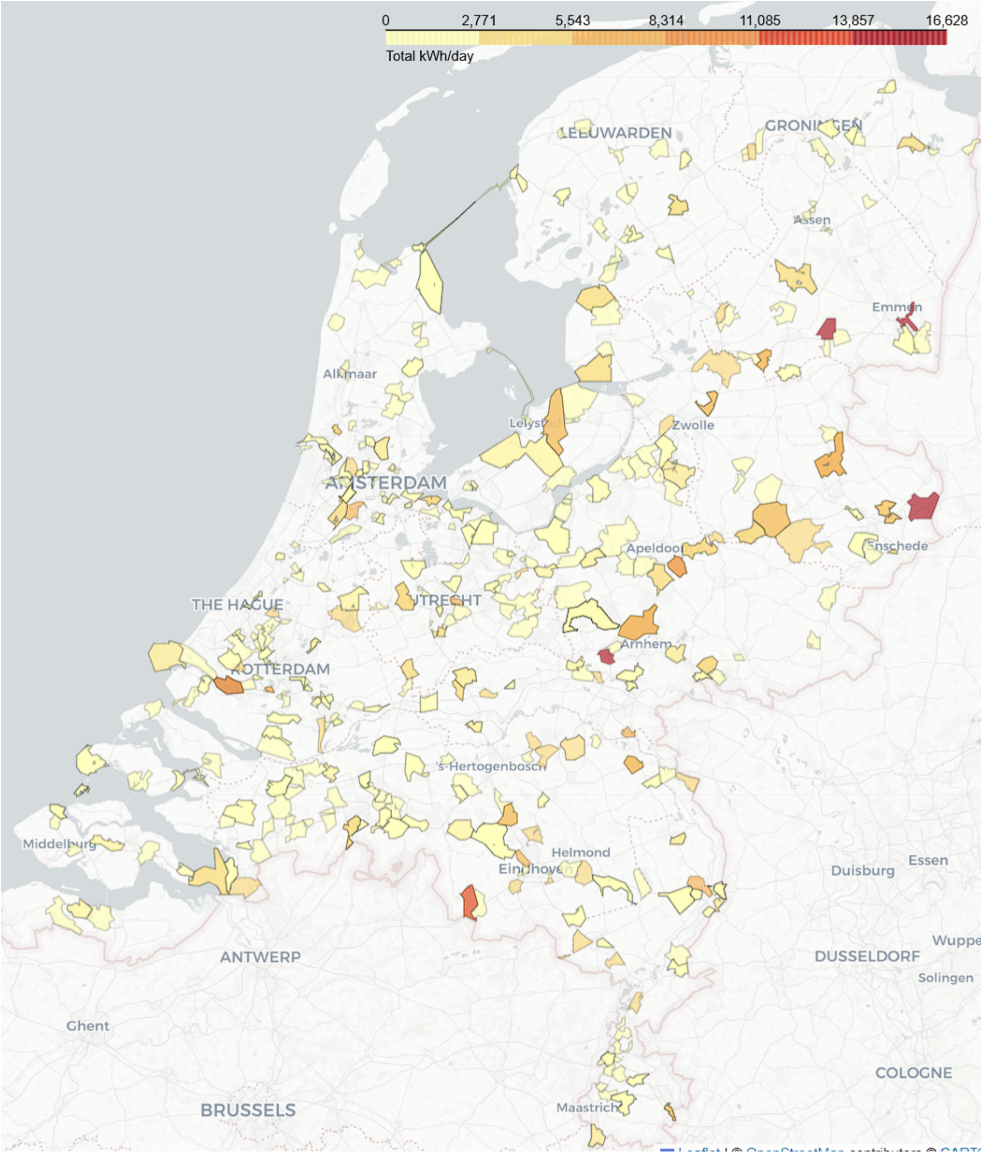

Figure 51: Spatial energy demand (DSO grid) — 5% electrification scenario.

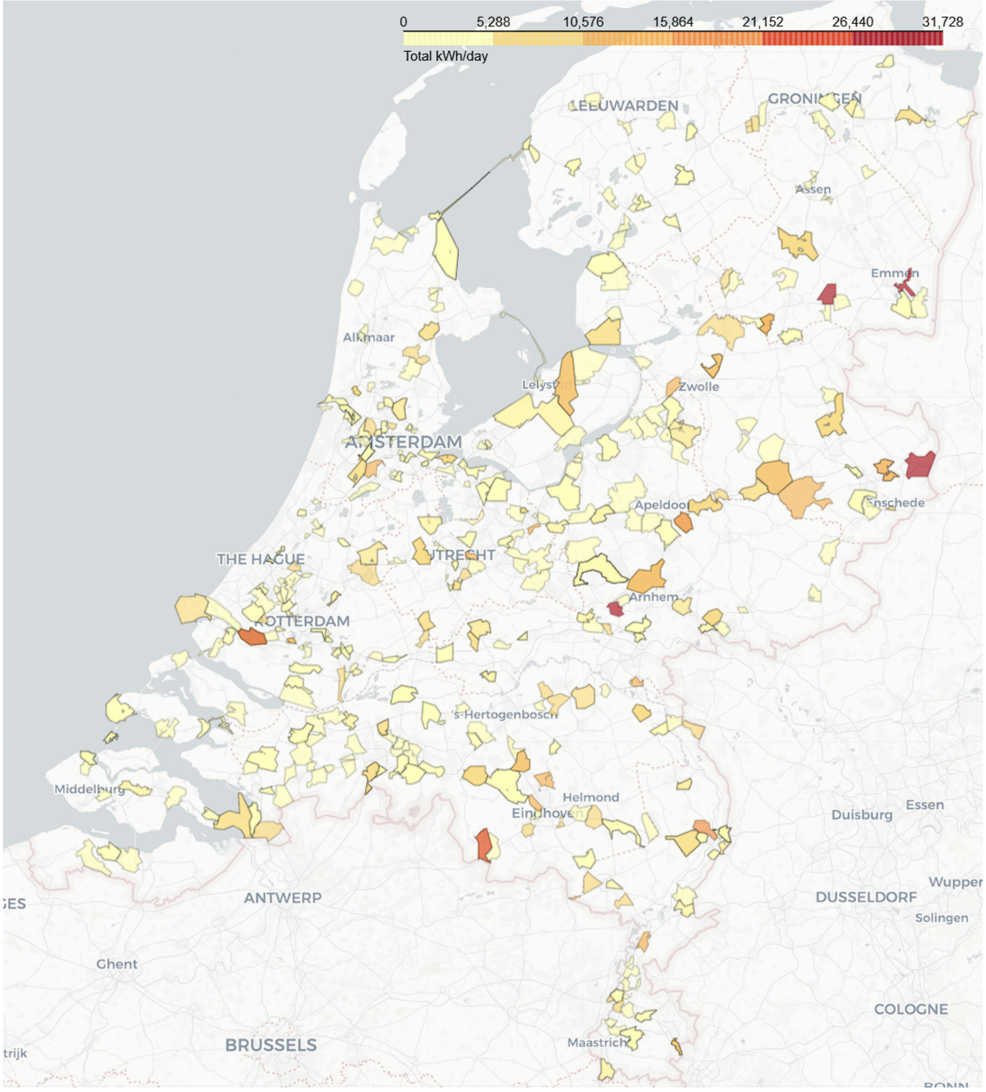

Figure 52: Spatial energy demand (DSO grid) — 10% electrification scenario.

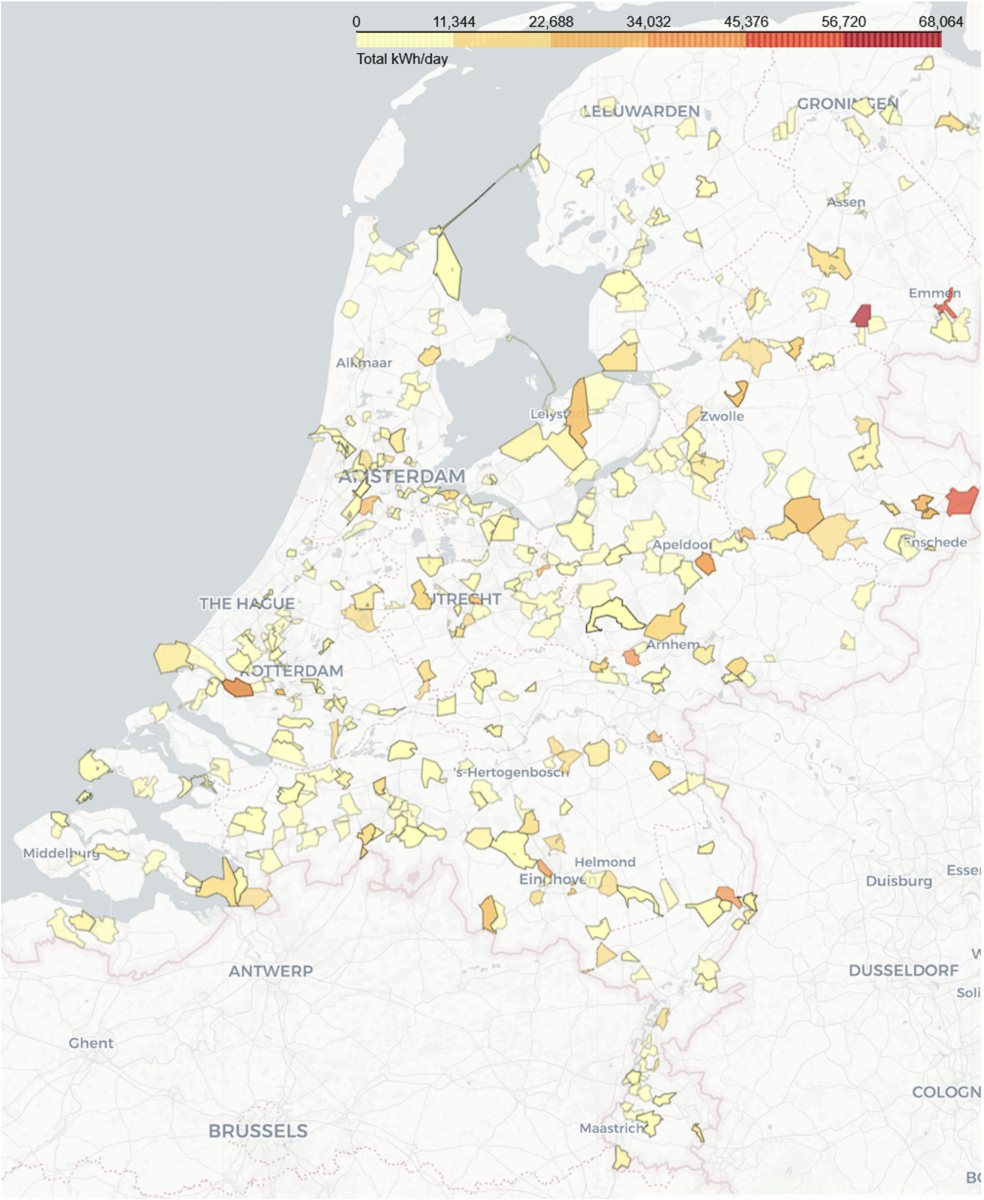

Figure 53: Spatial energy demand (DSO grid) — 20% electrification scenario.

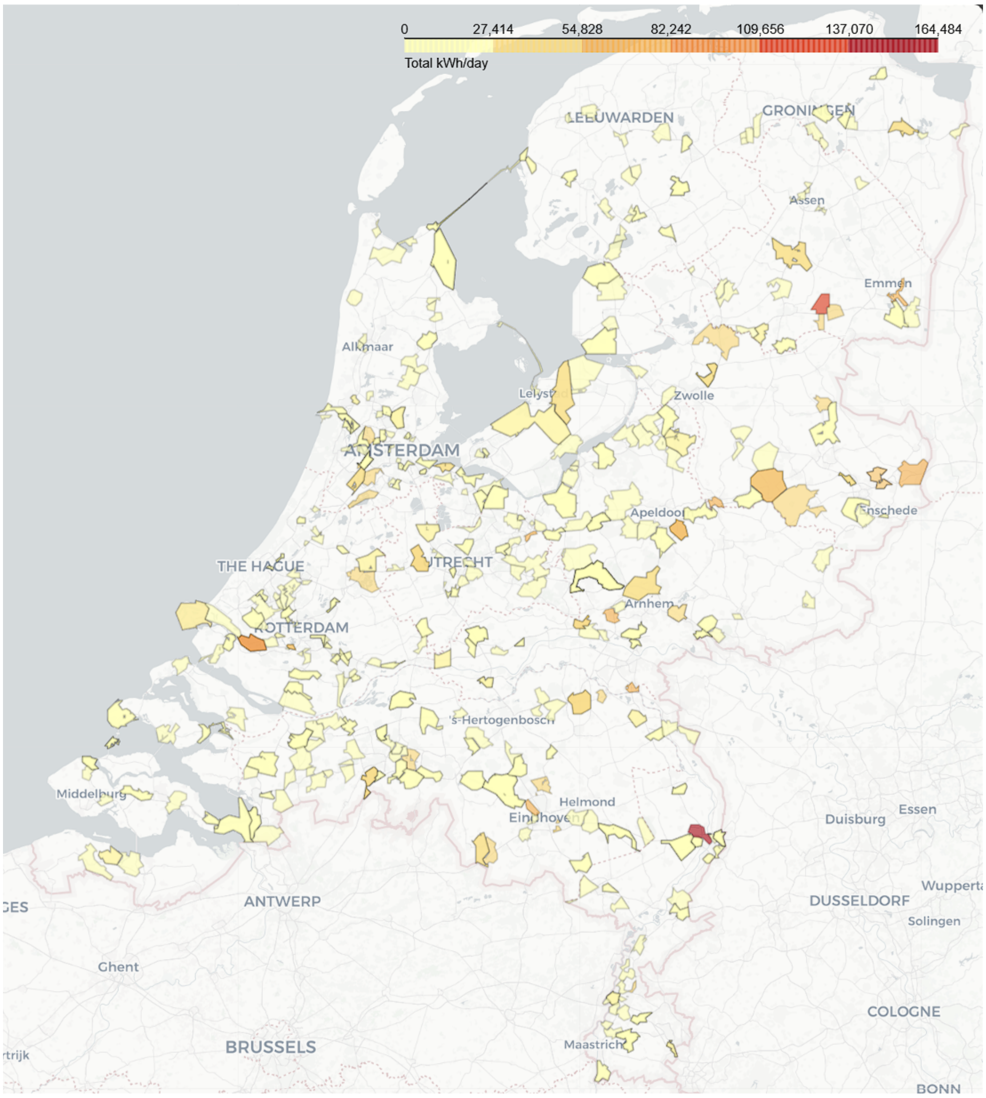

Figure 54: Spatial energy demand (DSO grid) — 40% electrification scenario.

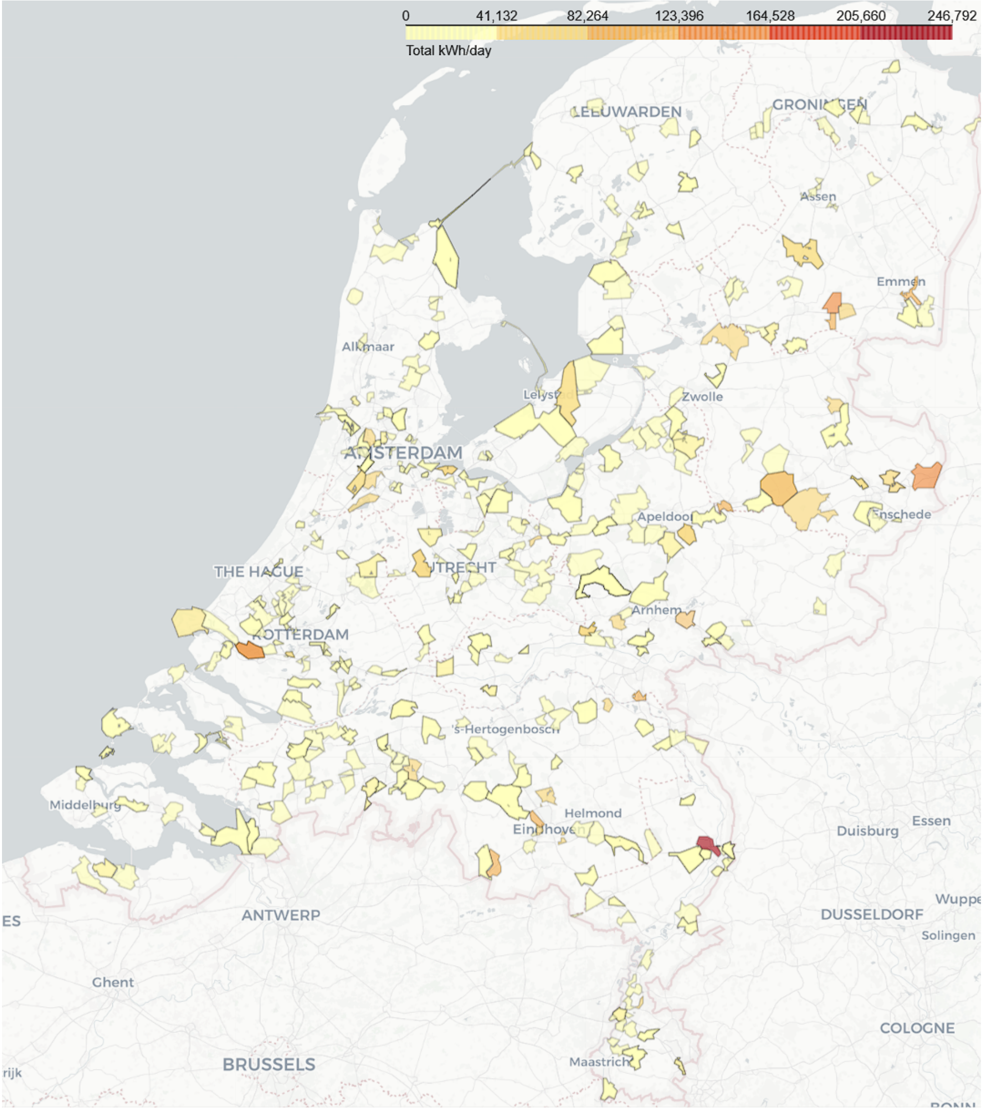

Figure 55: Spatial energy demand (DSO grid) — 60% electrification scenario.

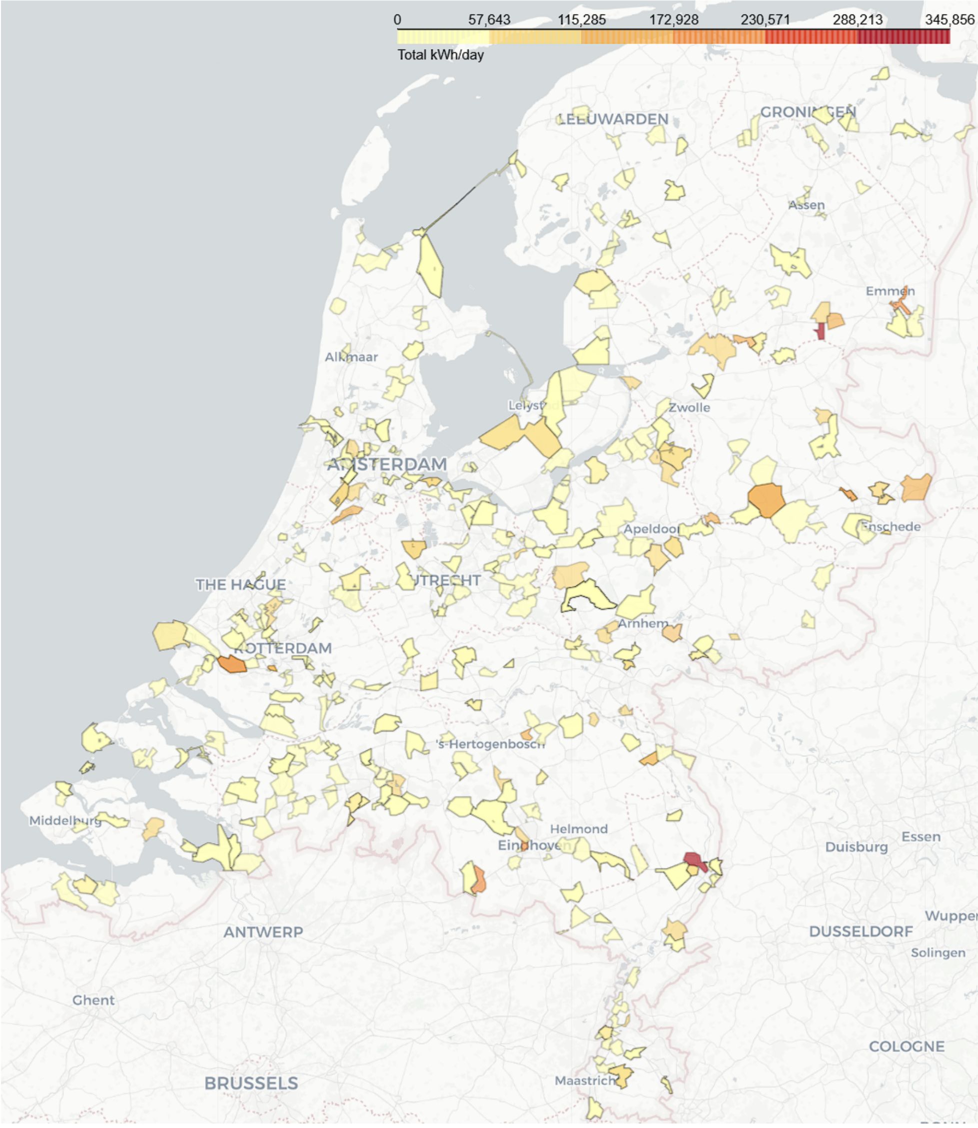

Figure 56: Spatial energy demand (DSO grid) — 100% electrification scenario.

A.12 Technical Implementation

This small section is a practical implementation of the agent-based model drafted in section 4. It entails the technical details such as library versions, HPC cluster bash files details and small alterations to prevent clustering errors.

A.12.1 Reproducibility

Environment: DelftBlue HPC cluster, 1 CPU per run, 3.9 GB memory per core, 24 hour time limit.

Seed: fixed seed per scenario to ensure replicability across runs. Seeds used: 2,3,4,5.

Steps: Scenarios with a electrification stage lower than 60% are simulated for 5 days which equals 7200 minutes. Electrification stage 60% and 100% are only simulated for 4 days (5760 minutes). Otherwise they would exceed the 24 hour limit on the DelftBlue HPC cluster.

How to run: regular run on pc starts with model_run.py, multiple scenarios are run through HPC cluster with bash file that uses run_multiple_delftblue.py

Library versions

Since runs are done both on the DelftBlue HPC cluster and a PC different versions of libraries have been used and proved compatible

Module	HPC	PC
python	3.10.12	3.12
geopandas	1.1.1	1.0.1
pandas	2.3.1	2.2.3
matplotlib	3.10.3	3.10.3
networkx	3.4.2	3.5cr0
numpy	2.2.6	2.2.5
shapely	2.1.1	2.1.0
scipy	1.15.3	1.15.3
tqdm	4.67.1	4.67.1
joblib	1.5.1	1.5.0
Mesa	3.0.3	3.2.0

Table 22: Python Modules versions compatible with project

It is of critical importance that the Mesa version is 3 or above. Mesa version 3 completely redid their methodology of scheduling and the project would therefore require complete rewrite to be compatible with Mesa version 2.

A.12.2 Floating point error prevention

When working with geographic data, small numerical inaccuracies can occur because computers cannot store all decimal values exactly. These so-called floating point errors may lead to coordinates that should be identical differing by a tiny margin, which can cause problems in network building or when matching locations. On the PC floating point errors did not occur but when transferring to the HPC cluster they did. To prevent this, all coordinates were rounded from 10 to three decimals after projecting them to EPSG:3035. Since this projection uses meters as units, rounding to 0.001 corresponds to a precision of 1 millimeter. This level of detail is far more precise than required in this project and prevents the floating error points.

A.13 AI Acknowledgment

During the process of my master thesis I have made use of AI for various cases. AI is a a very helpful tool that can replace a lot of the platforms previously used by students to guide them during their studies. However, it comes with the danger of presenting misinformation or making a student overly reliant. Therefore, I will be transparent about the cases or situations in which I myself was reliant on AI.

The AI model that I have used during this study was ChatGPT. ChatGPT has been very helpful, especially during the coding part of my model. AI is pretty bad at handling models such as mine when they get more complex, but it is very helpful when used in small compartments such as debugging single functions. I have encountered many bugs in the process of creating my model, and many of the bugs i myself could not find at first have been found by ChatGPT. Furthermore, the interactive maps presenting some of my results are partly made with html code. The sliders, sizes and colors specifically are made with html, I myself am not proficient with html so the credits for this are due to ChatGPT. The last part of coding ChatGPT helped me with was working with the Delft High Performace Cluster (DHPC) for my results. the DHPC uses a different python environment as my own and I needed AI help to make them compatible. Furthermore, the DHPC resulted in floating point errors in my model which I myself was unable to figure out, but ChatGPT was able to trace this problem.

ChatGPT has also in a lesser extent been used in helping me write my master thesis. For this AI was mainly used as sparring partner on how to structure my thesis such as, which sections should be appendix, or what structure does an introduction normally follow. Also after writing a section I would ask the opinion of AI, not to change the content but to improve on either academic tone, spelling mistakes, incorrectly structured sentences or if I was missing something. Many spelling errors have been spotted by AI which I myself always read over. Lastly, AI has also been used in some aesthetic parts of the thesis. The tables in appendix A.9.2 for instance have been created with the help of ChatGPT. These tables contain almost a thousand values together and would have been very tedious to create by hand in overleaf. Therefore, I presented the data to AI and let it create the overleaf code for the tables. I did have to ensure the data was still the same as in my original csv but overall this saved me several hours of filing in tables by hand.