Electrification of road freight transport – public fast charging infrastructure and the market diffusion of battery electric trucks

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften (Dr. rer. pol.)

von der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

Dissertation

von

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Tag der mündlichen Prüfung:	08.05.2024
Referent:	Prof. Dr. Martin Wietschel
Korreferent:	Prof. Dr. Kay Mitusch

Karlsruhe, Juni 2024

Danksagung

An dieser Stelle möchte ich mich bei allen bedanken, die mich bei der Erstellung dieser Arbeit unterstützt haben.

Diese Dissertation entstand im Rahmen meiner Tätigkeit am Fraunhofer-Institut für System- und Innovationsforschung (ISI). Ich darf mich bei allen Kolleginnen und Kollegen bedanken, die mich mit konstruktiven Rückmeldungen unterstützt haben und mir im Projektalltag die notwendige Zeit zum Verfassen dieser Dissertation eingeräumt haben. Ein besonderer Dank gilt an dieser Stelle meinem Mentor Dr. Patrick Plötz, der mich stets neu motivierte und durch seine regelmäßigen Anmerkungen zum Gelingen der Arbeit beigetragen hat. Sowohl auf wissenschaftlicher als auch auf persönlicher Ebene hätte ich mir keine bessere Betreuung wünschen können.

Insbesondere möchte ich mich bei meinem Doktorvater Prof. Dr. Martin Wietschel bedanken. Sein Vertrauen in meine Arbeit sowie der eingeräumte Freiraum ergaben den Rahmen für das Gelingen meiner Dissertation. Seine konstruktiv-kritischen Rückfragen halfen mir stets die einzelnen Puzzleteile zu einem Gesamtbild zusammenzufügen.

Ebenso danke ich Prof. Dr. Kay Mitusch für das Korreferat, Prof. Dr. Frank Schultmann und Prof. Dr. Martin Klarmann für die Prüfung und den Vorsitz der Prüfungskommission.

Nicht zuletzt gilt mein Dank meinen Freunden, meiner Familie und meiner Freundin. Sie waren es, die mit ihrer unermüdlichen Unterstützung diese Dissertation überhaupt erst ermöglicht haben.

Daniel Speth

Kurzfassung

Der schwere Straßengüterverkehr ist in Deutschland und Europa jeweils für rund 7% der energierelevanten Treibhausgasemissionen verantwortlich. Batterieelektrische Lkw sind eine vielversprechende Option, um die europäischen Klimaziele im schweren Straßengüterverkehr einzuhalten. Eine öffentliche Schnellladeinfrastruktur mit hoher Leistung gilt dabei als Voraussetzung für den Einsatz im Langstreckenverkehr. Diese Arbeit untersucht den Bedarf an öffentlicher Megawatt-Ladeinfrastruktur für schwere Nutzfahrzeuge in Deutschland im europäischen Kontext sowie dessen Auswirkungen auf den Markthochlauf batterieelektrischer Lkw.

Zuerst wird der Bedarf an öffentlicher Megawatt-Ladeinfrastruktur anhand des regional aufgelösten Verkehrsaufkommens analysiert. Unter Berücksichtigung von Verkehren zwischen 1.630 Regionen in Europa und der lokalen Parkplatzverfügbarkeit wird mittels gemischt-ganzzahliger Optimierung ein minimales Ladestationsnetzwerk für Deutschland errechnet. Zusätzlich wird mit einem weiteren Ansatz, der Ladeinfrastruktur in regelmäßigen Abständen vorsieht, ein nutzerfreundlicheres Ladenetzwerk in verschiedenen Ausbaustufen entworfen. Im zweiten Schritt wird ein agentenbasiertes Modell entwickelt, das den gemeinsamen Markthochlauf öffentlicher Ladeinfrastruktur und batterieelektrischer Lkw in Deutschland bis 2050 simuliert. Unter Berücksichtigung von 2.410 Tagesfahrprofilen wird mittels zeitlich aufgelöster Fahrsimulation die technische Machbarkeit batterieelektrischer Lkw geprüft. Die ökonomische Bewertung der Einzelfahrzeuge erfolgt auf Basis der Gesamtkosten unter Berücksichtigung der Infrastrukturkosten. Die Simulation zeigt den marktgetriebenen Bedarf an öffentlicher Megawatt-Ladeinfrastruktur bis 2050 und dient als Input für die integrierte Infrastrukturplanung.

Die Ergebnisse zeigen, dass für eine vollständige Flottenumstellung circa 5.000 Megawatt-Ladepunkte an wenigen Hundert Standorten in Deutschland nötig sind. Große Standorte mit geringem Abstand sind insbesondere an den Korridoren zwischen den Häfen in Belgien und den Niederlanden sowie Polen und Österreich notwendig. Aufgrund der hohen Energiemenge von circa 5 TWh jährlich an öffentlicher Megawatt-Ladeinfrastruktur in Deutschland bei nahezu vollständiger Flottenumstellung, kostet die Infrastruktur weniger als 0,1 $€_{2020}$/kWh. Sie hat damit nur geringen Einfluss auf den mittelfristig in dieser Arbeit identifizierten hohen Kostenvorteil batterieelektrischer Lkw gegenüber Diesel-Lkw. Die Analysen zeigen, dass nur etwa 15% der Fahrzeuge, die für 30% der Fahrleistung verantwortlich sind, auf öffentliches Megawatt-Laden angewiesen sind. Mehr als die Hälfte der nach 2035 benötigten knapp 35 TWh elektrischer Energie kann an privater Infrastruktur mit weniger als 44 kW Leistung geladen werden. Zukünftig sollte die private Langsamladeinfrastruktur daher stärker berücksichtigt werden.

Diese Thesis wurde im Rahmen meiner Forschungsarbeit am Fraunhofer-Institut für System- und Innovationsforschung (ISI) erstellt und von Prof. Dr. Martin Wietschel am Institut für Industriebetriebslehre und Industrielle Produktion (IIP) am Karlsruher Institut für Technologie betreut (KIT).

Abstract

Today, heavy road freight transport is responsible for about 7% of energy-related greenhouse gas emissions in Germany and Europe. Battery-electric trucks are a promising option to meet the European climate targets for heavy road freight. Yet, a public fast-charging infrastructure with high power is considered to be mandatory for their use in long-haul transport. In this thesis, the need for megawatt charging infrastructure for heavy-duty vehicles in Germany in a European context and its impact on the market diffusion of battery-electric trucks is investigated.

As a first step, the need for public megawatt charging infrastructure is analyzed based on the regionally resolved road traffic volume. Considering traffic between 1,630 regions in Europe and local parking availability, a minimum charging location network for Germany is calculated, using mixed-integer optimization. In addition, a more user-friendly charging location network in different expansion stages is designed, using another approach that provides charging infrastructure at regular intervals. As a second step, an agent-based model is developed that simulates the joint diffusion of public charging infrastructure and battery electric trucks in Germany up to 2050. Taking into account 2,410 daily driving profiles, the technical feasibility of battery-electric trucks is tested, using time-resolved driving simulation. The economic evaluation of single vehicles is based on the total cost of ownership, taking infrastructure costs into account. The simulation shows the market-driven demand for public megawatt charging infrastructure up to 2050 and serves as input for the integrated infrastructure planning.

The results show that approximately 5,000 megawatt charging points are needed at a few hundred locations in Germany for a complete fleet conversion. Locations with many charging points and a short distance between the single locations are particularly necessary along the long-distance corridors between the port regions of Belgium and the Netherlands and Poland or Austria. Due to the high amount of electricity of about 5 TWh per year recharged at public megawatt charging infrastructure in Germany with almost complete fleet conversion, the infrastructure costs significantly less than 0.1 $€_{2020}$/kWh and thus has no relevant influence on the identified high cost advantage of battery electric trucks over diesel vehicles in the medium term. The analyses also show that only about 15% of the vehicles that are responsible for 30% of the mileage rely on public megawatt charging infrastructure. More than half of the nearly 35 TWh of total electricity demand after 2035 can be charged at private infrastructure with less than 44 kW of power. In the future, therefore, more consideration should be given to private slow charging infrastructure.

This thesis is based on my research conducted at the Fraunhofer Institute for Systems and Innovation Research (ISI) under the supervision of Professor Dr. Martin Wietschel at the Institute for Industrial Production (IIP) at the Karlsruhe Institute of Technology (KIT).

Contents

List of Figures

List of Tables

Abbreviations

AC	Alternating current
ABM	Agent based model
AFIR	Alternative fuels infrastructure regulation
A-TCD	Automated traffic count data (dataset)
BET	Battery electric truck
CFRLM	Capacitated flow refueling location model
CCS	Combined charging system
DC	Direct current
DT	Diesel truck
EC	European Commission
ERFT	European road freight transport survey (dataset)
ETIS	European transport policy information system (dataset)
ETIS-U	ETIS updated (dataset)
ETS	EU emissions trading system
EU	European Union
FCET	Fuel cell electric truck
FCLM	Flow capturing location model
FRLM	Flow refueling location model
GER	Germany
GHG	Greenhouse gas
GPS	Global positioning system
GT	(Natural) gas truck
GVW	Gross vehicle weight

HDV	Heavy-duty vehicle (gross vehicle weight > 12 t, if not stated otherwise)
ICEV	Internal combustion engine vehicle
KiD	Kraftfahrzeugverkehr in Deutschland (dataset)
MCLM	Maximum covering location model
MCS	Megawatt charging system
MIP	Mixed-integer optimization problem
M-TCD	Manual traffic count data (dataset)
NUTS	Nomenclature des unités territoriales statistiques
OD	Origin-destination
OSM	Open street map
R	Rigid truck
SCLM	Set covering location model
TCO	Total cost of ownership
TSL	Truck stop locations (dataset)
TT	Tractor-trailer truck
VVP	Verkehrsverflechtungsprognose (dataset)
ZET	Zero emission truck
ZEV	Zero emission vehicle

1 Introduction

1.1 Motivation

Both, policymakers and scientists have recognized anthropogenic climate change as a key challenge of today's world. Scientists have shown that climate change is already having adverse effects, for example on human health, economic welfare and humanitarian crises (IPCC, 2022). In the official statement of 112 political world leaders at the United Nations Climate Change Conference 2022 (COP27), the climate crisis is described as "[...] a predominant threat to our planet with cross-cutting implications on the stability, safety and sustainability of communities globally." (COP27, 2022, p. 1). The statement further emphasizes the responsibility to act in accordance with the Paris Agreement that aims to limit the global temperature increase to below 2 °C, and undertake efforts to limit it to 1.5 °C, compared to pre-industrial levels (UN, 2015).

In the European Union (EU), road transport accounted for one quarter of total energy-related greenhouse gas (GHG) emissions in 2020 and 2021. In Germany, the relative share of road transport amounted to 22% of total GHG emissions. Heavy-duty trucks and buses exceeding a gross vehicle weight (GVW) of 3.5 t are responsible for 7% of energy-related GHG emissions at both EU and German level. Even though absolute GHG emissions from heavy-duty trucks and busses decreased from 209 Mt to 192 Mt CO_{2eq} at EU level and from 46 to 43 Mt CO_{2eq} at German level from 2019 to 2020 due to the COVID pandemic, the value has increased by more than a quarter since 1990 (Eurostat, 2022b). Efficiency improvements have not fully compensated the increasing traffic volume (Kubáňová et al., 2021; Meza et al., 2020).

In the "Fit for 55" policy package, the EU aims to reduce GHG emissions by 55% by 2030 compared to 1990 level (EU, 2021). The package consists of various legislative measures on EU climate and energy policy (EPRS, 2022). In particular, the transport sector is addressed as a "[...] challenging sector for climate action" (EPRS, 2022, p. 2). Four central scopes of action can be identified for heavy-duty vehicles (HDV):

- firm-level emission performance standards of new vehicles
- infrastructure mandates
- CO_2 limitation for fuels (mandatory blends, cap-and-trade scheme)
- subsidies for investments and research

A broader overview can be found at Ovaere and Proost (2022). Especially relevant are the firm-level emission performance standards that demand an average reduction of 30% of CO_2 emissions from newly sold trucks with a laden mass of more than 16 t or at least three axles by 2030 compared to 2019/2020 (EU, 2019). Plötz, Wachsmuth, et al. (2023) state "[...] that parts of the 'Fit for 55' for transport are still not ambitious enough to align with a 1.5 °C scenario."

(Plötz, Wachsmuth, et al., 2023, p. 343). Consequently, a further tightening of the firm-level emission performance standards is currently in the political process (EC, 2023). As shown in Figure 1-1, zero emission vehicles (ZEV) are necessary to reach the target valid at the time of writing. Even with the implementation of many technically feasible measures to increase the efficiency of diesel vehicles, the 30% target cannot be reached without ZEV (Breed et al., 2021). The proposed tightening to a reduction of 45% by 2030, further increases the need for ZEV.

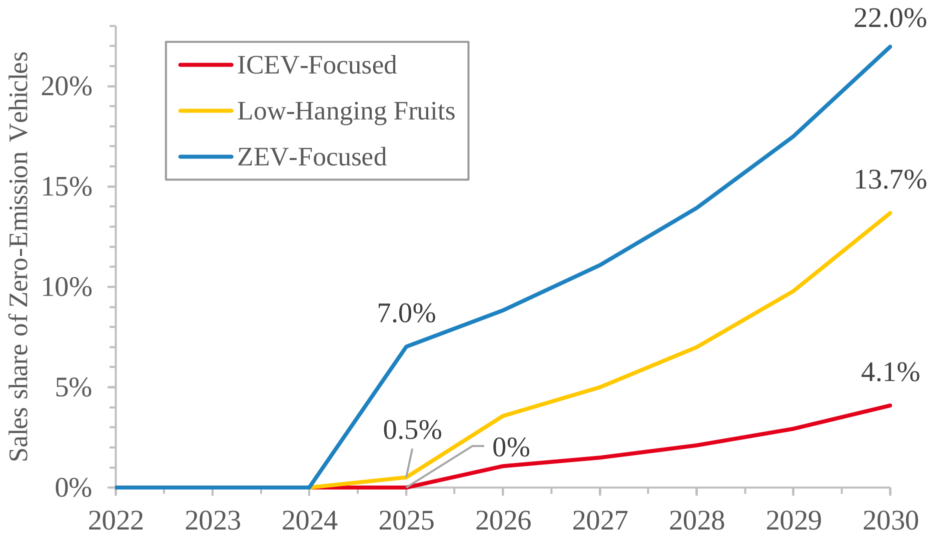

Figure 1-1: Percentage of zero emission vehicles (ZEV) sales share in the EU to meet 30% tail-pipe emission reduction by 2030 compared to 2020 in newly sold trucks. ICEV-Focused: Efficiency improvements for internal combustion engine vehicles fully implemented, Low-Hanging Fruits: Efficiency improvements for internal combustion engine vehicles partly implemented, ZEV-Focused: Efficiency improvements for internal combustion engine vehicles only implemented, if applicable for zero emission vehicles too (Breed et al., 2021).

While the EU is aiming for climate neutrality by 2050 (EU, 2021), Germany wants to become climate neutral by 2045 (Deutscher Bundestag, 2019). By 2030, a reduction of GHG emissions of 65% compared to 1990 is planned for Germany. For the transport sector, a reduction of 48% is legally binding (Deutscher Bundestag, 2019). In addition, one third of the mileage of HDV in Germany shall be fulfilled electrically or with electricity-based fuels (Deutsche Bundesregierung, 2019).

In summary, regulations at European level and national German level necessitate the introduction of ZEV for HDV with noteworthy market shares by 2030.

Furthermore, the future of heavy road freight transport plays an important role for the German economy. On the one hand, German road freight vehicles provide the second highest transport volume in the EU (307 bn tkm of a total of 1,920 bn tkm, equivalent to 16%). Only Polish vehicles achieve a higher market share with 380 bn tkm (Eurostat, 2022a). On the other hand, German truck manufacturers achieved a market share of 51% for medium and heavy-duty trucks above 3.5 t in Europe[1] in 2020 (ACEA, 2022a; Basma & Rodríguez, 2021). For heavy trucks with a gross vehicle weight (GVW) of above 16 t - 66% of all HDV above 3.5 t sales -, the share is almost identical (Basma & Rodríguez, 2021).

In 2021, the registration share of ZEV in the medium and heavy-duty vehicle segment over 3.5 t GVW was well below one percent (ACEA, 2022b; KBA, 2022). However, there are research studies that show a high potential especially for battery electric trucks (BET) from an economic point of view[2]. From a technical point of view, infrastructure availability represents a crucial parameter for the spread of BET. Several surveys show that logistic companies regard a lack of charging infrastructure as a key obstacle[3]. The European Commission (EC) also highlights the importance of charging infrastructure for BET and proposes a public fast charging infrastructure at regular intervals along the TEN-T road network[4] in the proposal for the Alternative Fuels Infrastructure Regulation (AFIR) (EC, 2021). The EC foresees charging infrastructure dedicated to trucks with a distance of 60 km along the TEN-T core network by 2025 and with a distance of 100 km along the TEN-T comprehensive network by 2030. In addition, every urban node should have charging infrastructure by 2025. However, uncertainties exist regarding the design and extent of the required charging infrastructure[5]. To reduce HDV charging times, the industry has announced the Megawatt Charging System (MCS). The MCS standard will build on the Combined Charging System (CCS), currently used for passenger cars. The MCS standard shall extend the maximal power output of 350 kW for CCS into the megawatt range (CharIN, 2023). The MCS standard will be tested in demonstration projects and is expected to be introduced in 2024 (HoLa, 2021). However, it is not yet explicitly included in the EC proposal, as the international standard for MCS is only expected for 2024 or 2025 latest. There are initial proposals regarding the extent of charging infrastructure for BET[6]. A regional distribution of a possible public fast charging infrastructure for HDV for a large area, as proposed as a first draft in Lahmann (2022) for Germany, is unique at this point. At most, studies of current truck parking (Plötz & Speth, 2021) or regionally limited considerations (Whitehead et al., 2021) can

[1] Europe: EU27, United Kingdom, Norway, Switzerland

[2] See e.g. Noll et al. (2022), Speth, Kappler, et al. (2022), Phadke et al. (2021), Burke and Kumar Sinha (2020) or Basma et al. (2021) for economic analysis of BET and other truck drives.

[3] See Kluschke, Uebel, and Wietschel (2019) for a survey among 70 logistics companies in Germany, Bae et al. (2022) for a survey among 20 logistics companies in California (USA), Pierre-Luis Ragon and Rodríguez (2022) for a survey among 23 logistics companies in Europe and Anderhofstadt and Spinler (2019) for a Delphi study in Germany.

[4] TEN-T according to EU (2013): Trans-European Transport Network. The "Core Network" consists of the most important European connections and is scheduled for completion in 2030. The "Comprehensive Network" covers all European regions and is scheduled for completion in 2050.

[5] The agreement of the European Parliament, the Council, and the Commission foresees charging points at 120 km intervals on the TEN-T core network and on the TEN-T comprehensive network in both directions by 2025. By 2030, the network should be densified to 60 km on the TEN-T core network and to 100 km on the TEN-T comprehensive network. In addition, coverage is limited to 15% of the considered network in 2025 and to 50% in 2027. Exceptions exist for road sections with less than 2,000 truck movements per day on average (Bernard (2023)). However, the final regulation is still pending at the time of writing of this thesis and will be in force at 12/10/2023.

[6] See e.g. ACEA (2021) for the position of the vehicle manufacturers, Mathieu (2020) for estimates regarding urban and regional charging demands by Transport&Environment or Lahmann (2022) for an initial distribution of approximately 200 possible charging locations in Germany.

be found. Technically detailed analysis for vehicle fleets with different infrastructure assumptions are also available[7]. However, these studies do not include modeling of BET market diffusion, but build on exogenous estimates. Conversely, there are multiple market diffusion scenarios for BET[8]. They all claim to consider the impact of infrastructure on the market diffusion of BET. However, they do not consider a detailed geographical design of a charging infrastructure, but usually model an increasing vehicle range via general infrastructure parameters. A scientific estimation of the charging demand taking into account the locations, the load profile and the amount of energy (Taljegård, 2019) has not yet been publically carried out. The effect of the infrastructure on the market ramp-up of BET and vice versa has also not yet been investigated.

In summary, it is concluded that (1) heavy-duty ZEV are required to meet legally binding climate targets, (2) Germany has a central role for heavy-duty road transport, (3) BET are a likely solution for heavy-duty road transport, and (4) public fast charging infrastructure for BET is needed. However, the design of the public infrastructure as well as its impact on the market diffusion of BET - and vice versa - is worth further investigation.

1.2 Research questions and outline

Based on 1.1, three research gaps can be identified: (1) design of a future public charging network for BET, (2) impact of public truck charging infrastructure on the market diffusion, and (3) effects of the electrification of road freight transport on the energy demand. Accordingly, this thesis handles three overarching research questions.

Q1: Taking into account the locally resolved demand for freight transport, how can a station-based public fast charging infrastructure for battery electric heavy-duty vehicles in Germany look like and which costs arise due to the infrastructure installation?

The development of a regionally resolved data basis of truck traffic volumes is the first step to answer this question. The focus is on Germany as a relevant lead market (see 1.1), yet the international orientation of freight transport necessitates the integration of a European dimension. In addition to station-based charging, other charging options, such as overhead catenary lines and battery swapping stations, exist and have specific advantages and disadvantages (Speth & Funke, 2021). However, since the focus of vehicle manufacturers is current-

[7] See e.g. Liimatainen et al. (2019) for a technical analysis of road freight transport in Switzerland and Finland or Çabukoglu et al. (2018) for a technical analysis in Switzerland. Link and Plötz (2022) show a technical investigation for a food retailer truck fleet in Germany.

[8] See e.g. Craglia (2022), MPP et al. (2022), Tol et al. (2022), Neuhausen et al. (2022), or Plötz, Link, et al. (2023) for scenarios for Europe. See e.g. Gnann, Speth, Krail, et al. (2022), or Gnann et al. (2023) for scenarios for Germany.

ly mainly on stationary charging, these alternatives are not considered here[9]. The first research question is further operationalized into two sub-questions:

Q1a: Where could a public fast charging infrastructure for battery electric heavy-duty vehicles be spatially located?

Q1b: How should the public charging infrastructure be technically dimensioned in terms of charging points and charging power?

The second research question deals with the interaction between charging infrastructure and the market diffusion of BET.

Q2: What impact does the development of public fast charging infrastructure have on the market diffusion of heavy-duty electric vehicles and which truck technology appears to be economically viable from the user's perspective in Germany up to 2050?

At this point, established total-cost-of-ownership (TCO) modeling[10] is used to calculate the market diffusion of battery electric trucks (BET). However, the findings from Q1 are taken into account and the infrastructure ramp-up is integrated into the modeling. The modeling includes the German vehicle population above 12 t GVW, since vehicles with a GVW larger than 12 t are responsible for approximately 70% of the CO_2 emissions of the German road freight transport (Wietschel et al., 2017). Following Noll et al. (2022) the thesis focuses on diesel trucks (DT) and natural gas trucks (GT) as existing technologies and on battery electric trucks (BET) and fuel cell electric trucks (FCET) as future technologies. To reach climate neutrality, PHET would have to be fueled with synthetic fuels. However, synthetic fuels will be scarce and expensive beyond 2030, and their use in avoidable applications may lead to lock-in effects (Ueckerdt et al., 2021). Therefore, a market diffusion of PHET is neglected in this thesis.

The integration of a charging location into the power grid takes between six months and up to ten years, depending on the required power (Kippelt et al., 2022). In order to enable a timely infrastructure ramp-up, it is necessary to consider the additional demand as well as the additional load in advance. Therefore, the requirements of road freight transport electrification on the energy system shall be estimated. According to Taljegård (2019), in addition to the geographical distribution, the total amount of energy and the load profile are relevant.

Q3: What is the impact of battery electric road freight transport in terms of (1) the total amount of electric energy and (2) the load profile in Germany up to 2050?

This thesis is, besides the scientific community, also relevant for representatives from policy and industry. The findings can be used to define policy frameworks for public fast charging

[9] See e.g. Speth and Funke (2021) or Plötz, Speth, et al. (2021) for an exemplary presentation of advantages and disadvantages and a first attempt to model a joint station-based and overhead-catenary charging infrastructure.
[10] See e.g. Noll et al. (2022) or Speth, Kappler, et al. (2022) for recent TCO calculations for trucks, Plötz et al. (2019). or Gnann, Speth, Krail, et al. (2022) for market diffusion modeling for trucks. An overview of market diffusion scenarios for heavy-duty vehicles is given in Kluschke, Gnann, et al. (2019).

infrastructure ramp-up. They can also support investment decisions of potential infrastructure operators. Energy suppliers and grid operators may include the potential future energy demand from battery electric trucks in their planning.

As mentioned earlier, this thesis focusses on HDV > 12 t GVW in Germany. HDV can be further distinguished in tractor-trailer trucks and rigid trucks. While tractor-trailers are designed to carry a trailer and do not have own cargo capacity, a rigid truck can directly carry goods and can be combined with a trailer. As part of the market diffusion modelling for trucks, both bodies are modeled separately and differentiated in their technical framework parameters. The demand for both bodies is assumed to be exogenous and is not part of this dissertation.

The thesis contains five central chapters. First, some background information on alternative fueled vehicles are given and the existing literature is summarized. The chapter addresses both content literature and methodological literature. Subsequently, chapter 3 presents data and assumptions that are relevant for the modeling process. Chapter 4 contains the modeling for the infrastructure models, as well as for the joint market diffusion model for vehicles and charging infrastructure. Chapter 5 presents and discusses the results of the modeling and contains summaries that answer the given research questions. Finally, chapter 6 summarizes the thesis and derives key conclusions, as well as future research needs. For the ease of reading, it should be noted that this thesis consists of two central components: First, the pure infrastructure modeling based on exogenously given parameters, and second, the joint modeling of the market diffusion of infrastructure and vehicles. Therefore, the chapters 4 and 5 are divided into two parts, presenting pure infrastructure modeling and market diffusion modeling separately.

Parts of this thesis build on excerpts from international peer-review publications by the author. Calculations in Breed et al. (2021) show the need for ZET to meet EU targets and thus provide a motivation for this thesis. Speth, Sauter, Plötz, and Signer (2022) describe a dataset on European traffic flows that serves as basis for infrastructure modeling. Speth, Plötz, et al. (2022), Speth, Sauter, and Plötz (2022), and Speth et al. (2024)[11] contain the geographically resolved public fast charging infrastructure modeling, used in this thesis. The agent-based simulation of the technical feasibility of BET in Speth and Plötz (2024) is part of the market diffusion model in this thesis. An early version of the economic assessment for BET is published as a conference paper (Speth, Kappler, et al., 2022). In the course of this thesis, references will be made to these and other, less central, publications by the author. Chapters that refer to those publications are marked accordingly.

[11] This publication is still under review at the time of submission of this thesis.

2 Background and existing literature

The following chapter summarizes the current state of research relevant to this thesis. The subchapter 2.1 introduces the current knowledge with respect to alternative fueled heavy-duty vehicles and their infrastructure. The subchapters 2.2 and 2.3 introduce the current knowledge regarding infrastructure modeling and market diffusion modeling.

2.1 Alternative fueled heavy-duty vehicles and their infrastructure

All European truck manufacturers commited to 100% zero-emission truck sales in 2040 (ACEA, 2020). However, the requirements for HDV are heterogenous. For example, requirements differ in terms of the vehicle body, the power, and the vehicle range. They depend on the intended use, for example regional transport, long-distance transport, or special operations like garbage service. Therefore, it is uncertain whether one technology will be suitable for all purposes in the future (ACEA, 2016). Accordingly, there is a broad selection of alternatives discusssed: (1) direct use of (renewable) electricity, (2) (synthetic) hydrogen, or (3) (synthetic) carbon fuels. In the following, a brief overview on each alternative is given. Afterwards, the current state of literature on a possible diffusion of BET, as the main technology in this thesis, is shown in more detail in subchapter 2.1.2. Finally, there is a section on public infrastructure needs for BET in subchapter 2.1.3.

2.1.1 Alternative fuel heavy-duty vehicles

In 2021, 95% of HDV with more than 3.5 t GVW sold in the EU were diesel trucks (DT). Alternative drive systems without BET, typically gas trucks (GT), accounted for 3.6% (ACEA, 2022b). At first glance, synthetic carbon fuels - for example synthetic diesel for DT or synthetic methane for GT - appear to be the simplest solution, as they can be used directly in existing vehicles (Plötz, Wachsmuth, et al., 2021). The necessary refueling infrastructure is also already in place. However, due to the initially highly limited availability of synthetic fuels (Odenweller et al., 2022; Ueckerdt et al., 2021), they should be used for applications with less options - such as aviation and shipping - and only in exceptional cases for HDV (Dahal et al., 2021; Plötz, Wachsmuth, et al., 2023). In addition, prices for synthetic fuels will be higher than for conventional fuels (Odenweller et al., 2022; Ueckerdt et al., 2021). However, both DT and GT are available today. GT are offered as compressed natural gas (CNG) vehicles and liquefied natural gas (LNG) vehicles, with LNG more widespread for HDV. In addition, depending on the manufacturer, the vehicles are offered with spark ignition or high-pressure direct injection. Spark ignition engines are cheaper than high-pressure direct injection, but have an approximately

22% higher fuel consumption compared to DT. High-pressure direct injection engines for DT reach almost the efficiency of a DT (Mottschall et al., 2020). The well-to-wheel efficiency of a DT is approximately 20% to 25%, when using renewable electricity. Relevant at this point is also the comparatively low tank-to-wheel efficiency of the vehicle of approximately 35% to 40% (Plötz et al., 2018).

In terms of sales share, hydrogen powered trucks do not play a relevant role in the EU up to now. However, first test fleets with several dozen vehicles are already in operation (IEA, 2022). In principle, hydrogen can be used in combustion engine trucks or in fuel cell electric trucks (FCET). In this thesis, the focus is on FCET, since the fuel cell, due to its higher efficiency, enables cheaper operating costs than the hydrogen combustion engine truck (Link et al., 2021). Here, the fuel cell supplements an electric powertrain. Today, the storage technology for hydrogen on trucks is uncertain. Some manufacturers, such as Hyundai, rely on compressed hydrogen at 350 bar. Other manufacturers, such as Toyota or Nikola, use compressed hydrogen at 700 bar. Daimler announced series production for an FCET powered by liquefied hydrogen at approximately -245°C at 16 bar in 2027. The main advantage would be the high range of up to 1,000 km, compared to several hundred km for compressed hydrogen. Even higher ranges could be achieved with cryo-compressed hydrogen at around -200 °C and 300 bar (H2 Mobility, 2021; IEA, 2022). A corresponding infrastructure setup would be necessary for all systems (H2 Mobility, 2021). The well-to-wheel efficiency of FCET is approximately 25% to 35%, when using renewable electricity (Plötz et al., 2018).

Battery-electric trucks (BET) also accounted for less than 1% of sales in the EU in 2021. However, all major manufacturers offer BET or will offer BET soon[1]. Some of them will even focus purely on BET (NOW, 2023). The most relevant factor is the vehicle range. Today's models offer up to 300 km range with a single battery charge (Mercedes Benz, 2023; Volvo, 2023b). Both, literature (Nykvist & Olsson, 2021) and manufacturers' estimates (NOW, 2023) assume that in the near future higher mileage will be possible. Furthermore, studies indicate that todays' payload loss due to the heavy batteries of 5% to 20% will almost disappear within this decade (Basma & Rodríguez, 2022; Basma et al., 2021). However, BET are dependent on a fast charging infrastructure. While trucks today use the CCS standard with typically up to 350 kW developed for passenger cars, MCS charging with at least 1,000 kW should be possible by the mid of the decade. MCS charging allows for recharging within 45 minutes mandatory break after 4.5 h of driving (CharIN, 2023; NOW, 2023; Nykvist & Olsson, 2021). Finally, BET profit from high well-to-wheel efficiency of approximately 80% (Plötz et al., 2018).

2.1.2 Overview of battery electric vehicles diffusion literature

Today, there are almost no alternative fuel vehicles in the German heavy-duty vehicles fleet. In 2021, the registration share of ZEV in the medium and heavy-duty vehicle segment was well

[1] According to NOW (2023), no manufacturer prioritizes overhead catenary trucks as BET. Therefore, they are excluded in this analysis.

below one percent (ACEA, 2022b; KBA, 2022). Simultaneously, peer-reviewed and gray literature shows a high potential for alternative fuel heavy-duty vehicles. A first literature review on the “market diffusion of alternative fuels and powertrains in heavy-duty vehicles” (Kluschke, Gnann, et al., 2019, p. 1010) was published in 2019. To reflect the current state of the scientific literature, an additional literature research was conducted. For this purpose, the original search string from Kluschke, Gnann, et al. (2019) was used:

$$\begin{gathered}(\text{"}trucks\text{"} \lor \text{"}heavy-duty\text{"} \lor \text{"}long-haul\text{"}) \cap \\ (\text{"}alternative\ fuels\text{"} \lor \text{"}alternative\ powertrains\text{"} \lor \text{"}decarbonization\text{"} \\ \lor \text{"}electrification\text{"} \lor \text{"}electric\ road\text{"}) \cap \\ (\text{"}market\ diffusion\text{"} \lor \text{"}market\ penetration\text{"})\end{gathered} \tag{2-1}$$

The research conducted in Scopus for the period from 2019 until March 2023 resulted in 234 entries without further filtering. Including the results from Kluschke, Gnann, et al. (2019), the period from 2011 to 2023 is covered. In addition, relevant publications known to the author were added.

Since this thesis focusses on BET, only publications that consider BET or - more general - zero emission trucks (ZET) as an option have been taken into account. Publications that explicitly do not include Germany were excluded, due to the German perspective of this thesis. For example, publications such as Alonso-Villar et al. (2022), Lajevardi et al. (2022), or Xue et al. (2023) were disregarded, since they refer explicitly to Iceland, Canada, and China. Publications such as IEA (2017) or Mulholland et al. (2022) were considered, since they present a global or European perspective that includes Germany. However, corresponding publications are cited below for partial aspects, when appropriate. In addition, only publications containing HDV with a GVW of more than 12 t were considered. Due to different definitions of vehicle segments, it was not always possible to exclude vehicles with a lower GVW from the analysis.

Table 2-1 gives an overview on studies dealing with the market diffusion of BET. The table is divided into three groups, presenting (1) publications taken from Kluschke, Gnann, et al. (2019), (2) publications from the additional literature review, and (3) publications added manually. The region and the weight column refer to the closest possible definition related to the object of investigation in this thesis. This means that the cited publications may include other regions or weight classes as well. Since multiple studies do not explicitly differentiate between the European Union and the European continent, EU can refer to both in this case. The period comprises the earliest and the latest reporting date. This does not mean that data is available for every year in between. The columns on registrations and stock indicate whether the publication reports vehicle registrations, vehicles stocks, or both. There are some publications that neither report registrations nor stocks for BET. Typically, these are publications that examine the economic or technical feasibility at a particular point in time without deriving a market diffusion. Finally, the format column evaluates the type of publication. A distinction is made between peer-reviewed journal articles, conference papers, and other studies.

Table 2-1: Overview of studies on the market diffusion of BET.

Author	**Region**	**Weight**	**Period**	**Registra-tions**	**Stock**	**Format**
Publications, adopted from Kluschke, Gnann, et al. (2019):						
Bründlinger et al. (2018)	GER	> 12 t	2015-2050	√	√	Study
IEA (2017)	Global	> 15.5 t	2015-2060		√	Study
Seitz (2015)	GER	> 6 t	2015-2035		√	Thesis
T&E (2017)	EU	> 16 t	2015-2050	√		Study
Publications, found during literature review:						
Breed et al. (2021)	EU	> 16 t*	2022-2030	√	√	Journal
Gnann, Speth, Krail, et al. (2022)	GER	> 12 t	2011-2050	(√)	√	Journal
Gray et al. (2022)	EU	40 t	2025-2040			Journal
Noll et al. (2022)	EU	> 12 t	2021			Journal
Manually added publications:						
Basma et al. (2021)	EU	40 t	2020-2030			Study
Basma et al. (2022)	EU	40 t	2020-2030			Study
Craglia (2022)	EU	> 7.5 t	2020-2050	√		Study
Gnann et al. (2023)	GER	> 12 t	2011-2050	√	√	Study
Hacker et al. (2020)	GER	> 12 t	2025			Study
Jöhrens et al. (2021)	GER	> 12 t	2025-2030			Study
Jöhrens et al. (2022)	GER	> 12 t	2030			Study
Kühnel et al. (2018)	GER	> 12 t	2015-2030			Study
MPP et al. (2022)	EU	> 16 t**	2020-2050		√	Study
Mulholland et al. (2022)	EU	> 16 t*	2020-2050	√		Study
Neuhausen et al. (2022)	EU	> 12 t	2020-2035	√		Study
NOW (2023)	GER	> 12 t	2023-2030	√		Study
Plötz, Link, et al. (2023)	EU	> 12 t	2020-2050		√	Study
Pierre-Luis Ragon et al. (2022)	EU	> 16 t**	2021-2035		√	Study
Speth, Kappler, et al. (2022)	GER	> 16 t**	2020-2050			Conference
Tol et al. (2022)	EU	> 16 t	2020-2040	√		Study
Unterlohner (2021)	GER	40 t	2020-2030			Study
Wietschel et al. (2017)***	GER	> 12 t	2030		√	Study

*The publication considers vehicles with a 4x2 axle configuration and a GVW of over 16 t, and vehicles with a 6x2 axle configuration.

**The report does not specify a definition of HDV. Since the report refers to the European regulation, it is plausible to refer to vehicles with a GVW of over 16 t.

*** The study contains values from 2015 to 2030. However, a value for the considered vehicle weight can only be derived for 2030.

All publications contain at least one scenario for the future market diffusion of BET. Depending on the goal of the publication, scenarios can be designed differently. According to Börjeson et al. (2006), there are three major types of scenarios. From a user's perspective, they differentiate predictive, explorative, and normative scenarios. Additionally, they define three questions to differentiate between the three scenario types. The first question, “What will happen?” (Börjeson et al., 2006, p. 725), is typical for predictive scenarios. The concept of predictive scenarios is strongly connected to forecasts and probabilities. Explorative scenarios focus on “What can happen?” (Börjeson et al., 2006, p. 725). Typically a set of scenarios, regarded as possible, is investigated. In comparison to predictive scenarios, explorative scenarios often focus on a longer timespan with more fundamental changes. Normative scenarios deal with “How can a specific target be reached?” (Börjeson et al., 2006, p. 725). They investigate how to reach a specified target, for example a political demand, from a current situation.

Among the publications mentioned, there are two types of predictive scenarios. On the one hand, there are older scenarios from the beginning of the debate on electrified HDV trucking. For example, early scenarios can be found in Wietschel et al. (2017) or T&E (2017). The publications outline one possible future perspective and indicate that BET HDV can be relevant in the future. On the other hand, industry-oriented publications, for example Neuhausen et al. (2022), try to design a plausible perspective for the future truck market. A special role is dedicated to NOW (2023), as the publication provides results from cleanroom talks with all major truck manufacturers. The described market diffusion therefore represents an industry perspective. In total, the manufacturers have announced a 57% BET registration share for HDV (> 12 t GVW) in 2030. Additionally, 17% FCET registration share is forecasted. It should be noted that these numbers may also be influenced by interests of the manufacturers, for example a rapid, funded infrastructure development.

Normative scenarios in the publications presented are aimed in particular at meeting GHG emission targets. Both Breed et al. (2021) and Mulholland et al. (2022) calculate the necessary sales share of ZEV to meet the EU emission performance standard for HDV (EU, 2019). While Mulholland et al. (2022) do not yet consider ZEV for heavy-duty vehicles in long-haul operation to meet the EU performance standard in 2030, Breed et al. (2021) announce at least 4% sales share for all regulated vehicles. However, for other regulated heavy-duty segments, Mulholland et al. (2022) calculate up to 12% sales share in 2030. Therefore, both publications agree that by 2030, first ZEV HDV have to be in use[2]. Mulholland et al. (2022) also show that even higher ZEV shares are necessary to fulfill the European climate law (EU, 2021). Pierre-Luis Ragon et al. (2022) assume a 60% reduction of GHG emission by 2030 and calculate a stock share of 7% ZEV relevant to the regulation. Similar results can be found for non-European analysis. For example, Talebian et al. (2018) converts a 64% GHG emission reduction target in British Columbia in 2040 to a necessary ZEV stock between 60% and 100%.

[2] Both publications do not yet consider the European Commisson's proposal EC (2023) to enhance the performance standards in 2030 to a reduction of 45% of GHG emission instead of 30% compared to 2019/2020.

A large part of the identified publications can be classified as explorative scenarios. They can be divided into two groups. First, there are scenarios that focus purely on the economic, technical, or techno-economic feasibility of BET HDV. Second, there are scenarios that include market diffusion analysis. Both groups are presented in the following.

Purely technical analyses, as presented in Liimatainen et al. (2019) or Çabukoglu et al. (2018) for Finland and Switzerland are not included in the literature review with a German perspective. Basma et al. (2021) show that BET HDV (40 t GVW) are already economically competitive in Germany, France, and the Netherlands compared to DT, taking the current policy framework into account. They examine different policy measures and show that even without any additional measures, BET will become economically feasible in all countries considered - France, Germany, Great Britain, Italy, the Netherlands, Poland, and Spain - by 2030. Basma et al. (2022) extend the analysis to FCET and find that FCET will become competitive to DT in Europe in 2030, if the hydrogen price at the pump will be around 4 €/kg. Regarding the economic potential of BET, similar results can be found at Unterlohner (2021), Speth, Kappler, et al. (2022), or Noll et al. (2022). The publication by Noll et al. (2022) is characterized by a broad parameter variation and identifies BET as a particularly attractive solution, not only for small and medium trucks, but also for HDV with a GWV of more than 12 t. However, those analyses include technical restrictions only to a very limited extent. In contrast, techno-economic analyses add a technical component to the approach. Similar to Noll et al. (2022), Gray et al. (2022) investigate a wide range of input parameters in a TCO analysis. However, they add assumptions regarding load reduction due to the battery weight. They find that for vehicles with a range of less than 450 km, BET is the most promising solution compared to synthetic fuels (power-to-liquid, power-to-methane, hydrogen). For higher ranges, they assume advantages for hydrogen. However, fast charging for BET with more than 350 kW is not considered. Jöhrens et al. (2021) and Jöhrens et al. (2022) use driving range distributions from a transport model, to identify a techno-economic potential of BET, overhead catenary BET, and FCET. In 2030, the authors assume that BET will achieve an economic advantage over FCET and diesel vehicles in the segment above 12 t GVW, even without subsidies. However, the economic advantage for BET and overhead catenary BET for long-distance transport depends on a fast-charging infrastructure or catenary lines. Analyses focusing on the required range and weight-constraints also exist for HDV in the USA. Mauler et al. (2022) and Hunter et al. (2021) assume that BET HDV with a GVW of more than 15t will be competitive to DT and FCET in long-haul operation with more than 750 km vehicle range, despite technical limitations.

However, the explorative scenarios presented so far do not derive possible market diffusion scenarios. Using a system dynamics modeling approach, Seitz investigated initial diffusion scenarios for alternative drives for HDV with more than 6 t GVW already in 2015. For 2035, he calculated a BET stock share of 11%, mainly limited by technical conditions, for example the vehicle range. More recent publications, for example Tol et al. (2022) or MPP et al. (2022), consider a nearly complete fleet conversion to BET to be possible and even probable compared to FCET. While Tol et al. (2022) show a full electrification potential as early as 2030, MPP et al. (2022) point out that vehicle supply as well as infrastructure development could inhibit the market diffusion of BET. However, they do not perform a detailed analysis of the described effects. Finally, Craglia (2022) considers vehicles with more than 7.5 t GVW in the EU and performs a Monte Carlo simulation with 1,000 scenarios on technical and economic parameters for 2020 to 2050. In the long-term, 90% of the fleet could be converted to BET. Depending on the scenario, BET sales shares increases significantly from 2025 at the earliest. In almost all scenarios, FCET are neither competitive with DT nor with BET.

Finally, there are publications that show both explorative and normative characteristics. These are publications that are intended to show different paths to reach a politically defined goal, like climate neutrality by 2050. These include IEA (2017), Bründlinger et al. (2018), Gnann, Speth, Krail, et al. (2022), Gnann et al. (2023), and Plötz, Link, et al. (2023). More recent studies show an increasing share of BET. The assumed development of charging infrastructure is identified as a key factor, especially when more recent results from the same model are compared with earlier calculations, for example in Gnann, Speth, Krail, et al. (2022) and Gnann et al. (2023). However, a fixed infrastructure expansion is still assumed; there is no dependency of the infrastructure expansion on the market diffusion of alternative fuel vehicles.

Figure 2-1 shows the bandwidth of the BET share in different scenarios. The figure includes all publications from Table 2-1 that report either registrations or stocks. For publications with multiple scenarios, the most extreme scenarios were selected. Publications with only one scenario were weighted double to avoid a bias. The figure shows the minima and maxima as well as the upper and lower quartiles of all scenarios in 5-year-steps. Gray indicates registration numbers, green stock numbers. In addition, the mean values are shown. The mean value is more stable than the median, which is vulnerable due to the choice of the extreme scenarios. This is also shown in Figure 2-2 and Figure 2-3 that show the values of the individual publications in 2030 and 2050.

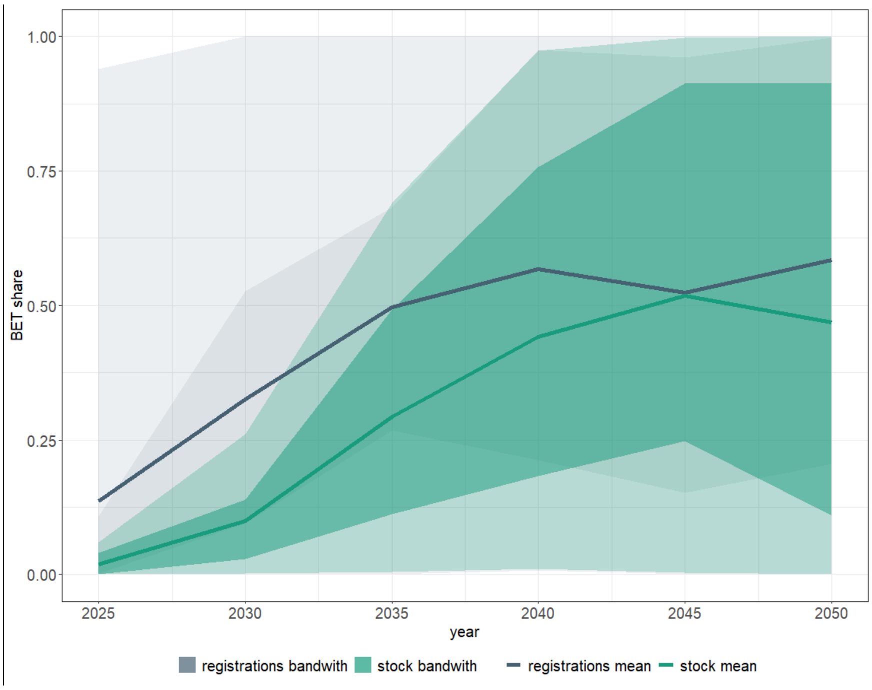

Figure 2-1: Future market diffusion of BET with a GVW higher than 12 t according to publications in Table 2-1 in 5-year-resolution. All considered publications refer to Germany or the EU. The two extreme scenarios of the publications are considered. For publications with one scenario, this scenario is weighted twice. Dark grey indicates the upper and the lower quartile of registrations of all scenarios reporting values for the considered year. Light gray indicates the minimum and maximum values. Dark green indicates the upper and the lower quartile of stock of all scenarios reporting values for the considered year. Light green indicates the minimum and maximum values.

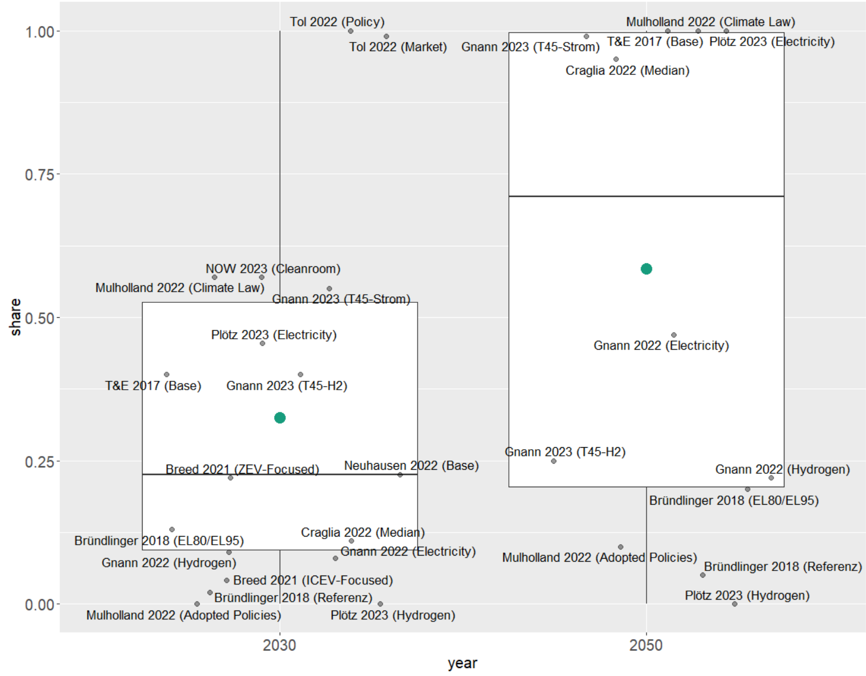

Figure 2-2: Registrations share of BET according to different studies in 2030 and 2050. For better readability, only the first author, the year of publication, and the scenario name are mentioned. The two extreme scenarios of the publications are considered. For publications with one scenario, this scenario is weighted twice. The green dot shows the mean value of all studies. All publications refer to Germany or the EU.

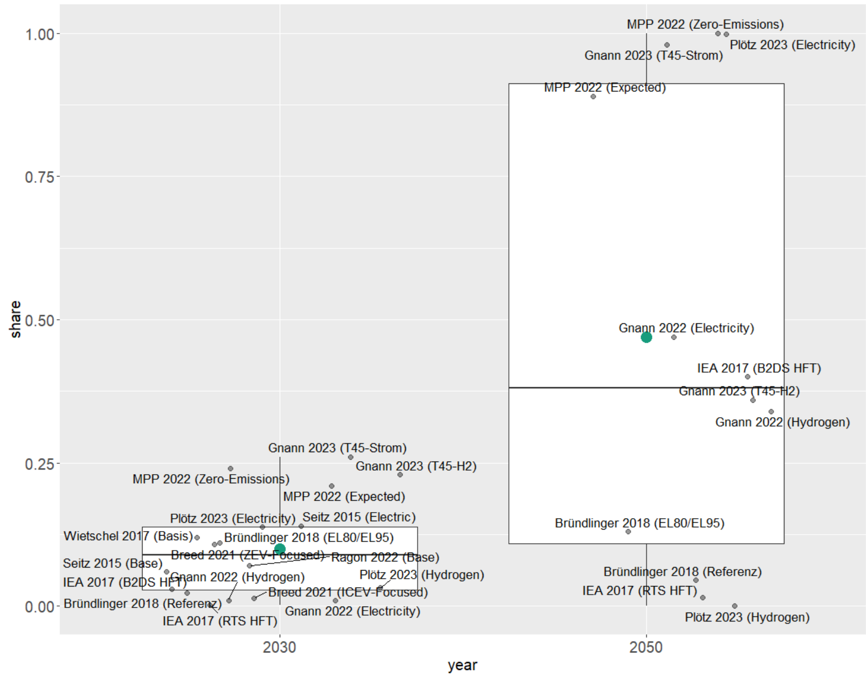

Figure 2-3: Stock share of BET according to different studies in 2030 and 2050. For better readability, only the first author, the year of publication, and the scenario name are mentioned. The two extreme scenarios of the publications are considered. For publications with one scenario, this scenario is weighted twice. The green dot shows the mean value of all studies. All publications refer to Germany or the EU.

In summary, the perspective up to 2030 - but also up to 2050 - shows a high bandwith with regard to the possible spread of BET. Recent studies show that BET will be economically competitive with DT at least for parts of the fleet in almost all scenarios. Scenarios without BET are older scenarios or extreme hydrogen worlds. However, uncertainty exists with regard to technical feasibility and influence of the infrastructure. Therefore, in current scenarios, the complete conversion of the fleet apperas to be just as possible as a limited use at low driving ranges.

2.1.3 Infrastructure needs of battery electric trucks

Both, vehicle manufacturers (see NOW (2023)) and vehicle customers (see subchapter 2.3.2) identified the development of a (public) charging infrastructure as a crucial parameter for the diffusion of BET.

However, Borlaug et al. (2021) showed for class 7 and class 8 HDV (~ >12 t GVW) in the USA that 70% of the vehicles drive less than 100 mi (161 km) per day and therefore will probably not use a public fast charging infrastructure. Similar results have been shown by Link and Plötz (2022) for a food retailer truck fleet in Germany. They found that at least half of the investigated 224 trucks with a GVW > 18 t can be electrified immediately without any public charging infrastructure with vehicles available today. However, while almost all of the solo trucks in the fleet can be electrified, the electrification of tractor-trailer combinations is more complicated without public recharging. Liimatainen et al. (2019) analyzed 18,500 driving profiles with data from three days or more from vehicles with more than 3.5 t GVW in Switzerland and Finland and found that under current infrastructure conditions (50 kW depot charging and 50 kW public charging) about half of the fleet can be electrified. However, they argued that even with technical improvement (larger batteries with up to 800 kWh and up to 400 kW public charging power) a full electrification in Finland will be complicated due to long and heavy truck-trailer combinations. They calculated a share of 80% of the trips in Finland and of 93% in Switzerland. Overall, it can be seen that there is a relevant electrification potential without a public charging infrastructure. However, it is also shown that a full fleet conversion to BET requires a public charging infrastructure.

Lajevardi et al. (2022) used a partial equilibrium simulation model for British Columbia and found that a rapid roll-out of charging infrastructure would enable BET to dominate for short-haul traffic shorter than 322 km and enables a share of approximately 40% for long-haul traffic in 2050. While trucks today use the CCS standard with typically up to 350 kW developed for passenger cars, Nykvist and Olsson (2021) showed that the introduction of megawatt charging may significantly increase the technical and economic efficiency of BET. Accordingly, CharIN (2023) supports the introduction of a megawatt charging system (MCS) standard. However, it is uncertain today to what extent public fast charging will be needed. Mathieu (2020) assumed a 10% public charging split with up to 600 kW in 2030 in the EU and calculated a demand for

14,400 public fast charging points (600 kW) in the EU in 2030. Pierre-Luis Ragon et al. (2022) found that almost 50% of all long-haul tractor trailers - segment 5-LH in EU (2019)[3] - have a daily electricity need of less than 680 kWh per day and can be operated purely by overnight-charging. 70% of the trucks can be operated with one CCS charging event. According to their analysis, 30% of the vehicles under investigation need more than 800 kWh electricity per day and therefore rely on MCS charging. Based on these assumptions, Pierre-Luis Ragon et al. (2022) estimated a need for 7,500 public MCS chargers, 9,000 CCS public CCS chargers, and 23,500 public overnight chargers (100 kW) in the EU in 2030. In contrast to the previous studies, the European Automobile Manufacturers' Association (ACEA) called for at least 40,000 public fast charging points and another 40,000 100 kW public charging points in the EU by 2030 (ACEA, 2021). However, ACEA (2021), Pierre-Luis Ragon et al. (2022), and Mathieu (2020) represent calculations of different nongovernmental organizations. There is a lack of scientific publications on the demand for public fast charging infrastructure.

Another open question is the spatial distribution of necessary infrastructure. As mentioned in subchapter 1.1, the AFIR proposal foresees public charging infrastructure at 60 km intervals along the EU TEN-T core network in 2025. Along the TEN-T comprehensive network, the proposal suggests a distance of 100 km by 2030. In Germany, the National Centre for Charging Infrastructure (NLL) is currently working on implementing the AFIR proposal in a public charging infrastructure network (see Lahmann (2022)). However, there is still no regionally resolved analysis for Germany or Europe. Using GPS data from current trucks, Plötz and Speth (2021) identified possible future charging locations in Europe. A similar approach is described by Dimatulac et al. (2023) for Ontario (Canada). Whitehead et al. (2021) used GPS data and an optimization approach to identify 10 charging locations in South East Queensland (Australia) for short-haul trucks. However, an extensive modeling to identify charging locations - as already existing for battery electric passenger cars (Metais et al., 2022) - is still missing.

Infrastructure needs also depend on BET's load profile throughout the day as well as its charging strategy. Tong et al. (2021) estimated that a majority of trucks in the USA start driving before 5:00 and derived load curves with a midday peak as well as high load in the afternoon hours. Dimatulac et al. (2023) determined a similar load curve for long-haul trucks in Ontario (Canada). Borlaug et al. (2021) focused on depot charging and implemented three different charging strategies. For the strategy "immediate (100 kW)", their load curve is similar to the other studies with a high demand between 12:00 and 23:00. As a second option, they implemented "delayed (100 kW)", where the vehicles charge as late as possible. This resulted in an increased charging demand from 20:00 to approximately 9:00. Finally, the "constant minimum power" charging strategy - charging as slow as possible to be recharged when the new tour starts - resulted in the flattest load curve with an increasing energy demand between approx-

[3] According to Breed et al. (2021) and Pierre-Luis Ragon et al. (2022), the vehicle segment 5-LH accounts for 60% of all vehicles under the EU's firm-level emission performance standards regulation EU (2019). However, this is the most relevant vehicle segment for MCS charging, so the share of vehicles with MCS charging need in the entire regulated fleet is lower.

imately 15:00 and 8:00. Analyses for 36 substations in Texas as an example with up to 100 vehicles per substation showed that in less than 25% of the cases extensions of the substation, the transformer, or the feeder breaker would have to be made. In summary, the publications show that fast charging for trucks may lead to an increased energy demand during the day, while depot charging may lead to energy demand overnight. Accordingly, initial load curves for exemplary charging locations in Germany in Burges and Kippelt (2021) showed both a daytime peak and a high demand at night. However, the size of the effect should be further investigated, especially when additionally considering a market diffusion scenario.

2.2 Infrastructure modeling[4]

This chapter describes different approaches to model public charging infrastructure and their advantages and disadvantages.

2.2.1 Modeling options

The modeling of refueling or charging infrastructure - or, more generally, of locations in networks - has been subject of scientific publications since the 1960s. Therefore, the following overview presents basic works as well as works with an influence on the specific question of charging infrastructure for BET. Metais et al. (2022) and Deb et al. (2018) identified three major groups of infrastructure modeling approaches: (1) node-based models, (2) path-based models, and (3) tour-based models. The following description follows this structure and the main findings from Metais et al. (2022) and Deb et al. (2018). Figure 2-4 shows a schematic illustration, the required input data, and qualitatively the strength and weaknesses of the three approaches.

[4] Parts of this subchapter are based on Speth, Plötz, et al. (2022) and Speth et al. (2024). Speth et al. (2024) is still under review at the time of submission of this thesis.

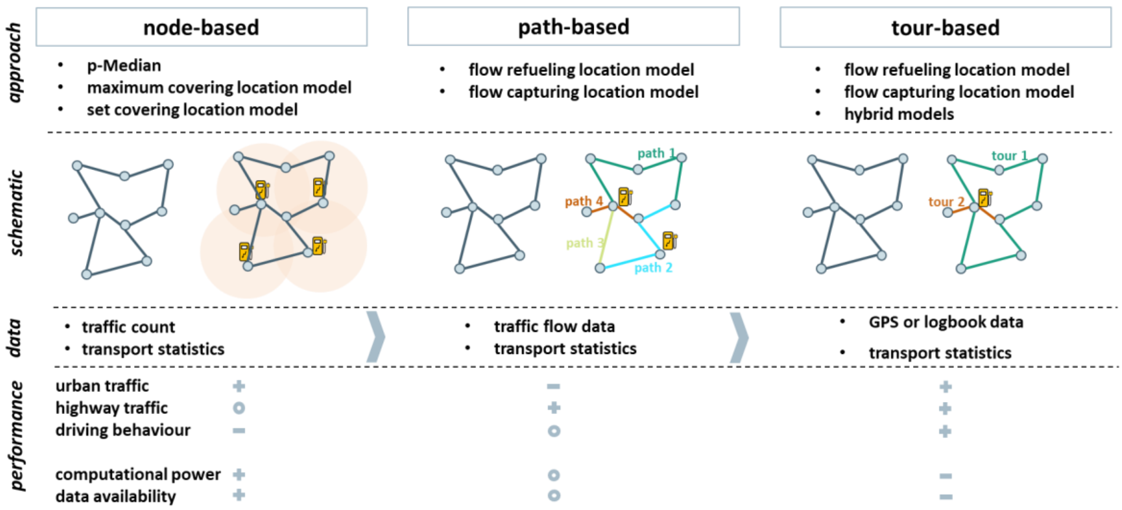

Figure 2-4: Schematic comparison of node-based, path-based and tour-based infrastructure location models. Performance evaluation is qualitative (+: positive, o: neutral, -: negative). Own illustration, based on Metais et al. (2022).

In all approaches, nodes and edges represent the infrastructure, in our case the road network. Nodes represent intersections or access points, but also relevant points in the road network. Edges model the connecting network.

Node-based models assign demand to specific locations - like traffic hubs or buildings -, represented as nodes. Facilities at nodes can fulfill the demand in a particular distance. The Set Covering Location Model (SCLM), places facilities such that a minimum number of facilities can serve all demands. In an early work, an SCLM placed emergency service facilities (Toregas et al., 1971). As a variation, the Maximum Covering Location Model (MCLM) places a given number of facilities to cover as much demand as possible (Church & ReVelle, 1974). More recently, SCLM and MCLM have been used for the positioning of charging stations for battery electric cars[5]. Neither SCLM nor MCLM consider the effects of the distance between the demand nodes and the positioned facilities, as long as it is smaller than the specified distance (Metais et al., 2022). Therefore, the ρ-median model, introduced by Hakimi (1964) to identify optimal locations for police stations and switching stations in communication networks, positions ρ facilities so that the weighted distance between demand and facilities is minimized. This approach is also regularly used in the literature to distribute charging stations[6]. Node-based models benefit from comparatively low data requirements. For example, traffic count data (S. Á. Funke, 2018)) or GPS parking data (Yang et al., 2017) and traffic statistics for calibration are

[5] See e.g. Csiszár et al. (2019) for a case study in Budapest (Hungary) (SCLM), Vazifeh et al. (2019) for a case study in Boston (USA), Dong et al. (2019) for a case study in London (Great Britain) (MCLM), Yang et al. (2017) for a case study on electric taxi charging stations in Changsha (China) (MCLM). For a more detailed overview, see Metais et al. (2022).

[6] See e.g. Gavranović et al. (2014) for a case study in Turkey or Zhu et al. (2017) for a network with 25 nodes. See S. Y. He et al. (2016) for a comparison of SCLM, MCLM, and ρ-median model. Again, for a more detailed overview, see Metais et al. (2022).

sufficient. With regard to BET, Dimatulac et al. (2023) used GPS data from diesel trucks in Ontario (Canada) to identify truck parking locations and estimate BET's future local public energy demand. The approach works particularly well, if vehicles have to be assigned to a specific regular charging location. This is exemplarily the case for taxi fleets in urban transport systems. A consideration on vehicle level or individual driving behavior, such as tour-data and breaks, does not take place. Both, GPS and traffic count data count one vehicle multiple times at different locations. This leads to a limitation of the node-based approach in highway traffic charging infrastructure modeling, since the actual charging demand of the counted vehicles cannot be determined exactly. However, even node-based models with low data requirements are NP-hard problems with high computational effort in large-scale applications (Metais et al., 2022; Yang et al., 2017). Therefore, heuristics are occasionally used and in some cases, optimization is completely omitted[7]. Motoaki (2019) showed that the real-world distribution of Tesla superchargers in the USA is similar to node-based modeling. The stations cover the area and have similar distances to each other.

Path-based models do not consider the traffic volume at nodes, but the traffic flow on origin-destination-paths (OD). Hodgson (1990) introduced the Flow Capturing Location Model (FCLM), basically a path-based version of the MCLM. A path is recharged or refueled, if at least one node with a refueling or charging infrastructure is passed. In contrast to the MCLM with road count data, vehicles are not considered multiple times for infrastructure positioning. This approach has also been successfully applied to charging stations for passenger cars[8]. To take the necessity of multiple stops into account, Kuby and Lim (2005) invented the Flow Refueling Location Model (FRLM). The FRLM, as originally formulated, is based on considering every possible combination of refueling locations. Since the FRLM is also an NP-hard problem (Vries & Duijzer, 2017), Lim and Kuby (2010) proposed several heuristics to keep the computation time manageable. Capar and Kuby (2012) and Capar et al. (2013) reformulated the problem. Instead of computing every possible combination of refueling locations, they determined for each arc in a path at which nodes a refueling location could be constructed to pass the arc. This allows the solution of larger, real-world problems. Jochem et al. (2019) used this approach to calculate a European charging network for battery electric cars with several hundred charging stations, 128 of them in Germany. However, problem size remained an issue. To reduce the problem size, they considered only paths that are driven by at least 5,000 vehicles per year. Y. He et al. (2019) calculated a fast charging network for cars in the USA, using flows between 4,486 regions. To keep the model solvable, they combined regions into 196 clusters, using the K-means algorithm. In summary, path-based models require a more complex data basis in the form of traffic flow data. Transport statistics are needed for calibration. Path-based models are thus well suited for modeling charging infrastructure for long-distance traffic on highways. As described earlier, data availability as well as computational power can be demanding.

[7] See e.g. Hosseini and MirHassani (2015) for a case study in Phengu County (China), S. Á. Funke (2018) for a case study in Germany without optimization, H. Wang et al. (2019) for a case study in Singapore without optimization.
[8] See e.g. J. He et al. (2018) for an FCLM including solving heuristic.

Tour-based models typically rely on large datasets, e.g. driver's logs or GPS data. In addition to OD-paths of the path-based models, the dataset provides the linking of individual paths to vehicle tours. Methodologically, they are not fully categorized. However, streams can be identified (Metais et al., 2022). For example, GPS data can be used as node data or path data. Using GPS data from eight million vehicle trips for an MCLM and 116 possible charging locations, Whitehead et al. (2021) identified up to 10 optimal charging locations for short-haul trucks in South East Queensland (Australia). Simulation of vehicle trips, sometimes in combination with optimization approaches, is also typical for tour-based models. For example, Xi et al. (2013) used trip data to simulate charging behavior of potential battery electric cars and identified optimal slow-charging locations in the city of Columbus (USA). Since tour-based data is hard to access for privacy reasons and can be biased (Metais et al., 2022), it is complicated to use for country-wide infrastructure modeling. By chaining individual OD paths, the required computational power further increases. However, modeling for both urban and highway traffic is possible. Individual aspects, such as breaks between tours, can be taken into account.

2.2.2 Capacity constraints

Capacity constraints can supplement the infrastructure modeling for battery electric vehicles. Typical capacity constraints include area constraints or limitations in locally available electricity power (Metais et al., 2022). This is highly relevant for planning actual charging locations, as unconstrained models can easily reach up to several hundred chargers per location, which almost always exceeds the local number of available parking lots and local electricity grid capacities.

In node-based models, the capacity constraint can be included as an additional constraint. For example, Zhu et al. (2017) integrated a maximum number of vehicles per timeframe, a maximum voltage, and a maximum current as additional constraints of a ρ-median model. Vazifeh et al. (2019) added a capacity constraint to an SCLM. They proposed to allow multiple facilities in a single node and to interpret them as multiple plugs in one station or multiple stations in the area of the node.

With regard to path-based models, Upchurch et al. (2009) criticized that in the FRLM the presence of one charging station is sufficient to supply all passing paths. They introduced a Capacitated Flow Refueling Location Model (CFRLM) that restricts the number of vehicles refueled at one station. To avoid too much refueling at one station, the CFRLM - in contrast to the FRLM - must determine exactly at which location each vehicle is actually refueled. This makes optimization much more difficult, especially since Upchurch et al. (2009) still used a by now deprecated form of the FRLM as a basis. They aimed to maximize the traffic covered by the stations and placed four refueling stations in a simplified road network of Arizona (USA) with 50 nodes. Cross-border traffic was excluded, and the system was designed to handle peak hour traffic. However, they stated that "the amount of refueling capacity that could be built at each node is potentially infinite " (Upchurch et al., 2009, p. 103). In the basic version of the model, they limited the amount of vehicles per station, but not the number of stations per node. Y.-W. Wang and Lin (2013) used a CFRLM to design a charging network for scooters in Phengu County (China) and took 12 paths into account. H. Zhang et al. (2018) included a power supply network as restriction to the CFRLM and applied it to a network with 25 nodes. While previous models typically limited the maximum amount of vehicles per station, Hosseini and MirHassani (2017) limited the amount of energy delivered from one station and improved performance. P. K. Rose et al. (2020) transferred the FRLM to FCET and designed a hydrogen refueling network for Germany with a capacity constraint for every node in the network. To run the whole German truck fleet above 26 t gross vehicle weight on hydrogen, they considered 2,655 origin-destination paths and identified 142 potential refueling stations with up to 30 t of hydrogen per day. Since the dataset focused on German traffic, it contained only few paths that have to be refilled multiple times during one trip. To further reduce model complexity, P. K. Rose et al. (2020) have refrained from calculating the exact fuel level at each node and estimated an average value before the actual calculation. As shown by Böhle (2021) this may lead to exceeding the maximum tank level. However, Böhle (2021) avoided an adjustment in favor of computing time and combined the model of P. K. Rose et al. (2020) with a multi-period approach. So far, the problem of unrealistically large stations has thus been solved for small datasets or by significant simplifications.

2.2.3 Queuing theory in infrastructure modeling

The models described in 2.2.1 allow for regional distribution of charging infrastructure. To dimension individual locations in terms of charging points per location, arrival and service patterns must be considered. Queuing models address the arrival process, the service process, and the waiting period (Salazar, 2020). For an introduction into queuing theory, see for example Adan and Resing (2017). Queuing theory has been used in modeling charging infrastructure for passenger cars. For instance, Hosseini and MirHassani (2015) included a queuing system into an FRLM. Yang et al. (2017) used queuing theory to calculate a maximum daily rejection rate in their MCLM. Zhu et al. (2017) calculated the maximum number of vehicles charged per timeframe per charging station. For a given arrival rate, S. Á. Funke (2018) used queuing theory to calculate the required number of charging points per charging location.

2.2.4 Summary

Based on the available input data, three directions for infrastructure modeling can be distinguished: node-based, path-based, and tour-based modeling. Node-based approaches use comparatively easy-to-obtain data, such as traffic count data. In return, the accuracy for long-distance traffic is reduced. A comparison with existing charging infrastructure networks shows that they are consistent with the basic idea of area coverage provided by node-based approaches. Path-based approaches require OD-paths as input, but allow for detailed modeling of long-haul traffic and thus more detailed solutions. In particular, the need for multiple refueling stops can be determined by the model endogenously by taking into account the entire path of a vehicle. Tour-based approaches consider the combination of individual paths to tours and can thus include the actual driving behavior and the required infrastructure on vehicle level. However, datasets are hard to obtain and potentially biased. All approaches can be combined with capacity constraints and queuing theory. All of the optimization approaches described require extensive computational power when applied to large datasets, so simplifications and heuristics are common.

The path-based FRLM is the most detailed type of modeling, given the available data (see subchapter 3.1). As a capacity-constrained FRLM, the model can map local conditions - for example, lack of parking capacities - and develop a minimum charging network for the early market diffusion. Due to the computational effort, a scenario analysis with multiple scenarios or a detailed sensitivity analysis is hardly possible. Therefore, a node-based approach is additionally used in this thesis, to model a public fast charging infrastructure for trucks with regular intervals between charging locations, as proposed by the AFIR (see chapter 1.1). As shown by Motoaki (2019), the node-based approach fits quite well to real-world charging infrastructure. The application of both approaches allows, on the one hand, the analysis of a minimal network, but also the modeling of a realistically developed network with multiple sensitivity analyses. Both approaches are combined with a queuing model. For a discussion of the advantages and disadvantages of both approaches in the context of this thesis, please also refer to subsections 4.1.4, 5.1.1.3, and 5.1.2.3.

2.3 Market diffusion modeling

After purely modeling charging infrastructure, this thesis combines public charging infrastructure modeling with market diffusion modeling for BET. In the following, options for vehicle market diffusion modeling are briefly discussed. Afterwards, requirements for market diffusion modeling for trucks are identified. Finally, the existing publications are evaluated and a conclusion for the market diffusion model in this thesis is drawn.

2.3.1 Modeling options

As shown by Gnann (2015)[9], there is no unique method to classify models for market and infrastructure diffusion. Therefore, Gnann (2015) applies a classification originally developed for energy system models, which is suitable for dynamic effect like the interaction between

[9] Gnann (2015) focusses on the joint diffusion of charging infrastructure and battery electric passenger cars. Therefore, this thesis builds on his analysis of modeling options for vehicle diffusion models.

recharging infrastructure and the market diffusion of electric vehicles. Figure 2-5 shows the adapted classification scheme[10].

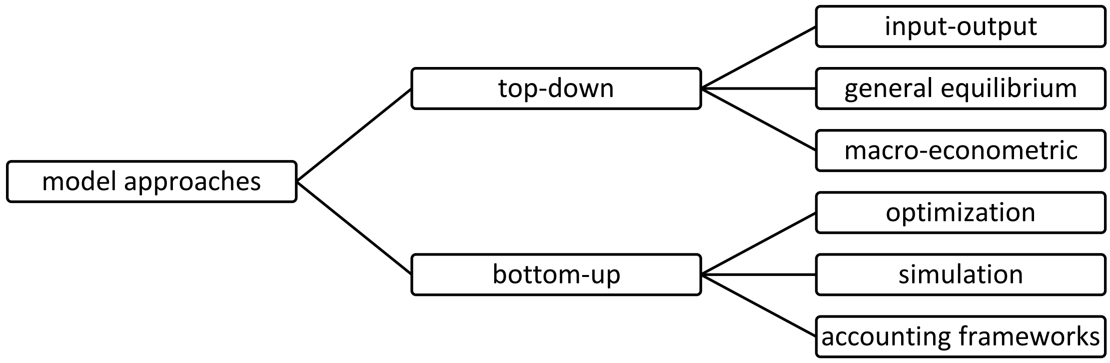

Figure 2-5: Classification of market diffusion models. (Gnann (2015), based on Dreher (2001), Sensfuß (2007), and Fleiter et al. (2011)).

The classification distinguishes two basic approaches: (1) Top-down models that are based on at least one main assumption, whose effects are analyzed. (2) Bottom-up models combine various detailed assumptions and compose them to an overall picture (Gnann, 2015).

Top-down models are typically used to consider macroeconomic effects and their impact on the investigated system (Dreher, 2001; Sensfuß, 2007). Based on Dreher (2001), Sensfuß (2007), Fleiter et al. (2011), and Gnann (2015) distinguished three model classes for top-down modeling: (1) Input-output models assess the changes in an economy due to exogenously given changes, for example in the demand or the investments. (2) General equilibrium models are based on the long-term balance between supply and demand and are typically used to evaluate effects of policy measures. (3) Macro-econometric models formulate equations calibrated on long run time series. Due to calibration, they can also represent imperfect market behavior.

For bottom-up models, Gnann (2015) considered three model classes: (1) Optimization models match demand and supply, while typically maximizing the overall economic surplus. Boundary conditions can be added as constraints on a detailed level. (2) Simulation models are based on rules that define processes in the model. Simulation models can be further divided into agent-based models and system dynamics models (Sensfuß, 2007). Agent-based models simulate the behavior of individual market participants. System dynamics models simulate the stepwise market development, taking feedback loops into account. (3) Accounting frameworks are a simplified version of simulation models. Instead of explicitly modeling decisions of market participants, they account for the outcomes of the assumed developments (Sensfuß, 2007).

The classification of existing publications is shown in subchapter 2.3.3.

[10] In this thesis, the focus is on mathematical methods to model market diffusion processes. For a more general approach on the diffusion of innovations, see Rogers (1962) or Geels (2002).

2.3.2 Modeling requirements from a logistics perspective

To ensure that the used market diffusion model covers the most relevant variables, a literature-based summary of the key requirements of logisticians for HDV is presented here. Different studies analyzed relevant factors for a truck purchase decision and therefore for the diffusion of alternative drivetrains in different markets. Table 2-2 lists different publications that rely on surveys or interviews to identify aspects that influence the purchase decision for or against an HDV, or especially an alternative fuel HDV. The factors mentioned include those classified as particularly important by the authors, either in the abstract or in the explanations of their results. However, each of the studies also contains other factors that are also relevant for the participants. Due to slightly different research questions and methods, the publications can give an impression of relevant factors, but cannot be directly compared. Based on their focus on Germany, the publications by Anderhofstadt and Spinler (2019), Göckeler et al. (2022), and Kluschke, Uebel, and Wietschel (2019) are of special interest for this thesis. Using a Delphi study among 23 experts from truck manufacturers, logistics service providers, infrastructure providers, consultants, and researchers, Anderhofstadt and Spinler (2019) identified factors affecting the purchasing decision of alternative fueled HDV in Germany. Kluschke, Uebel, and Wietschel (2019) retrieved their results from an online survey with 70 participants from logistics service providers. They retrieved reliability of the vehicles, infrastructure availability, different cost aspects, and the possibility to enter low emission zones as crucial parameters for the buying decision of an HDV. The results are confirmed by 139 responses to an online questionnaire in Göckeler et al. (2022). The participants identified reliability in relation to respective logistics tasks, including payload losses, and infrastructure availability as the most relevant factors. The factors identified in those three studies should be considered in the market diffusion modeling.

Table 2-2: Factors influencing the purchase decision for HDV according to different survey publications.

Authors	Year	Country	Participants	Most important factors
Anderhofstadt and Spinler	2019	Germany	23	• reliability • infrastructure • low emission zones • fuel costs
Bae et al.	2022	USA	20	• functional suitability • fuel price • fuel infrastructure • environmental consciousness • fleet regulations • financial incentives
Cantillo et al.	2022	Colombia	119	• competitive price • fuel consumption
Göckeler et al.	2022	Germany	139	• reliability (including payload) • infrastructure
Kluschke, Uebel, and Wietschel	2019	Germany	70	• total cost of ownership • reliability
Konstantinou and Gkritza	2023	USA	74	• business model • product availability • charging time
Pierre-Luis Ragon and Rodríguez	2022	Europe	22	• infrastructure • vehicle availability
Y. Zhang et al.	2019	China	192	• vehicle safety • driving range

Alle three publications from Germany mentioned reliability as a key factor. Reliability can be reflected by a technical analysis in the modeling. Two out of three publications refered to an economic analysis, by mentioning fuel costs (Anderhofstadt & Spinler, 2019) or the totcal costs of ownership (Kluschke, Uebel, & Wietschel, 2019) as an highly important aspect. Finally, Anderhofstadt and Spinler (2019) and Göckeler et al. (2022) named infrastructure as a third aspect. From the publications' context, it can be assumed that the infrastructure criterion aims especially on public infrastructure, that cannot be influenced by the logistics providers. Overall, these three aspects also coincide with other publications mentioned in Table 2-2.

2.3.3 Classification of existing work

In the following, the publications identified in subchapter 2.1.2 are classified with regard to their model type and the integration of a technical analysis, an economic analysis, and an infrastructure analysis.

As shown in Table 2-3, 14 out of 16 publications that include a market diffusion used bottom-up modeling[11]. Eight publications relied on simulation models that estimate purchasing behavior based on technical and / or economic aspects. However, the level of detail varied widely, ranging from system dynamics approaches (Seitz, 2015) to Monte Carlo simulations (for example Gray et al. (2022) or Craglia (2022)) and agent-based models with several thousand driving profiles (for example Gnann et al. (2023)). Optimization was used in one publication, with the aim of achieving a specific target in terms of GHG emissions. Another five publications used some kind of accounting frameworks, often with simplified assumptions regarding different measures and their effects. NOW (2023) represents a special case. The publication summed up a market diffusion based on individual manufacturers' estimates. Only two publications used top-down modeling. In both cases, the effect of a policy measure - a firm-level emission performance standard of new vehicles - on the vehicle fleet was examined. The given emission performance standard can be interpreted as an exogenous input that increases the ZEV registrations output.

Regarding the aspects identified in subsection 2.3.2, Table 2-3 shows that the majority of the publications included technical and / or economic analyses. Many publications also examined the impact of a charging infrastructure on the market diffusion of BET, for example by allocating infrastructure costs to the vehicles or by considering higher ranges due to the infrastructure. Conversely, Pierre-Luis Ragon et al. (2022) estimated the infrastructure needs based on the market diffusion of BET. However, there is no publication that has examined both, the impact of limited infrastructure on the vehicle market diffusion and the regionally distributed infrastructure needs from the market diffusion of BET.

[11] The assignment was made to the best of the author's knowledge, but is not fully unambiguous due to incomplete documentation, especially in the case of not peer-reviewed studies. The boundaries between bottom-up simulation and accounting frameworks and top-down evaluation of policy measures are also fluid.

Table 2-3: Classification of existing publications with regard to the modeling approach.

Author	**Model type**	**Technical analysis**	**Economic analysis**	**Infrastructure analysis**
Bründlinger et al. (2018)	accounting framework		√	
IEA (2017)	optimization	√	√	↓
Seitz (2015)	simulation	√	√	↓
T&E (2017)	accounting framework			
Breed et al. (2021)	input-output	(√)		
Gnann, Speth, Krail, et al. (2022)	simulation	√	√	↓
Gray et al. (2022)	-	√	√	↓
Noll et al. (2022)	-		√	
Basma et al. (2021)	-		√	↓
Basma et al. (2022)	-		√	↓
Craglia (2022)	simulation	√	√	↓
Gnann et al. (2023)	simulation	√	√	↓
Hacker et al. (2020)	-	√	√	↓
Jöhrens et al. (2021)	-	√	√	↓
Jöhrens et al. (2022)	-	√	√	↓
Kühnel et al. (2018)	-	√	√	↓
MPP et al. (2022)	simulation	√	√	↓
Mulholland et al. (2022)	input-output	(√)		
Neuhausen et al. (2022)	accounting framework	(√)	(√)	(↓)
NOW (2023)	accounting framework			
Plötz, Link, et al. (2023)	simulation	√	√	↓
Pierre-Luis Ragon et al. (2022)	accounting framework	(√)		↑
Speth, Kappler, et al. (2022)	-		√	
Tol et al. (2022)	simulation	√	√	↓
Unterlohner (2021)	-		√	↓
Wietschel et al. (2017)	simulation	√	√	↓

-: No market diffusion modeling, only analysis for a certain point in time.
√: Criterion fulfilled.
(): Criterion included, but not in the focus.
↓: Impact of infrastructure on market diffusion included.
↑: Impact of market diffusion on infrastructure included.

2.3.4 Summary and implications

In summary, bottom-up modeling, and especially simulation, is typically used to investigate the market diffusion of BET. In particular, bottom-up modeling allows for the integration of logisticians’ requirements to the vehicles. Technical as well as economic analyses are integrated in many studies. As shown in different surveys, logistics experts consider infrastructure as a third criterion for purchasing alternative fuel trucks. Previous literature examines the influence of infrastructure as an additional cost parameter or as a technical restriction that affects the vehicle range. However, there is no publication that investigates both, the impact of the infrastructure on the market diffusion of BET and the infrastructure demand based on the BET market diffusion.

As formulated in research question Q2 - "*What impact does the development of public fast charging infrastructure have on the market diffusion of heavy-duty electric vehicles and which truck technology appears to be economically viable from the user’s perspective in Germany up to 2050?*" -, the market ramp-up in this thesis will be considered from the user’s perspective. Furthermore, research question Q3 - "*What is the impact of battery electric road freight transport in terms of (1) the total amount of electric energy and (2) the load profile in Germany up to 2050?*" - requires a detailed understanding of user behavior in order to generate load profiles. As shown in subchapter 2.3.1, agent-based simulation is particularly well suited for studying the behavior of individual actors and their interaction, and is used by the majority of the reviewed publications. In addition, it allows the detailed integration of agent-specific criteria - such as individual technical requirements, economic considerations, and individual infrastructure needs - on a highly detailed level. Therefore, this thesis develops an agent-based simulation model that iteratively models the interaction between BET market diffusion and public fast charging infrastructure. Private charging infrastructure is controlled by the agent, the logistics provider. Public infrastructure is controlled by another agent, the infrastructure provider, and can influence the diffusion of BET. Therefore, the need for private infrastructure is identified but not included as a restriction for the diffusion of BET. The focus in thesis is on the interaction between the diffusion of BET and public fast charging infrastructure.

The ALADIN - Alternative Automobile Diffusion and INfrastructure - model family provides a framework for agent-based simulation for market diffusion of alternative drivetrains. The model has been used in the past for the simulation of passenger cars[12] as well as for the simulation of trucks[13]. However, the detailed integration of charging infrastructure requires a completely new modeling, so that only the very basic logic of the model family can be used. More details can be found in chapter 4.2.

[12] See e.g. Gnann (2015); Gnann et al. (2015); Gnann et al. (2019); Gnann, Speth, Krail, et al. (2022).
[13] See e.g. Gnann et al. (2023); Gnann, Speth, Krail, et al. (2022); Plötz, Link, et al. (2023); Wietschel et al. (2017) from the literature review.

3 Data, scenarios, and assumptions

In the following, the input data required for modeling are presented. First of all, truck traffic datasets are presented and their advantages and disadvantages are elaborated. The subsequent subsection contains data on the parking capacity in Germany along the highway network. Subsection 3.3 focusses on the techno-economic data for charging infrastructure. All relevant parameters for the pure infrastructure modeling are shown in subsection 3.4. Finally, subsection 3.5 contains the parameters for the joint simulation of infrastructure and vehicle market diffusion.

3.1 Truck traffic data

This subchapter aims to introduce different truck traffic datasets and evaluate them with regard to their suitability for modeling in this thesis. Here, the role of traffic data is twofold: On the one hand, traffic data is needed to model the charging infrastructure (see e.g. Metais et al. (2022) for an overview). On the other hand, traffic data is used to model the technical feasibility as well as economic efficiency within the market diffusion process (see e.g. Gnann (2015) or Wietschel et al. (2017) for a description of the general approach). Both roles impose different requirements on traffic datasets. For charging infrastructure modeling, regionally resolved data is needed. The dataset should be as complete as possible, highly resolved, and representative for the modeled region (Metais et al., 2022; P. Rose, 2020). Depending on the methodological approach, point data - for example traffic count data - or origin-destination data - for example recorded tour profiles - can be used. The latter one is more data intensive, but can significantly improve the results when searching for a minimum infrastructure (Metais et al., 2022). A high temporal resolution enables the determination of the hourly traffic volume and thus the dimensioning of the individual charging locations. To model the market diffusion of alternative drivetrains as a bottom-up process, data on the individual requirements of individual users are needed (Gnann, 2015; Wietschel et al., 2017). These individual requirements include information on the annual mileage, but also on single trips and vehicle idle times.

Table 3-1 provides an overview of the most relevant datasets for Germany. The table contains datasets that are either publicly available or can be used for scientific purpose. As shown, no dataset meets all defined requirements. Plötz and Speth (2021) identified truck stop locations (TSL) based on GPS data from approximately 400,000 vehicles. Based on the published data, it is not possible to draw conclusions about individual vehicles. It is also not fully clear how well the vehicles represent the entire European fleet. Therefore, the dataset is not suitable for the purposes described in this thesis. The Federal Highway Research Institute in Germany (BAST - "Bundesanstalt für Straßenwesen") provides manual (M-TCD) and automated (A-TCD) traffic count data for German highways (BAST, 2017, 2022). While the M-TCD presents daily averages on more than 2,500 counting stations, the A-TCD contains hourly values from approximately 1,200 counting stations. The BAST datasets are suitable for distributing and dimensioning charging infrastructure due to their high regional resolution, but do not contain individual vehicle data for market diffusion modeling. More than 2,800 HDV were recorded as part of the “Kraftfahrzeugverkehr in Deutschland (KID)” survey (WVI et al., 2012b). For these vehicles, temporally resolved datasets are available. They are thus suitable for market diffusion modeling. In principle, the dataset can also be used for charging infrastructure modeling due to the available OD-data. However, the sample is comparatively small and European transports are not included (P. Rose, 2020). The “Verkehrsverflechtungsprognose (VVP)” (BVU et al., 2014) serves as a forecast to plan German road infrastructure until 2030. This dataset also contains OD matrices that would allow for charging infrastructure modeling. Again, the focus is limited to Germany. Eurostat (2023a) provides anonymized data from continuous road freight transport surveys (ERFT) conducted by the respective national authorities. A survey queries the full operating schedule of one truck, including trip-specific distances and payload information, and has a regular period of one week. This data is available from 2011 to 2020, covering around 330,000 to 390,000 heavy-duty trucks (GVW > 12 t) annually. However, the dataset is useable for scientific purpose only, does not include temporal resolution of tours, and is geographically resolved only at NUTS-2[2] level. Thus, despite its size, the dataset is not suitable for this thesis. In 2010, the European Transport policy Information System (ETIS) project modeled European traffic flows (Szimba et al., 2012). The dataset includes OD-flows between NUTS-3[1] regions. This makes the dataset suitable for modeling an international charging infrastructure ramp-up. However, there is no individual vehicle data.

Table 3-1: Overview of truck traffic data for Germany and Europe.

	Plötz and Speth (2021)	BAST (2017)	BAST (2022)	WVI et al. (2012b)	BVU et al. (2014)	Eurostat (2023a)	Szimba et al. (2012)
Metadata							
Abbr.	TSL	M-TCD	A-TCD	KiD	VVP	ERFT	ETIS
Latest year	2021	2015	2021	2010	2030	2021	2010
Availability	limited	public	public	scientific	scientific	scientific	public
Method	GPS data	manual count	automated count	questionnaire	modeling	questionnaire	modeling

Coverage							
Region	Europe	GER	GER	GER*	GER**	Europe	Europe
Resolution							
Regional	pinpoints	pinpoints	pinpoints	NUTS-3[1]	NUTS-3[1]	NUTS-2[2]	NUTS-3[1]
Temporal	-	Daily average	Hourly	Time-stamps	Time-stamps	-	-
Individual vehicles	-	-	-	√	-	√	-
OD-data	-	-	-	√	√	√	√

*The dataset considers German vehicles. Some of the vehicles also drive in other European countries. **Border regions are mapped with a lower level of detail.

In summary, no singular dataset meets all the requirements. Therefore, different datasets are used in this thesis. To model the public charging infrastructure, mainly the ETIS dataset is used. The KiD serves as basis for the market diffusions simulation of the vehicles. Both datasets and their processing are described in more detail below.

3.1.1 Regional distribution: European truck traffic data[3]

As described previously, the ETIS dataset serves as the basis for spatial infrastructure modeling in this thesis. Based on ETIS, an updated dataset was created. Speth, Sauter, Plötz, and Signer (2022) document the data preparation. Speth et al. (2021) contains the actual dataset. The following provides a shortened summary. For all the details, please refer to Speth, Sauter, Plötz, and Signer (2022).

The ETIS dataset from 2010 (Szimba et al., 2012) represents an extension of its predecessor project, which ended in 2005, and to date provides one of the most comprehensive surveys of European transport. Numerous transport data tables from Eurostat, as well as national databases, were used within the ETIS project to generate a Europe-wide OD-matrix for transported goods between NUTS-3 regions[4]. As shown in transport statistics (Eurostat, 2023b), freight and traffic volumes have changed since 2010. In addition, the OD-matrix provides values for transported goods between the regions in tons. The number of vehicles as well as travel routes are not included in the dataset. Therefore, a three-step processing is necessary: (1) update of road

[1] NUTS-3: Nomenclature des unités territoriales statistiques. In Germany, level 3 corresponds to districts and independent cities.

[2] NUTS-2: Nomenclature des unités territoriales statistiques. In Germany, level 2 corresponds to administrative districts.

[3] Parts of this subchapter are based on Speth, Sauter, Plötz, and Signer (2022).

[4] For project details see Szimba et al. (2012). See ETIS (2012) for the original dataset.

freight volumes, (2) conversion from road freight transport volumes to number of trucks, and (3) routing. Figure 3-1 illustrates the data preparation and the input data used.

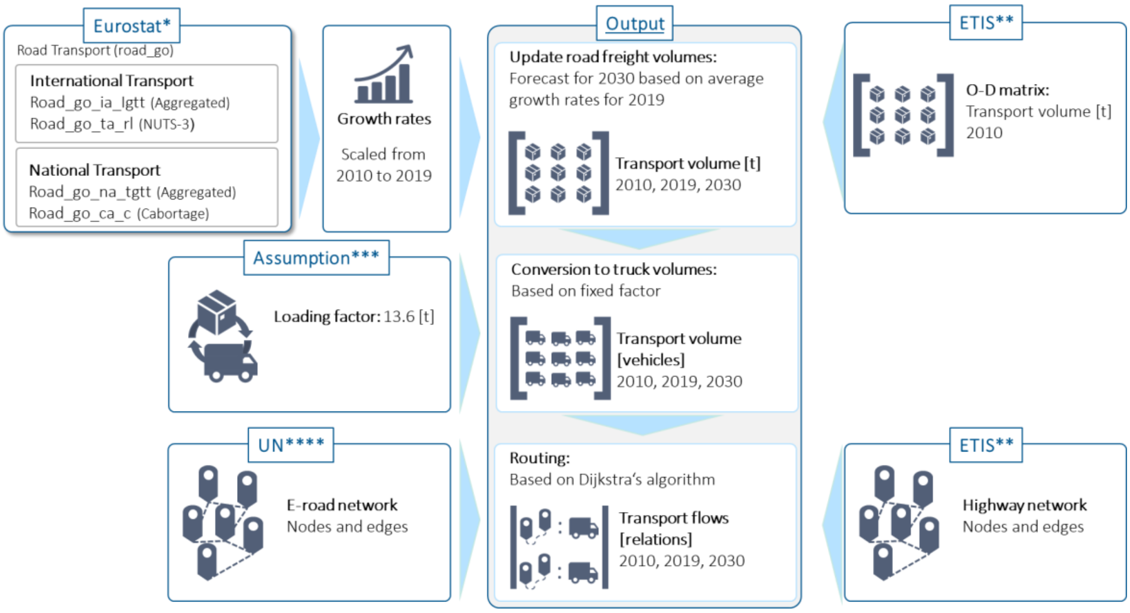

Figure 3-1: Illustration of the preparation of the ETIS traffic data. Own illustration, based on Speth, Sauter, Plötz, and Signer (2022). *Eurostat (2023b), **ETIS (2012), ***EC (2011) and Eurostat (2018), ****UN (2016)

To update the road freight volumes between NUTS-3 regions, the dataset was scaled up to 2019 numbers and a forecast for 2030 was added. The O-D matrix of the ETIS dataset is based on transport volume data collected by Eurostat (Eurostat, 2023b). To achieve the highest possible consistency, the scaling also refers to these data tables. However, the data availability on NUTS-3 level is quite incomplete. Several years and even countries are not available mainly due to data confidentiality. Therefore, country-specific national and international percentage growth rates are calculated. To calculate the national growth rate, the value from 2019 is taken from the *road_go_na_tgtt* table in Eurostat (2023b). The table contains the annual national transport volume of each country. These transport volumes are additionally supplemented by the annual road cabotage *road_go_ca_hac*. Road cabotage is the transport of goods by a vehicle registered in one country, carried out in the national territory of another country. To calculate the growth rates for the international transport flows, the growth rates of the exports of all EU28 countries, England, Norway, and Switzerland are considered separately. Since the average growth rates of exports (3.7%) and imports (3.64%) hardly differ from each other, the country-specific export growth factor is used to scale all international transport flows. Due to the large number of missing values, the growth rate can only be calculated for half of the countries from the export flows provided at NUTS-3 level (*road_go_ta_rl*). For those countries where the data set contains too many values that are not available in Eurostat (2023b), the aggregated exports from the table *road_go_ia_lgtt* are used. To be able to analyze the charging infrastructure required in the future, the current traffic flows must be projected to the year 2030. Since no single growth value can be found in the literature - the European Commission quotes values between 26% and 40%[5] -, it is assumed that the countries will continue to grow between 2019 and 2030 with the same growth rates as between 2010 and 2019. In addition to the EU, Norway, Switzerland and Great Britain, the ETIS dataset also considers other countries on the European continent. Since they only count for 0.12% of the total ETIS transport volume, the average growth rate of 25% is assumed for them.

The ETIS project data (ETIS, 2012) provides freight flows ins tons. To convert these values to vehicles traveling, a loading factor is needed. According to EC (2011), the average loading factor in the EU in 2010 was 13.6 t per truck. This value remained almost constant within the last years. To account for empty runs, an additional factor of 25% is added (Eurostat, 2018). This is a simplification, as the proportion of empty runs usually varies between different goods and routes.

Finally, routing must be performed to allocate OD traffic flows to highways. The relevant highway network for trucks was extracted from the ETIS road network which is part of the land networks (ETIS, 2012). To focus on long-haul routes and to lower complexity, the network is reduced to road sections that are part of a highway or the international E-road network. Thus, only road sections that have the attribute M (highway), ME (highway and part of European road network), D (four-lane road), DE (four-lane road and part of European road network) or OE (side road and part of European road network) in the ETIS dataset are used for modeling. To ensure that all E-roads (UN, 2016) are part of the final graph, all European roads are checked, and the missing edges are manually added. In total, the road network is represented by 17,435 nodes and 18,447 edges. In this thesis, this network is referred to as main road network. By calculating the shortest distance between the middle point of a region and all network nodes, each NUTS-3 region is assigned to exactly one node in the road network. These nodes define the start and ending points of each transport route. For the determination of routes with minimum distances, Dijkstra's algorithm, as a standard algorithm to define a shortest path in a graph, is used. For each OD pair within the traffic flow matrix, an optimal route is computed in terms of edge and node paths using Dijkstra's algorithm, implemented in the Python library NetworkX (NetworkX, 2020). This approach comes with some simplifications: (1) The algorithm always chooses the shortest route. (2) Each region is assigned to exactly one network node at which transport routes start and end. (3) If a transport process takes place exclusively within a NUTS-3 region, it cannot be mapped in the highway network. In addition, all routes defined as regional traffic are excluded from the analysis, since the regional grid of NUTS-3 regions is not dense enough to map these transports in a meaningful way. Regional traffic includes all routes that do not have a network node within either the origin or destination region and are less than 50 km apart or directly adjacent.

In total, the newly created dataset includes 1,514,573 directed traffic flows between 1,630 different origins (NUTS-3) and 1,667 destinations (NUTS-3). As an example, Table 3-2 shows an

[5] See Schade et al. (2018), EC (2019), EC (2020).

extract for two relations. For a deeper overview, please refer to Speth, Sauter, Plötz, and Signer (2022).

Table 3-2: Exemplary extract of the newly created truck traffic flow dataset. Based on Speth, Sauter, Plötz, and Signer (2022).

	Name Origin	**Name destination**	**Path E-road**	**[...]***
1	Mittelburgenland	Mostviertel-Eisenwurzen	[1034974, 1008535, ..., 1008578]	[...]*
2	Mittelburgenland	Sankt Polten	[1034974, 1008535, ..., 1008682]	[...]*
n	[...]*	[...]*	[...]*	[...]*
	Distance [km] origin to E-road	**Distance [km] within E-Road**	**Distance [km] E-road to destination**	**Total distance [km]**
1	30	160	9	199
2	30	110	5	145
n	[...]*	[...]*	[...]*	[...]*
	Flow 2019 [trucks/a]	**Flow 2030 [trucks/a]**	**Flow 2019 [t/a]**	**Flow 2030 [t/a]**
1	511	534	6,953	7,259
2	576	601	7,837	8,177
n	[...]*	[...]*	[...]*	[...]*

*Table shows a shortened illustration of the dataset 01_Trucktrafficflow from Speth et al. (2021).

Figure 3-2 shows the modeled road network in the EU, Great Britain, Norway and Switzerland with a total length of 142,000 km. The line width illustrates the truck traffic volume. The highest traffic volume of up to 36,500 vehicles per day occurs in the port hinterland, for example near Calais and Dover. Germany accounts for 14,000 km[6], as shown in Figure 3-3.

[6] The modeled network is slightly longer than the German highway network, which comprises 13,155 km according to BMDV (2023). While smaller highway sections are partially not included, relevant federal highways, for example along the Lake Constance, are additionally modeled.

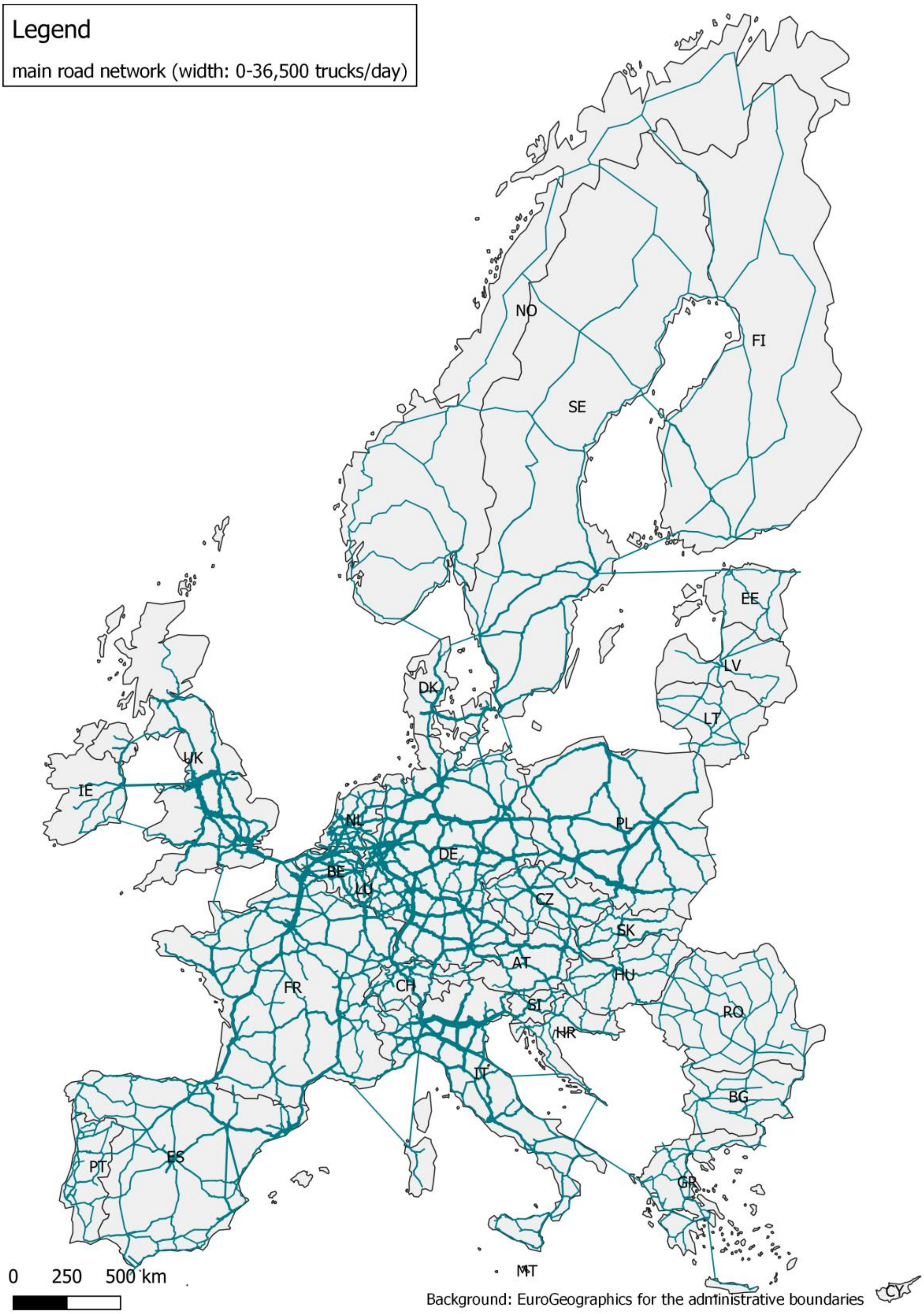

Figure 3-2: Modeled European truck traffic flow in 2019. Own illustration, based on Speth, Sauter, Plötz, and Signer (2022) and Speth et al. (2021).

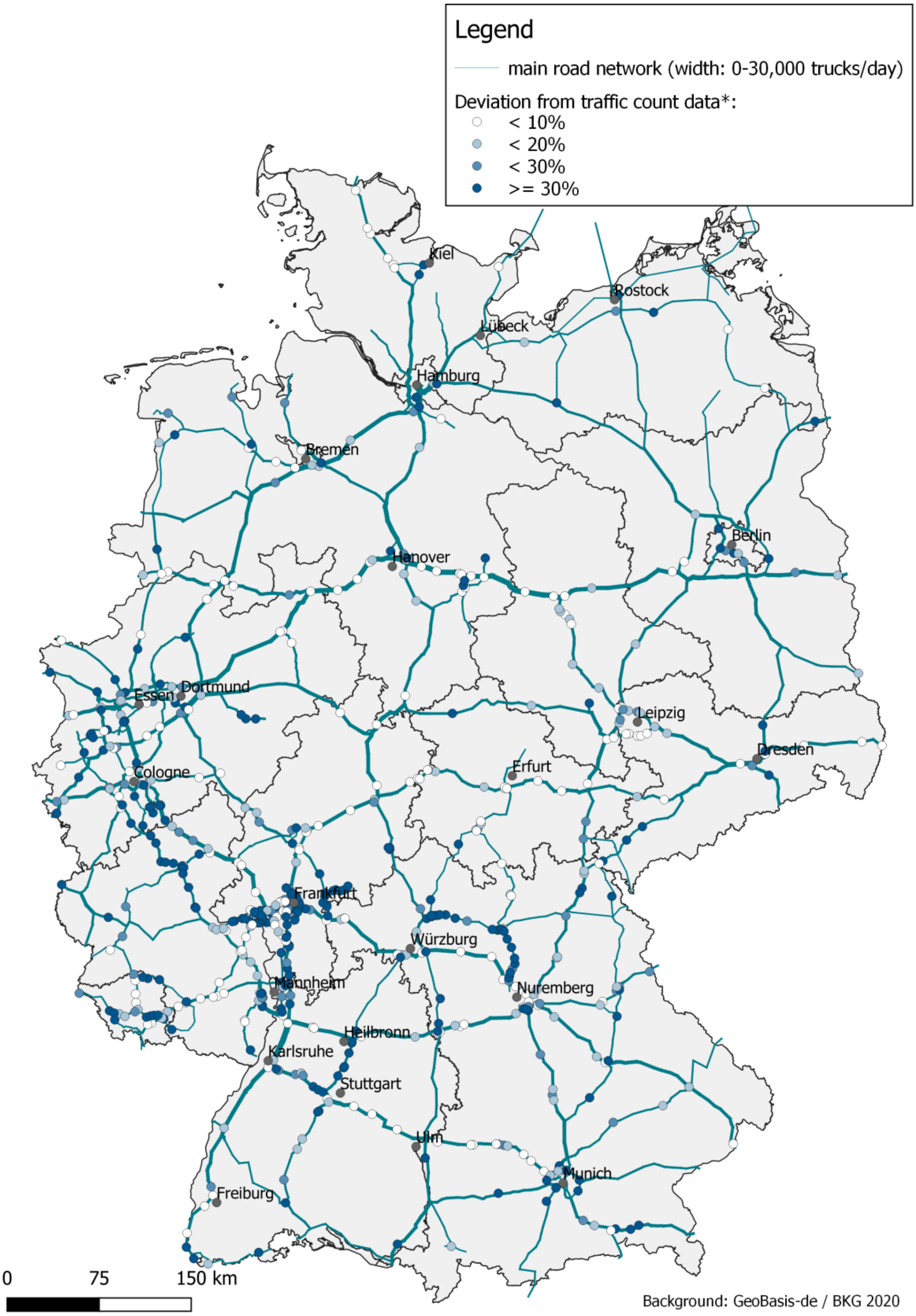

Figure 3-3: Modeled German truck traffic flow in 2019 including deviation from traffic count data. Own illustration, based on Speth, Sauter, Plötz, and Signer (2022) and Speth et al. (2021). *Deviation from BAST (2022) data for 2019.

In order to assess the quality of the dataset, Figure 3-3 additionally shows the relative deviation of the modeled traffic flows compared to the A-TCD data (BAST, 2022). Each counting point was assigned to the nearest node of the modeled network[7] and the daily traffic was compared. As shown in Figure 3-3, the modeling achieves a high consistency on long-range corridors, for example highway BAB 2 from the Rhine-Ruhr area via Hanover towards Berlin and Poland. Significant deviations can be explained by the modeled assumptions: High deviations near cities are due to non-modeled traffic within a NUTS-3 region. This traffic also uses the highway network there. Examples are Berlin, Frankfurt, or Munich. Deviations also occur at parallel routes, for example between Cologne and Mannheim. These deviations are due to the fact, that the algorithm strictly chooses the minimal shorter distance. Figure 3-4 additionally shows the scatter of the deviation. In summary, the dataset is well suited for modeling long-range public charging infrastructure.

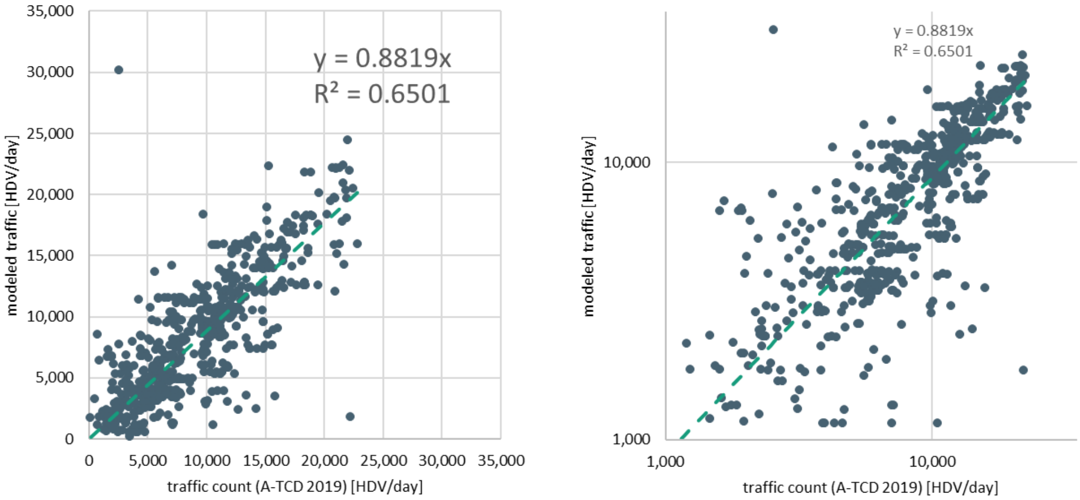

Figure 3-4: Comparison of modeled traffic volume with traffic count data in Germany.

In the following, the updated ETIS dataset is referred to as ETIS-U.

3.1.2 Temporal resolution: A-TCD and KiD

In addition to the regional distribution of truck traffic, the temporal distribution over the day is also relevant. In particular, the distribution of traffic volumes throughout the day is relevant to size the charging infrastructure accordingly. Moreover, a temporal resolution of driving profiles allows identifying potential charging slots.

As shown in chapter 3.1 in Table 3-1, the A-TCD dataset contains hourly resolved traffic volumes at counting stations along German highways. The KiD dataset contains time-resolved

[7] The modeled network contains 2,787 nodes in Germany. This corresponds to an average distance of 5 km between two nodes. Therefore, nodes with a maximum distance of 3 km - covering 6 km road - were considered.

driving profiles. Both datasets serve as input in this thesis. Therefore, datasets and the necessary data preparation are briefly presented.

For each hour of a year, the A-TCD dataset provides the number of vehicles passing through a counting station on the German highway network. The following analysis is based on the 2018 dataset and is thus not affected by the COVID-19 pandemic or the war in Ukraine. In total, A-TCD 2018 provides data from 846 counting stations. Of these, 370 counting stations are located on the particularly relevant single-digit highways. The counting stations are able to distinguish different types of vehicles (BAST, 2020). At this point, the analysis focusses on data for combinations of a vehicle and a trailer (> 3.5 t GVW). The analysis considers rigid trucks with trailers and tractor-trailer combinations. Both directions of travel are considered together. Figure 3-5 shows the median number of trucks across all counting stations and all days of the year. In addition, the quartiles are shown. However, single counting stations reach up to 2,000 vehicles during the peak hour. The HDV traffic volume during the week is clearly higher than on weekends. Over the course of a day, traffic increases significantly from 6 a.m. onwards, peaks at midday, and decreases considerably after 3 p.m.

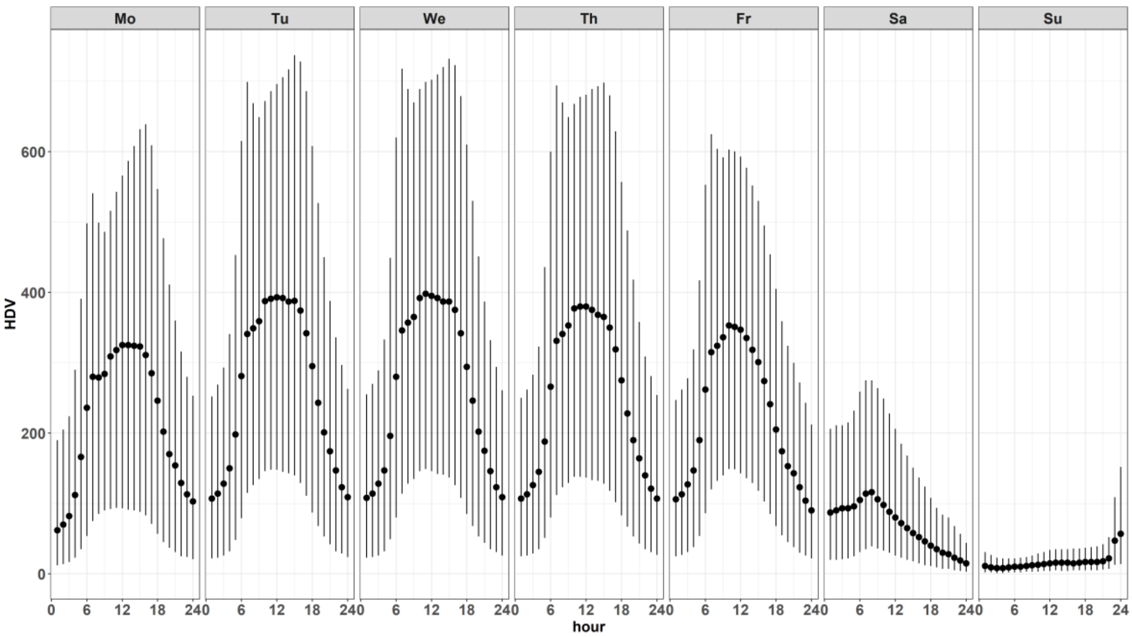

Figure 3-5: Hourly counted HDV at automated traffic count stations on the German highway network. Own illustration, based on 2018 A-TCD (BAST, 2022). Black dots indicate median, whiskers indicate lower and upper quartile.

Figure 3-6 shows the distribution HDV traffic volumes at the traffic counting stations throughout the day. To do this, for each hour of a week, the mean traffic over all weeks is calculated. Subsequently, the data are normalized to the traffic volume of Tuesdays, as a typical weekday. The most trafficked hour of the day thus accounts for almost 6% of the daily traffic volume on working days. As shown in Figure 3-7, there are small differences between different highways.

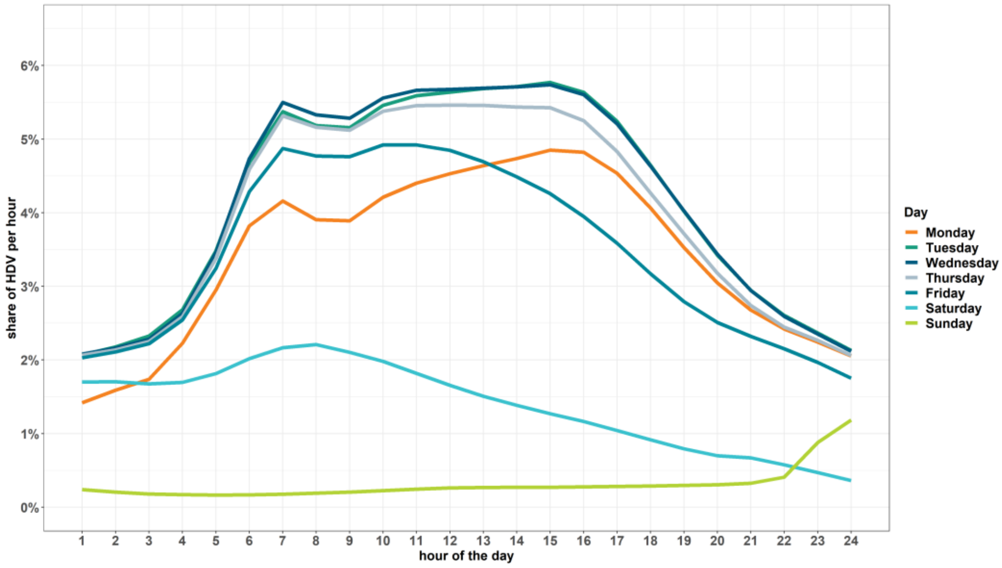

Figure 3-6: Share of HDV per hour on German highways over the course of the day. Own illustration, based on 2018 A-TCD (BAST, 2022).

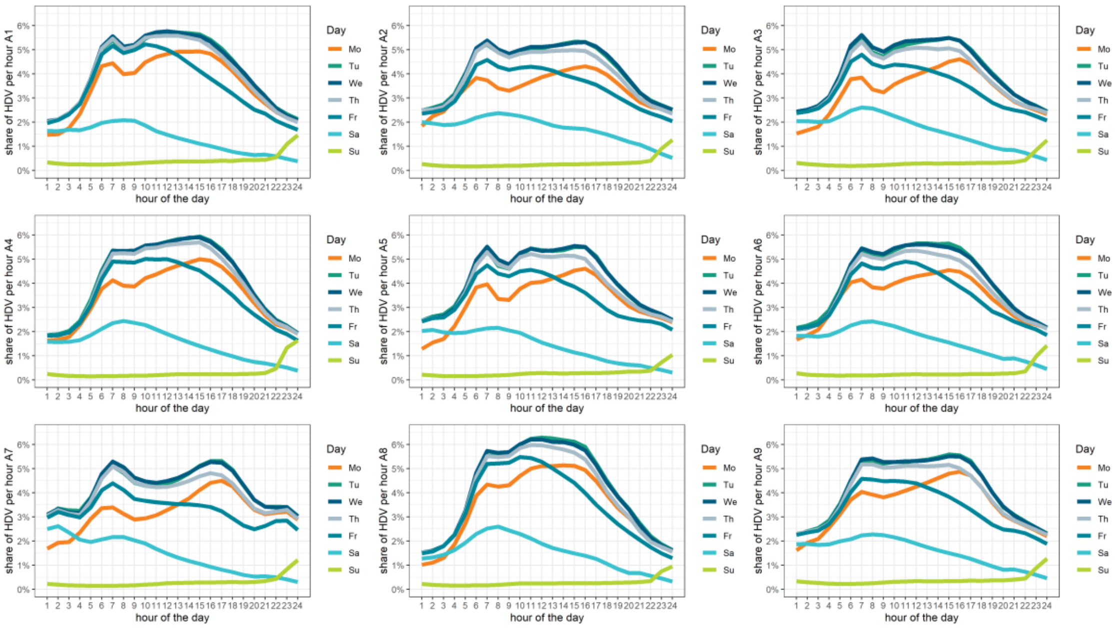

Figure 3-7: Share of HDV per hour on single-digit German highways over the course of the day. Own illustration, based on 2018 A-TCD (BAST, 2022).

The KiD dataset describes the driving behavior of the vehicles selected for the sample over a single day. The dataset contains, among other things, the following information for each vehicle:

- day of observation (Mo, Tu, We, Th, Fr, Sa, Su),
- vehicle size (rigid or tractor-trailer),

- gross vehicle weight,
- daily mileage,
- area of operation (company site, town, within 50 km, Germany, Europe), and
- information about the individual trips, including
    - start of the individual trip,
    - end of the individual trip,
    - passed distance during the trip, and
    - type of parking location (for example public streetscape, private area).

For a full overview, compare WVI et al. (2012a).

The KiD dataset contains 2,810 vehicle datasets for vehicles with a GVW over 12 t. 1,635 profiles stem from rigid trucks, 1,175 from tractor-trailers. However, incomplete datasets with regard to the individual trip information must be sorted out, leaving 2,410 datasets for further analysis with 1,350 rigids and 1,060 tractor-trailers. Figure 3-8a shows the share of driving and parking HDV, according to the KiD dataset. Publicly parking vehicles are shown separately[8]. Data from all days of observation are included[9]. Additionally, Appendix A.1 shows the distribution of daily mileage in the KiD dataset.

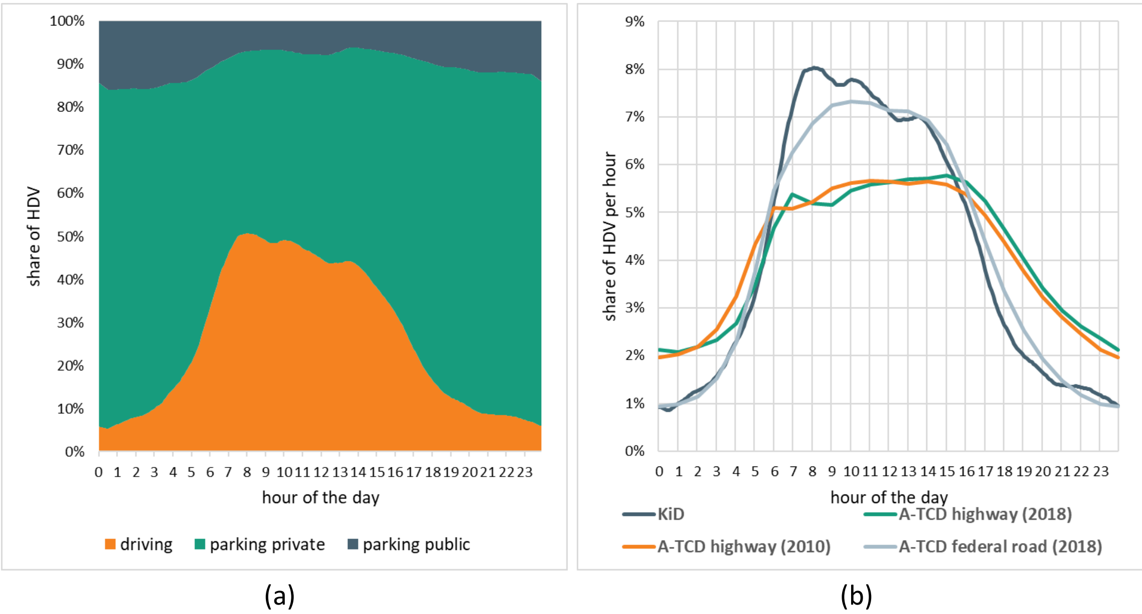

Figure 3-8: (a) Share of HDV per hour driving and parking, and (b) proportion of hourly HDV traffic to daily HDV traffic. Own illustration, based on WVI et al. (2012b).

Figure 3-8b shows the proportion of the hourly HDV traffic to the daily HDV traffic in the KiD dataset. These numbers are compared with the data of the A-TCD in Figure 3-6. Obviously, the

[8] Approximately one quarter of the vehicles declared as publicly parked are vehicles with missing information about their location.
[9] Analyses only for weekdays were performed, but show no relevant differences.

KiD dataset differs from the A-TCD traffic volume on highways in 2018. To investigate the deviation, two additional evaluations of the A-TCD dataset are added to Figure 3-8b. Analysis of the A-TCD dataset for highways from 2010 - the year of the KiD dataset - shows that there is almost no change over time. However, there is a similarity to A-TCD data from federal roads. The comparisons show that the KiD dataset represents both highway and federal road traffic sufficiently well, even though there are some deviations.

3.2 Parking capacity[10]

In this thesis, the available parking spaces along German highways serve as capacity constraint in the CFRLM, as actual charging locations cannot contain more charging points than parking lots. As shown in Irzik (2019), truck parking lots along highways in Germany are highly used or even overloaded and therefore need to be used efficiently. An overview with public parking areas - typically public rest areas - along German highways provided by the Autobahn GmbH serves as input (Autobahn GmbH, 2021)[11]. The dataset contains 2,090 locations with a total of 63,971 truck parking lots (mean per location = 31, median = 18, σ = 33). The parking locations are assigned to the nearest node on the German road network in the ETIS-U dataset, if the distance is less than 2 km[12]. One node can aggregate multiple parking areas. After the aggregation, the dataset contains 688 parking locations with 38,563 parking spaces (mean = 56, median = 36, σ = 57). However, there are also locations with more than 300 parking lots, as shown in Figure 3-9.

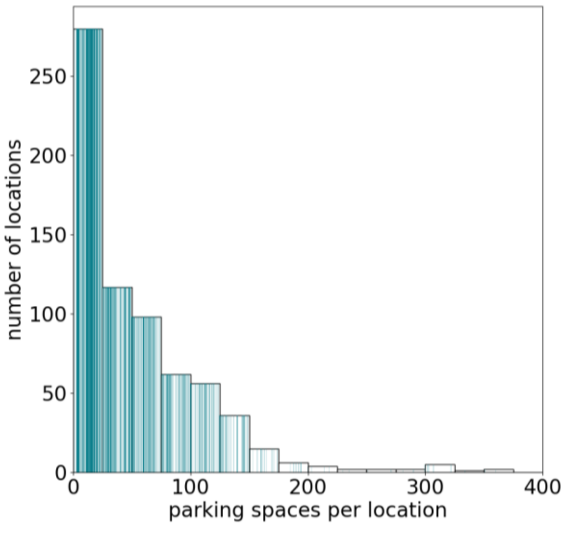

Figure 3-9: Aggregated parking spaces at nodes of the German highway network. Nodes in the ETIS-U network serve as highway network representation. Illustration based on data from Autobahn GmbH (2021). Color intensity indicates the distribution within the bins. Originally published in Speth et al. (2024).

[10] Parts of this subchapter are based on Speth et al. (2024) (under review at the time of submission of this thesis).
[11] This dataset is not publicly available. In principle, parking capacities could also be derived from public Open Street Map (OSM) data. However, this would involve a higher level of uncertainty.
[12] The maximum distance was chosen in an iterative process to avoid detours for recharging.

3.3 Techno-economic infrastructure parameters

Estimating the costs of public fast charging infrastructure for HDV is still subject to high uncertainties today, in particular due to local circumstances. Especially the distance to the power grid and the required grid connection influence the infrastructure costs (Burges & Kippelt, 2021; Kippelt et al., 2022). Kippelt et al. (2022) distinguished a low and a high costs scenario in four expansion stages. Table 3-3 sums up the most important information regarding the grid connection. For cost distribution to individual components, compare Kippelt et al. (2022).

Table 3-3: Electricity grid connection configurations and costs according to Burges and Kippelt (2021) and Kippelt et al. (2022).

Connection	**Rated Power**	**Realization**	**Low costs**		**High costs**	
			distance	**costs**	**Distance**	**costs**
	[MVA]	**[a]**	**[km]**	**[k€$_{2020}$]**	**[km]**	**[k€$_{2020}$]**
Existing medium voltage ring	< 8	< 2	0.5	65	2.0	320
New medium voltage connection	< 20		2	350	10	1,690
Extension medium voltage station	< 30		2	1,650	10	4,290
New medium voltage station	> 30	< 10	2	5,400	10	15,500

In addition, a power factor for reactive current compensation of 0.95 and an efficiency of 0.95 are assumed (Kippelt et al., 2022). Due to their charging curve, not all vehicles need full power at the same time. Therefore, a simultaneity factor of 0.6 is assumed, according to expert opinion (HoLa, 2021). This means the charging locations are designed for 60% of their nominal power. Taking all aspects into account, a location with 8 MVA could supply 12 MCS charging points with a nominal peak power of 1 MW ($8\,MVA * 0.95\,\frac{MW}{MVA} * 0.95 : 1\,\frac{MW}{charging\ point} : 0.6 = 12$). The same logic applies to CCS charging. However, a nominal output of 350 kW per charging point must be assumed.

In addition to the grid connection costs, there are costs per charging point for the pole, including transformer unit (AC/AC) and converter (AC/DC). In accordance with Bernard et al. (2022), 616 k€$_{2020}$ are assumed per MCS charging point today, including hardware and software, planning, and installation. Similar values can be found in Plötz et al. (2020) and Burges and Kippelt (2021). For CCS charging, 232 k€$_{2020}$ are assumed per charging point. Additionally, a cost reduction of 2% p.a. is assumed for charging points, since they represent a new technology (Bernard et al., 2022). Figure 3-10 shows the costs of charging locations in dependence of the number of MCS charging points today and in 2045. It can be seen that the grid connection - recognizable as jumps - plays a subordinate role for small- and medium-sized charging locations. As a company, one also only pays a cost subsidy that is determined individually (BNetzA, 2009). Figure A-2 in Appendix A.2 shows the same information for CCS charging infrastructure.

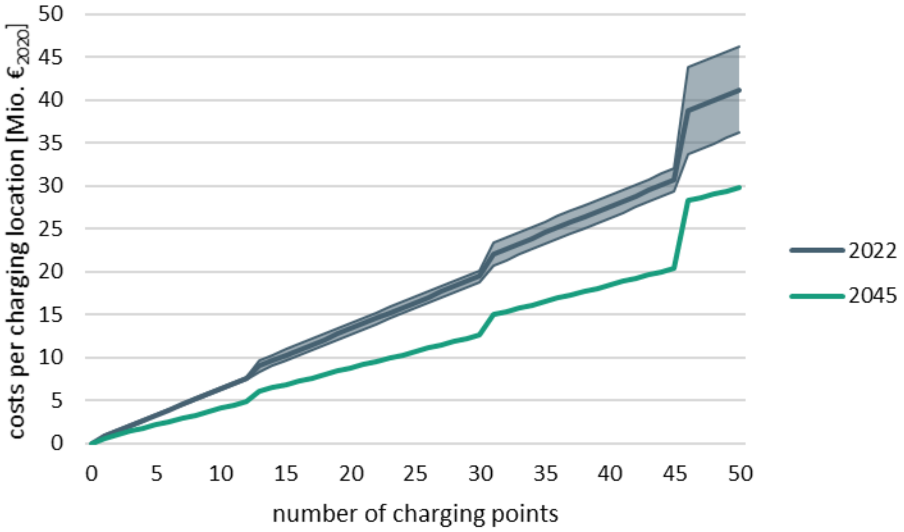

Figure 3-10: Costs of charging locations in dependence of the number of MCS charging points. Shaded area for 2022 shows the difference between low and high grid connection costs. Own illustration.

The annual costs of a charging station can be determined, using annual capital expenditures a^{capex} and annual operating expenditures a^{opex}[13]. Equation (3-1) shows the calculation.

$$TCO_a^{infra} = a^{capex} + a^{opex} = I_0^{infra} * \frac{(1+i)^T * i}{(1+i)^T - 1} + a^{opex} \tag{3-1}$$

The cost per charging location, as calculated in Figure 3-10 serve as invest I_0^{infra}. To calculate the annual capital expenditures, an interest rate i of 9.5% is assumed (Basma et al., 2021). With regard to the depreciation period T, 40 years are assumed for cables, 30 years for outgoing feeders, 25 years for transformers, and 15 years for charging poles (Bernard et al., 2022; Deutsche Bundesregierung, 2005; Kippelt et al., 2022). As annual operating expenditures, 1.2% of the investment for charging poles without the costs for installation and planning are considered (Bernard et al., 2022). This corresponds to $440{,}000\ €_{2020} * 0.012\ \frac{1}{a} = 5{,}280\ \frac{€_{2020}}{a}$ for MCS and $170{,}000\ €_{2020} * 0.012\ \frac{1}{a} = 2{,}040\ \frac{€_{2020}}{a}$ for CCS.

[13] For an introduction into accounting, see Wöhe et al. (2020).

Figure 3-11 shows the annual costs per MCS charging location in dependence of the number of charging points. Figure A-3 in Appendix A.2 shows the same information for CCS charging infrastructure.

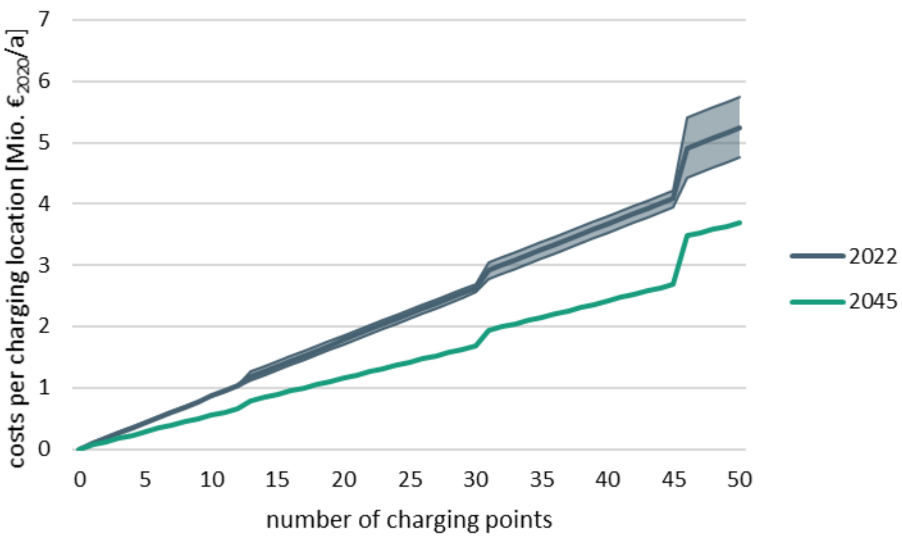

Figure 3-11: Annual costs of charging locations in dependence of the number of MCS charging points. Shaded area for 2022 shows the difference between low and high grid connection costs. Own illustration.

3.4 Scenario parameters for pure infrastructure modeling

Without the integrated calculation of a market diffusion for BET, the infrastructure modeling in the first part of this thesis relies on additional parameters, for example regarding the electrified share of traffic. These parameters are explained below for different scenarios.

This thesis presents two approaches to model public charging infrastructure (see subchapter 2.2 or 4.1). The first approach models charging infrastructure at regular intervals. The second approach minimizes the necessary number of charging locations. While the first approach maps a kind of a typical network, insights into a minimum necessary network can be obtained from the second approach. The following sections present the key assumptions, framework parameters, and scenarios.

3.4.1 Parameters for charging infrastructure at regular intervals

To compare different infrastructure characteristics and to identify the influence of individual variables, this thesis investigates a wide range of scenarios. They differ in the modeled region, the year under consideration, the expected share of battery electric trucking BET_{share}, the average distance between two charging locations d_{avg}, and the annual mileage of the truck fleet AM_{total} according to the respective data source.

From a temporal perspective, the analysis examines two situations: the early market ramp-up and the full extension. As shown by Breed et al. (2021), the introduction of BET must begin no later than 2025. A relevant market share must be achieved by 2030. In 2045, Germany shall reach climate neutrality (Deutscher Bundestag, 2019). Following Breed et al. (2021) and expert opinions (HoLa, 2021), the scenarios assume 5% battery electric trucking in 2025, 15% battery electric trucking in 2030, and 100% battery electric trucking in 2045.

The distance between two charging locations is assumed 50 km, or 100 km. This is slightly below or above the EC's recommendation of 60 km for the TEN-T core network (EC, 2021). The defined scenarios assume increasing densification of the network over time. One charging location can serve both directions of travel.

As shown in section 3.1.1, freight flows and thus truck traffic is moving all over Europe. Therefore, the analysis covers the EU27-countries, United Kingdom, Norway, and Switzerland. However, since the focus of this thesis is Germany, an additional analysis is performed for Germany using both the ETIS-U and the M-TCD datasets. The dataset has implications for the selection of roads to be considered. M-TCD covers 12,563 km and thus almost the entire German highway network with a total length of 13,155 km (BMDV, 2023). As shown in 3.1.1, ETIS-U focuses on main European highways and especially on the E-road network (UN, 2016). The E-road network considered for electrification in the scenarios covers 9,428 km in Germany. Table 3-4 sums up the considered network length for the two datasets. All distances rely to the single network length, which can be traveled in two directions.

Table 3-4: Road network length considered for electrification at regular intervals in the datasets ETIS-U and M-TCD. All distances rely to the single network length, which can be traveled in two directions.

	Total length	**Length considered for electrification**
ETIS-U (Europe*)	142,057 km	95,476 km
ETIS-U (Germany)	15,799 km	9,428 km
M-TCD (Germany)	13,155 km	12,563 km

*Europe: EU27, United Kingdom, Norway, Switzerland

The selection of the dataset also influences the annual mileage of the HDV fleet. ETIS-U models 176 bn. km for Europe[14] in 2019 and 231 bn. km in 2030. 2025 is simplified and calculated as a mean value. For Germany, there is a mileage of 39 bn. km in 2019 and 55 bn. km in 2030. Unlike the ETIS-U dataset, the point data from M-TCD does not provide mileage data. The annual mileage of the HDV fleet in Germany varies significantly between different sources. KBA (2023) calculates conservatively 27 bn km for HDV with a GVW over 12 t in 2020. Eurostat (2022c) reports 30 bn. km for all vehicles, almost constant over time. However, vehicles with a GVW lower than 12 t account for less than 5% (KBA, 2023). Other sources assume higher

[14] Europe: EU27, United Kingdom, Norway, Switzerland

values of 36 bn. km in 2020 (Gnann et al., 2023) or 31 bn. km in 2015 (Wietschel et al., 2017). For calculations based on M-TCD data from 2015, Wietschel et al. (2017) serve as starting point and, according to BMVI (2016), 30% growth is assumed until 2030. The analysis thus represents a compromise between the conservative estimates of KBA (2023) and the progressive growth of ETIS-U. Due to the high degree of uncertainty, there is no projection up to 2045 at this stage. Instead, the 2030 values are used for 2045.

Table 3-5 summarizes six scenarios under consideration.

Table 3-5: Scenario definition for charging infrastructure modeling at regular intervals. Share of battery electric trucking as BET_{share}, distance between charging locations as d_{avg}, and total annual fleet mileage as AM_{total}.

Scenario	Year	BET_{share}	d_{avg}	Region	Dataset	AM_{total}
Startup2025	2025	5%	100 km	Europe[15]	ETIS-U	204 bn. km
Wide2030	2030	15%	100 km	Europe[15]	ETIS-U	231 bn. km
Dense2030	2030	15%	50 km	Europe[15]	ETIS-U	231 bn. km
Dense2045	2045	100%	50 km	Europe[15]	ETIS-U	231 bn. km
Wide2030_Ger_ETIS-U*	2030	15%	100 km	Germany	ETIS-U	55 bn. km
Wide2030_Ger_M-TCD	2030	15%	100 km	Germany	M-TCD	40 bn. km

*Wide2030_Ger_ETIS-U is part of Wide2030

Table 3-6 lists further parameters with relevance to the modeling of charging infrastructure at regular intervals.

The battery size and thus the range of the vehicles needs to ensure that vehicles can drive 4.5 hours, before they are required to make a mandatory break (EU, 2006). A speed limit of 80 km/h exists for trucks on German highways, but the actual speed driven varies between different highway sections (Löhe, 2016). Therefore, the average speed is lower than 80 km/h. In agreement with experts (HoLa, 2021), 300 km in 4.5 h seems plausible.

As an assumption, 25% of all truck charging events occur publicly. KiD-data shows that almost half of HDV drives less than 500 km per day (Speth & Funke, 2021)[16]. Simplified, it is assumed that these vehicles charge almost exclusively at the depot (Pierre-Luis Ragon et al., 2022). For

[15] Europe: EU27, United Kingdom, Norway, Switzerland

[16] The mean value of the daily mileage for tractor-trailer trucks with more than 12 t GVW in the KiD-dataset is 423 km, the average is 445 km (n=1175). For rigid trucks, the mean value is 187 km, the average is 249 km. BET with a range of 300 km to 400 km are already available today (Mercedes Benz (2023); Volvo (2023b)). Therefore, it seems plausible, that within the next years, half of the vehicles will not depend on a public fast charging infrastructure. Pierre-Luis Ragon et al. (2022) assume that up to 680 kWh, which is approximately equal to 500 km, can be recharged with a single slow charging event per day.

the other half of the vehicles, 50% of the charging events could also take place in the depot. However, this is a plausible initial estimate that should be further evaluated.

The analysis mainly focusses on highway traffic. According to the A-TCD data in section 3.1.2, 6% of the daily traffic on highways takes place in the most trafficked hour. Therefore, the charging demand in the peak hour accounts for 6% of the daily charging demand. As mentioned earlier, the KiD dataset shows a higher peak, probably due to the inclusion of regional traffic off the highway network. Therefore, the peak traffic parameter is included into the sensitivity analysis.

The charging process should take place in the mandatory break of 45 min (EU, 2006). Taking the MCS standard into account, experts consider an average charging time of 30 min and an average waiting time of 5 minutes to be realistic (CharIN, 2023; HoLa, 2021). Given an exemplary energy demand of 1.2 kWh/km (Kühnel et al., 2018; Speth, Kappler, et al., 2022; Wietschel et al., 2017), this would result in an average charging power of 720 kW. A simplified assumption of approximately 1 MW peak power can be made.

As mentioned, the described parameters are subject to uncertainties. Subchapter 5.1.1.1 contains corresponding sensitivity analyses.

Table 3-6: General input parameters for infrastructure modeling at regular intervals.

Parameter	**Abbreviation**	**Value**	**Reference**
Range in 4.5 h	$range_{BET}$	300 km	Own calculation
Share of public charging events	CE_{public}	25%	Own calculation
Share of charging events in peak hour	$peak\_hour$	6%	BAST (2022)
Average charging time	$charging_q$	30 min	HoLa (2021)
Average waiting time	w_q	5 min	HoLa (2021)

3.4.2 Parameters for optimized charging infrastructure[17]

In contrast to the infrastructure modeling at regular intervals, the number of charging locations, or respectively their distance, is not specified for the optimized charging infrastructure network. Rather, the network is optimal in the sense that the number of public charging locations is minimized, considering constraints.

[17] Parts of this subchapter are based on Speth et al. (2024). This publication is still under review at the time of submission of this thesis.

European OD traffic flows serve as main input. For this purpose, the ETIS-U dataset is used. For this calculation, the model uses the 2030 forecast. As mentioned in section 3.1.1, the dataset contains 1.5 million directed truck traffic flows between 1,675 NUTS3 regions in Europe. Traffic flows within a NUTS3 region are not considered. In accordance with section 3.4.1, the model assumes that trucks drive a maximum of 300 km ($range_{BET}$) during one driving period of 4.5 hours. Traffic flows shorter than 300 km therefore do not need to be publicly recharged and are therefore not relevant. Across Europe, 1.4 million flows with a total of 172 bn. kilometers traveled remain. Of these, around 1 million flows with 72 bn. vehicle kilometers traveled pass Germany. Following the idea of Jochem et al. (2019), the model focuses on flows that are served at least weekly (> 50 trucks/a). For Europe, this measure reduces the problem to 374,000 flows and 156 billion kilometers traveled. For flows passing Germany, 236,000 flows and 61 billion kilometers traveled are received. To keep the problem solvable, the described procedure has significantly reduced the number of paths - and therefore the problem size -, while still considering more than 85% of the vehicle kilometer traveled. The level of detail is also well above P. K. Rose et al. (2020), who considered 2,655 flows in Germany. In contrast to the infrastructure modeling at regular intervals, the relevant traffic for public fast charging is not estimated as a share of public charging events CE_{public}, but derived directly from the ETIS-U dataset based on the vehicle range $range_{BET}$.

As described for the infrastructure modeling at regular intervals, the geographical focus is Germany. However, since truck traffic is international, a European network without a capacity restriction is first calculated. Again, Europe refers to the 27 countries of the EU, as well as the United Kingdom, Switzerland, and Norway. Second, an optimal German public charging infrastructure with capacity constraint is calculated. The parking space availability in section 3.2 serves as capacity constraint. For international OD-paths, the results from the first step serve as the minimum available infrastructure outside Germany and can be used by the vehicles. The capacity-constrained network can be compared with the unconstrained German network, derived from the European unconstrained network.

To focus on the most challenging scenario, a 100% electrified scenario is assumed, similar to the *Dense2045* scenario for charging infrastructure at regular intervals. Again, due to the high degree of uncertainty, there is no projection of the mileage up to 2045 at this stage. Instead, the 2030 values are used for 2045.

Table 3-7 sums up the modeled scenarios for optimized charging infrastructure.

Table 3-7: Scenario definition for optimized charging infrastructure modeling. Share of battery electric trucking as BET_{share}.

Scenario	Year	BET_{share}	Region	Dataset	Capacity constraints
Optimization2045	2045	100%	Europe[18]	ETIS-U	False
Optimization2045_Ger*	2045	100%	Germany	ETIS-U	False
Optimization2045_Ger_C	2045	100%	Germany	ETIS-U	True

*Optimization2045_Ger is part of Optimization2045

Further parameters are described for infrastructure modeling at regular intervals and are also valid for the modeling of optimized infrastructure. This is especially true for queuing model parameters. Again, the infrastructure is designed for peak hour traffic. The assumptions regarding energy consumption as well as charging capacity, which serve as plausibility checks for the charging infrastructure at regular intervals, also continue to apply and are used as the basis for investigations of the utilization of the optimized charging infrastructure.

Table 3-8 sums up the most important parameters.

Table 3-8: General input parameters for optimized infrastructure modeling.

Parameter	Abbreviation	Value	Reference
Range in 4.5 h	$range_{BET}$	300 km	Own calculation
Share of charging events in peak hour	$peak\_hour$	6%	Own calculation
Average charging time	$charging_q$	30 min	HoLa (2021)
Average waiting time	w_q	5 min	HoLa (2021)
Electric energy demand	$cons_e$	1.2 kWh/km	Own estimation, based on Kühnel et al. (2018), Speth, Kappler, et al. (2022), and Wietschel et al. (2017)
Average charging power	$p_{average}$	720 kW	Own estimation
Peak charging power	p_{peak}	1,000 kW	Own estimation

[18] Europe: EU27, United Kingdom, Norway, Switzerland

3.5 Techno-economic parameters for market diffusion modeling

Different technical and economic assumptions are needed to model the market diffusion of alternative drivetrains. As shown in chapter 2.3, agent-based simulation is particularly well suited for studying the behavior of individual actors and their interaction. As outlined in subsection 2.3.4, the ALADIN - ALternative Automobiles Diffusion and INfrastructure - model represents a well-established, agent-based simulation framework that is suited for this thesis. However, due to extensive adjustments as described in chapter 4.2, the model is fundamentally rebuilt. Nevertheless, the technical and economic assumptions also generally follow the assumptions of the ALADIN model in the most current version. A current documentation can be found in Plötz, Link, et al. (2023) and Gnann et al. (2023). A complete overview of parameters used in this thesis with brief explanations can be found in the Appendix A.3. In addition, particularly relevant parameters are briefly described below.

All prices and costs are given as $€_{2020}$. All numbers therefore relate to the 2020 price level; in particular no future inflation is taken into account. This means that data from different years are directly comparable.

3.5.1 Framework parameters

Framework parameters are parameters that are not directly related to the vehicles, but influence the market development. This also includes the framework assumptions on the infrastructure development.

3.5.1.1 Energy prices

Due to the high mileage of HDV, the operating costs, and thus also the energy prices, highly influence the economic efficiency of the vehicles (see e.g. Noll et al. (2022) or Speth, Kappler, et al. (2022)). The energy prices in this thesis are basically taken from the long-term scenarios (Gnann et al., 2023). The long-term scenarios are a central study for the Federal Ministry for Economic Affairs and Climate Action (BMWK) in Germany. Gnann et al. (2023) considered three main scenarios that favor different technologies. In this thesis, the most favorable price path is used for each energy carrier, in order not to favor any technology. For BET, this is actually a rather conservative estimate, since they benefit less from low energy carrier prices than other alternatives due to their high energy efficiency. When the long-term scenarios were drawn up, the impact of the war in the Ukraine on the energy prices could only be partially foreseen. While the development for methane and diesel was well estimated, the increase in the electricity price was underestimated. In this thesis, the electricity price is corrected using BDEW (2022). The additional increase is assumed to regress until 2025, similar to increases of other energy carriers. Figure 3-12 shows the assumed energy prices from 2020 to 2050. Additionally, some basic assumptions are summarized in the following[19].

For CO_2 emissions from sectors not covered by the EU emissions trading system (ETS), there is a national CO_2 price added to the fuel costs at pump. According to Gnann et al. (2023) and Sensfuß et al. (2022), the price increases from 25 €$_{2020}$/t in 2021 to 115 €$_{2020}$/t in 2030 and 300 €$_{2020}$/t from 2040 onwards. Additionally, synthetic fuel is blended to the conventional fuels to ensure climate neutrality by 2045. Blending increases to 4% by 2030, to 50% by 2040, and to 100% by 2045. Both effects lead to increasing diesel and methane prices. The given prices are prices at the pump and include taxes, profit, and infrastructure.

Hydrogen is currently used in small quantities in the transport sector. The price was previously capped at 9.5 €/kg including VAT, but was increased to 12.85 €/kg in 2022 (H2 Mobility, 2023). Since the price increase is assumed to be due to the price increase for natural methane gas, the long-term scenarios continue to assume a price cap at 9.50 €/kg. The price cap equals a hydrogen price of 0.24 €$_{2020}$/kWh excluding VAT. In general, a price for synthetic hydrogen is assumed, as soon as the price is lower than the price cap. In the optimistic price path used in this thesis, an additional tax relief is taken into account that corresponds to the tax relief for natural methane gas in road applications in recent years. The given prices are prices at the pump and include taxes, profit, and the construction of a corresponding refueling infrastructure.

In the context of this thesis, an industrial electricity price is assumed for truck charging. BDEW (2022) provides an industrial energy price for sales volumes of 160,000 kWh per year or more. With an average consumption of more than one kWh per km (compare annex A.3) and an annual mileage of approximately 100,000 km per year (compare for example Wietschel et al. (2017) or subchapter 5.2.1.1), the minimum quantity would already be reached with two vehicles. Therefore, it is likely that both trucking companies and charging infrastructure providers will receive industry electricity prices at their locations. It should be noted that the price of electricity for industrial customers in Germany varies depending on power demand and energy demand. In general, high energy demand with low power demand leads to low electricity prices per kWh (BNetzA, 2023c). The rough calculation above shows that a charging station or a depot will be well above the minimum value of the energy demand given in BDEW (2022) for industry customers. Therefore, an average industry price, as provided by Gnann et al. (2023), seems to be a good proxy. Since the charging infrastructure is in the focus of this thesis, the corresponding surcharges are calculated separately (compare subchapter 3.3) and are not part of the electricity price.

[19] The explanations are intended to increase the understanding of the price paths used. They do not represent the entire price modeling. For more details, please refer to Gnann et al. (2023) and the material provided at https://www.langfristszenarien.de.

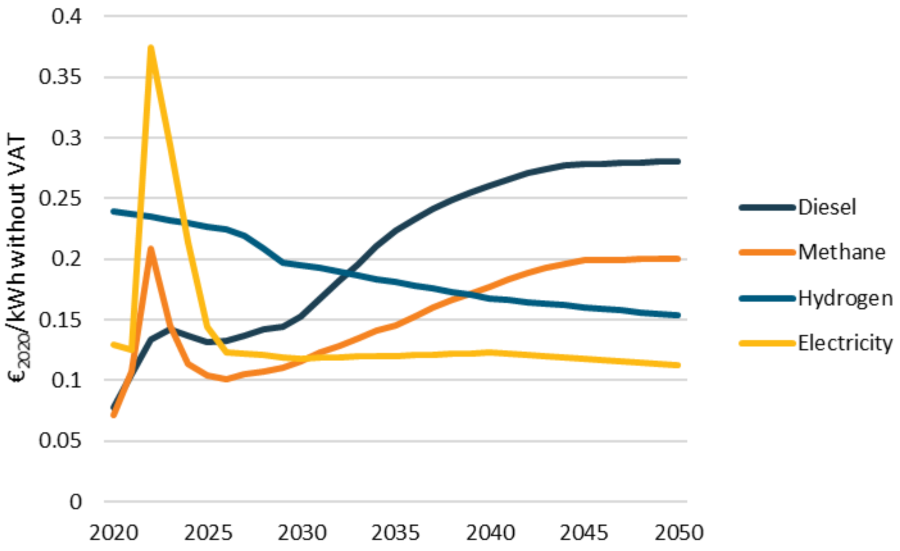

Figure 3-12: Assumed energy prices from 2020 to 2050, based on Gnann et al. (2023).

3.5.1.2 Vehicle availability

As shown in the literature review in subchapter 2.1.2, BET are at least partially competitive from an economic perspective by 2030. This makes the vehicle availability even more important, which reduces the sales share of alternative drivetrains in early years. As outlined in Wietschel et al. (2017), the limited choice of brands and models is a barrier to the diffusion of a new technology. Due to the small number of manufacturers and model variants, an estimate based on model announcements, as shown by Gnann (2015) for passenger cars, is hardly possible for trucks. In the past, logistic curves were estimated for trucks, based on expert guesses for market uptake (Wietschel et al., 2017). However, this is associated with high uncertainties. Instead, manufacturer announcements are used at this point. As part of NOW's cleanroom talks, all major manufacturers were asked about their sales targets for alternative drivetrains in Germany up to 2030 (NOW, 2023). As shown in the literature review in subchapter 2.1.2 in Figure 2-2, their estimate is the highest of all studies[20]. Thus, the manufacturers' estimate represent an upper bound and serve as input to fit logistic curves for the availability of BET and FCET. Equation (3-2) and equation (3-3) represent the curves for BET and FCET, using ordinary least squares (r^2 = 0.99 in both cases).

$$veh_{available}{}_{BET}^{t} = \frac{1}{1 + e^{-\frac{t-2029.1}{2.03}}} \tag{3-2}$$

$$veh_{available}{}_{FCET}^{t} = \frac{1}{1 + e^{-\frac{t-2032.8}{1.72}}} \tag{3-3}$$

[20] It should be mentioned that Tol et al. (2022) is significantly higher, but should be understood as a purely economic estimate of the potential.

NOW (2023) does not show any relevant market shares for GT, but corresponding vehicles are already available today. Therefore, it is assumed that no further development will take place and that the current level from Gnann et al. (2023) remains constant. DT serve as fallback option and are always fully available (Gnann et al., 2023). Figure 3-13 shows the development of the vehicle availabilities. The relative vehicle availability can be interpreted as the realizable proportion of all desired (cost-optimal) vehicles. For example, 60% of all vehicles declared as cost-optimal when being a BEV will be realized as a BEV in 2030. 40% of them will choose a second-best drivetrain, due to limited availability of the vehicles.

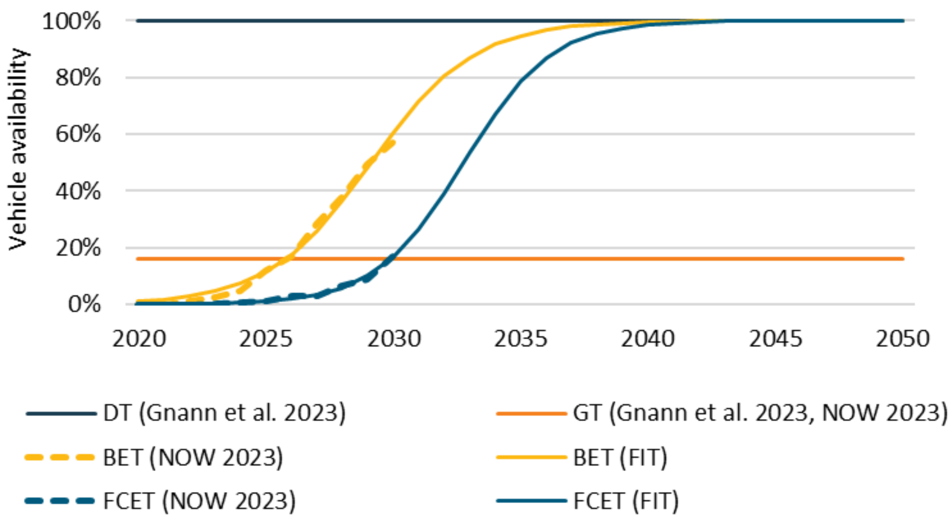

Figure 3-13: Assumed vehicle availability from 2020 to 2050 in the truck diffusion model.

3.5.1.3 Infrastructure

The infrastructure modeling in the pure infrastructure part of this thesis aims to show the possible range of public fast charging infrastructure from different perspectives. The modeling shows how an optimized minimum network with highly used charging locations could look like and how a more comfortable network with regular intervals between stations could be designed. As part of the market diffusion model, infrastructure should continue to be built at locations that are attractive in terms of freight flows and expected utilization. Simultaneously, the network should consider (politically) defined framework conditions. As a guideline, the specifications of the AFIR proposal (EC, 2021) are used. In 2025, the proposal foresees one charging location for 60 km of TEN-T core network and a charging location for every urban node. For Germany, 6,360 km TEN-T core network (CEDR, 2020) and 13 urban nodes (EU, 2013) correspond to 120 charging locations. By 2030, the TEN-T comprehensive network shall be equipped with charging infrastructure at 100 km intervals. Another 40 locations are therefore needed to equip the TEN-T core network (CEDR, 2020). By 2035, it is assumed that the maximum distance of 60 km between service areas in the German highway network (FGSV, 2011) is also achieved on average for charging locations. As an example, Milence - a joint venture of Volvo, Daimler, and Traton, and only one potential charging point operator - has planned at least 1,700 charging points in Europe by 2027 at the latest. Although the number of charging points per location and the share of charging points in Germany are uncertain, the announcement shows the ambitions of at least a part of the industry. German policy also supports a rapid expansion via the National Centre for Charging Infrastructure (NLL) and prepares corresponding tenders for the near future (Lahmann, 2022). Therefore, the targets of the AFIR proposal appear to be ambitious, but achievable for Germany[21]. Since the targets of the AFIR proposal are considered ambitious and will probably even be lowered as part of a final agreement (Bernard, 2023; T&E, 2023), the values for 2025 and 2030 are also interpreted as maximum values.

For the market diffusion model, there is a limit regarding the number of charging points per location. As shown by Kippelt et al. (2022), the maximum usable grid connection within two years at one location is approximately 8 MVA. As shown in subchapter 3.3, this corresponds to 12 charging points. By 2030, it is assumed that the next expansion stage - a maximum of 20 MVA or 30 charging points - can be achieved. According to Kippelt et al. (2022), this corresponds to a new medium voltage connection[22]. To avoid completely new connections to the high voltage grid with realization periods of up to 10 years (Kippelt et al., 2022), 30 MVA or 45 plugs are considered as the maximum from 2035 onwards. Table 3-9 sums up the most important parameters.

Table 3-9: Minimum and maximum number of public fast charging locations in the market diffusion model.

	2025	**2030**	**2035**	**2050**
Minimum charging locations	120	160	220	220
Maximum charging locations	120	160	-	-
Maximum plugs per location	12	30	45	45

For private charging, it is assumed that the vehicle operator is able to install a corresponding infrastructure, if he is able to buy a BET. Accordingly, the infrastructure constraint is implicitly included in the vehicle availability. For public fast charging infrastructure, the development is explicitly modeled in the market diffusion model, as shown in subchapter 4.2.2. Therefore, the availability for slow and fast charging infrastructure at private and at public locations is initially set to 100%.

[21] For comparison: From March 2022 to March 2023, 4,537 new fast charging points (> 50 kW) for passenger cars were built in Germany. By March 01, 2023, 13,714 fast charging points had been established. The stock of fast chargers with at least 300 kW power increased by 1,565 charging points to 3,540 charging points from 2022 to 2023 (BNetzA (2023b)).

[22] See Table 3-3 in subchapter 3.3.

Costs assumptions for slow charging infrastructure - in this thesis up to 44 kW - are based on Basma et al. (2021). Taking into account one charging event per day (33% temporal utilization) per charging point, Basma et al. (2021) calculates 0.038 $€_{2020}$/kWh in 2020 and 0.027 $€_{2020}$/kWh in 2030 for hardware, installation, and maintenance. The reduction is due to slightly decreasing hardware and installation costs. After 2030, constant costs are assumed. For fast charging, including megawatt charging, infrastructure costs are endogenously updated in the model, as described in 4.2.3.4 based on values from chapter 3.3. For initialization, the assumptions from Basma et al. (2021) on fast charging infrastructure are used, which assume 1.223 $€_{2020}$/kWh in 2020 and 0.055 $€_{2020}$/kWh in 2030 for hardware, installation, and maintenance. Basma et al. (2021) assumed a utilization of 1% in 2020 and 16% in 2030. It is evident that a low utilization leads to high initial costs. In accordance with Plötz, Link, et al. (2023), it is assumed that from 2020 to 2025, the infrastructure costs are capped on the level of 2025. Assuming an annual percentage decrease in fast charging infrastructure costs, the costs will amount to 0.26 $€_{2020}$/kWh in 2025. Therefore this value is assumed from 2020 to 2025.

An overview is given in Table A-4 in the appendix.

3.5.2 Technical vehicle assumptions

The parameters used in the ALADIN market diffusion model for trucks are continuously updated, taking into account current literature. Additionally, the assumptions are regularly discussed with industry experts. The parameters used in this thesis were defined mainly in the context of Plötz, Link, et al. (2023) and Gnann et al. (2023). They are documented in Appendix A.3. References to underlying sources are added. However, since this thesis goes beyond the existing status of the ALADIN model with regard to BET, the technical assumptions for the battery are discussed separately. The assumed charging behavior should also be briefly explained at this point.

3.5.2.1 Battery

The needed battery is defined by range requirements. In accordance with currently available models, a minimum distance of 200 km is assumed (Mercedes Benz, 2023; Volvo, 2023a, 2023b)[23]. The minimum distance defines the minimum battery size that is provided, regardless of the range actually required. Additionally, a maximum range - the maximum range that can be provided with one battery charge - is required. For 2020, a range of 250 km is assumed on the basis of current models that provide up to 300 km today (Mercedes Benz, 2023; Volvo, 2023b). Based on Plötz, Link, et al. (2023), an increase to 450 km by 2030 and to 750 km by 2050 is assumed. It should be mentioned that these assumptions are rather conservative, taking current industry estimates between 350 km and 1,000 km by 2030 into account (NOW, 2023). However, to avoid weight loss, more conservative estimates are assumed in this thesis

[23] The references show vehicles that are typical today. For a comprehensive overview of the vehicles available, see ifeu (2023).

(Mauler et al., 2022). Usually, the vehicles will not fully utilize the maximum range. It is assumed that - if possible - a charging stop will be scheduled as soon as 75% of the maximum range would be exceeded. The value is chosen so that by 2030 the usual driving time of 4.5 h can be driven without an interruption. Taking into account a usable battery size of 70% in 2020, 75% in 2030, and 85% in 2050 (Mauler et al., 2022; Plötz, Link, et al., 2023), the battery is finally scaled in 100 kWh modules. The modular design of the battery is already apparent in this order of magnitude (see Mercedes Benz (2023) or Volvo (2023b)).

All numbers can be found in Table A-2 in the appendix.

3.5.2.2 Charging strategy

Initial research suggests that larger batteries can support the market-diffusion more than additional infrastructure (Gnann, Speth, Link, & Plötz, 2022). Therefore, it is assumed that logistics companies will increasingly avoid additional charging stops as the available battery size increases. The model anticipates that a charging stop is scheduled, if the distance driven with the next trip to be completed exceeds 75% of the maximum range of available batteries. To avoid charging during short trip interruptions, 30 min is assumed to be a realistic minimum parking time for recharging.

With regard to the charging power, it is assumed that charging with the MCS standard will be possible after 2025. This means that the average charging power will be higher than 350 kW typical today for the CCS standard. From 2030 onwards, it is assumed that the average charging power will be sufficient to recharge the maximum range in 30 min (CharIN, 2023; HoLa, 2021).

As shown by Borlaug et al. (2021), the flattest load curve results from constant charging at minimum power, so that the vehicle is fully charged at the start of the next trips. In order to keep the grid connection as small as possible, this charging strategy is implemented in this thesis.

More details on the assumptions can be found in Table A-2 in the appendix. The implementation of the charging strategy is described in subchapter 4.2.

3.5.3 Economic vehicle assumptions

Similar to the technical vehicle assumptions, the economic vehicle assumptions rely on the latest version of the ALADIN market diffusion model and are documented in Appendix A.3. Therefore, only some basic ideas are shown in the following.

3.5.3.1 Vehicle investment

The vehicle investment is composed of different vehicle parts (see Speth, Kappler, et al. (2022) for more information). The individual component costs are documented in Appendix A.3. As an example, Figure 3-14 shows the resulting purchase prices and the residual values for a tractor-trailer truck with a GVW of more than 12 t for all drivetrains under investigation. It can be clearly seen that the DT is the most cost-efficient alternative in terms of investment. The GT has a very similar cost structure, but requires an additional compressed gas tank. The FCET also requires an additional tank for liquefied hydrogen. Although the hydrogen tank is more expansive than the gas tank per kWh, it can be dimensioned smaller due to the higher efficiency of the FCET. The BET requires a battery that can vary in its size, depending on the desired range. The technically assumed range is between 300 kWh and 700 kWh in 2030, and between 300 kWh and 900 kWh in 2050. The effects on the vehicle investment are shown as color gradient. The FCET also has a buffer battery. Overall, the BET and the FCET are still more expensive than the DT in 2030, but this is offset by the assumed continuation of the purchase price reduction of 80% of the additional costs compared to the DT (BaLM, 2023). This support is no longer taken into account after 2030. However, the difference to the DT decreases for both the FCET and the BET - depending on the battery size - by 2050.

Following Kleiner and Friedrich (2017) and in consultation with experts from the automotive industry (Plötz, Link, et al., 2023), a relative residual value of 25% of the investment is assumed. Due to the batteries, there is a high uncertainty regarding the residual values of BET and FCET. For this reason, it is also conservatively assumed that the purchase price premium, which is basically to compensate for the high costs and the uncertainty of the new technology, is not considered for the residual value.

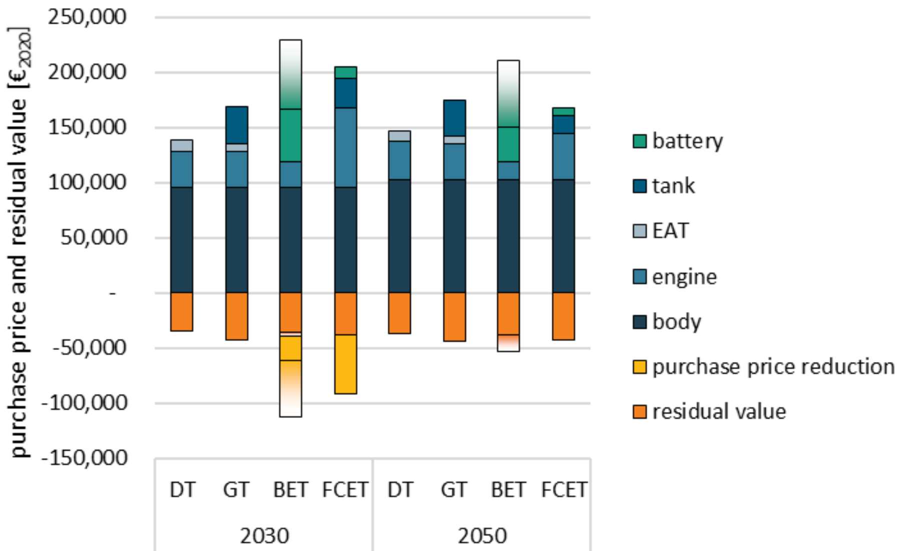

Figure 3-14: Tractor-trailer (> 12 t GVW) purchase price and residual value for 2030 and 2050. Shaded bars indicate different battery ranges.

3.5.3.2 Operating costs

In addition to fuel costs (see subchapter 3.5.1.1), the operating costs include operation and maintenance, road tolls, vehicle taxes, and insurance.

Based on Speth, Kappler, et al. (2022) and taking into account Basma et al. (2021), LastAutoOmnibus (2018), Wietschel et al. (2017), Jöhrens et al. (2018), and Marcinkoski et al. (2019), GT are assumed to have a small cost advantage over DT in terms of operation and maintenance. For BET, the cost advantage is higher, due to the simpler vehicle, and especially engine, structure. FCET can also achieve cost benefits in the 2050 perspective.

The considered road toll is based on Toll Collect (2023). The introduction of a CO_2-dependent toll, as suggested by Deutsche Bundesregierung (2023), is not implemented. Up to now, the CO_2-dependent toll has been discussed with a corresponding reduction of the CO_2-dependent part of the fuel costs to avoid double taxation (Umweltbundesamt, 2021). Since a CO_2-price is part of the fuel costs in this modeling, the toll does not contain a CO_2-dependent part. At the beginning, GT, BET, FCET are still partially exempt from tolls. In the long term, only BET and FCET are exempt from the air pollution factor, which is a small part of the total toll.

Vehicle insurance and taxes are included according to today's usual values. All number can be found in Table A-3 in Appendix A.3.

4 Model development

This thesis contains two main topics: (1) The development of a possible German- and Europe-wide public fast charging infrastructure, and (2) the influence of a German public fast charging infrastructure on the market diffusion of BET in Germany and vice versa. Therefore, two modeling approaches for a public fast charging infrastructure are described below, followed by a model for the coupling of the market diffusion of BET with a further adopted infrastructure model. While the pure infrastructure modeling picks specific scenarios that can be associated with a given point in time (see chapter 3.4), the coupled diffusion of vehicles and infrastructure is modeled on yearly basis.

4.1 Infrastructure models

As shown in section 2.2, there are at least three major options to model charging infrastructure for battery electric vehicles. In this thesis, two approaches are applied. First, the infrastructure is considered at regular intervals, as proposed by the EC (EC, 2021). As proposed in node-based models, local demand - in other words the local traffic volume - serves as a proxy for sizing the single charging locations. Second, an FRLM determines the optimal - in this case the minimum - number of charging locations. Due to the international nature of road freight transport, both Europe[1] and Germany are considered. As described in subchapter 2.2.4, comparing the node-based and the path-based approach can lead to a better understanding of infrastructure needs and identify critical parameters.

4.1.1 Infrastructure at regular intervals[2]

The methodological procedure to calculate a charging infrastructure network with regular intervals between the charging locations is divided into two major steps: First, the charging locations are determined and charging events are distributed to the charging locations. Second, the number of charging points per charging location is calculated. Figure 4-1 provides an overview of the methodological procedure.

[1] Europe: EU27, United Kingdom, Norway, Switzerland.

[2] Parts of this subchapter are based on Speth, Plötz, et al. (2022) and Speth, Sauter, and Plötz (2022).

Step 1: Define charging locations:

1. For each road:
   i. Position charging location every d_{avg} km along the road (equation (4-1))
2. Calculate the total number of charging events in the considered area (equation (4-2))
3. For each positioned charging location:
   i. Determine the maximum traffic in one of the subsections within the section that is covered by the charging location
   ii. Determine the share of charging events at the location by comparing the maximum traffic in the section of the charging location to the sum of maximum traffics in all sections (equation (4-3))
   iii. Multiply the local share of charging events by the total number of charging events to calculate the number of local charging events (equation (4-3))

Step 2: Define charging points per location:

1. For typical number of charging points (e.g. 1 ... 100):
   i. Using queuing theory, calculate the number of vehicles that can be served per hour
2. For each positioned charging location:
   i. Multiply the number of local charging events by the share of peak hour traffic to determine peak hour traffic at the location
   ii. Choose the number of charging points so that peak hour traffic at the location is less than the number of vehicles that can be served by the local charging points

Figure 4-1: Procedure description for infrastructure modeling at regular intervals (Speth, Sauter, & Plötz, 2022).

4.1.1.1 Determination of charging locations

In Europe, odd numbers indicate roads from north to south, even numbers indicate roads from east to west. This applies to German highway numbers as well as to the European E-road numbers. Following S. Á. Funke (2018) every single road is traversed successively one after another in ascending order. Each node in the considered road network serves as a possible charging location. Locations are positioned at regular intervals. If the distance to the last charging location exceeds the defined distance between two charging locations, a new location is introduced. Equation (4-1) shows this approach, where CL_L is a bivariate variable indicating whether infrastructure is built in L or not. $d_{CL,L}$ indicates the distance between the last positioned charging location and location L. d_{avg} defines the distance between two charging locations in the network. It is assumed that one charging location can serve both directions of travel.

$$CL_L = \begin{cases} 1, if\ d_{CL,L} \geq d_{avg} \\ 0, else \end{cases} \tag{4-1}$$

The procedure for the first and the last charging location of a highway section is slightly different. To consider highway changes, the distance to the end or the start of the considered highway is half of d_{avg}. Highways with a total length of less than 25 km, typically urban highways, are not considered for charging locations.

Equation (4-2) gives the total number of daily public charging events in the considered area, for example Europe or Germany. BET_{share} stands for the share of BET on the total cumulative annual mileage AM_{total} of all HDV. The annual mileage is divided by 313 to derive daily mileage, excluding Sundays. $range_{BET}$ refers to the range that a truck can cover in 4.5 hours of driving. This corresponds to the maximum driving time, before a mandatory break is required. Finally, only the share of public charging events CE_{public} is considered.

$$CE_{total,public} = \frac{BET_{share} * (AM_{total}/313)}{range_{BET}} * CE_{public} \tag{4-2}$$

Finally, the expected daily public charging events have to be allocated to individual charging locations. According to S. Funke and Plötz (2017), the local traffic volume serves as proxy for the local charging demand. The maximum traffic volume in the area in front of and behind the location is calculated and compared with the total maximum traffic volume of all locations. The number of trucks in both directions is considered together. This means that one location can serve both directions.

Equation (4-3) describes the calculation of the daily charging events at each realized charging location. $MAX_{CL_{i-0.5}}^{CL_{i+0.5}}(TV_j)$ describes the maximum traffic volume of all subsection j on half the distance between the realized charging location i and the realized station before this location $CL_{i+0.5}$ and half the distance to the subsequent location $CL_{i+0.5}$. The individual maximum traffic volume is set in relation to the sum of all maximum traffic volumes of all realized stations.

$$CE_{CL_i} = CE_{total,public} * \frac{MAX_{CL_{i-0.5}}^{CL_{i+0.5}}(TV_j)}{\sum_{CL_i} MAX_{CL_{i-0.5}}^{CL_{i+0.5}}(TV_j)} \tag{4-3}$$

Figure 4-2 shows a simplified draft to visualize the procedure.

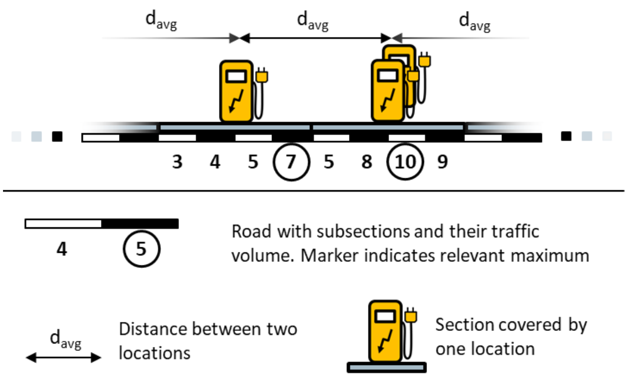

Figure 4-2: Simplified draft for infrastructure modeling at regular intervals. Based on Speth, Sauter, and Plötz (2022).

4.1.1.2 Dimensioning of charging locations

Following the explanations in chapter 2.2.3, the calculation of the number of charging points per location is based on queuing theory. To define a queueing system, the time between arrivals (A), the service time distribution (S), the number of service channels - or charging points - (c), the discipline of the queue (d), the capacity of the queue (k), and the number of jobs to be served (m) need to be defined. Typically, the Kendall notation (A/S/c/d/k/m) is used.

In accordance with Gnann et al. (2018), Poisson-distributed arrivals characterize the arrival process. The average arrival rate is defined as follows:

$$\lambda_{CL_i} = CE_{CL_i} * peak\_hour \tag{4-4}$$

CE_{CL_i} represents the daily charging events at the realized location i. For the charging location dimensioning, the share of charging events that happens during the peak hour $peak\_hour$ is considered. The inter-arrival times A are therefore exponentially distributed (Markovian Distribution M). This means A = M.

With regard to the service time distribution S, Gnann et al. (2018) showed that a General distribution G with normally distributed service times fits quite well. The average number of customers served per period is defined by µ. For example an average charging time $charging_q$ of 30 min results in an average service rate µ = 2 trucks/hour.

The number of service channels c - charging points - shall be calculated. For D, k, and m, the default values are assumed. The queue's discipline d follows the first-in-first-out principle. This means that the trucks are served in the order of their arrival. The number of customers waiting in the queue k is assumed to be infinite. The same applies to the number of customers - jobs to be served - in total. In summary, the queuing system is defined as M/G/c system. Since exact solution for the mean waiting time of M/G/c systems are not known, the mean waiting time is approximated, according to S. Á. Funke (2018):

$$W_q^{M|G|c} = \frac{C^2 + 1}{2} W_q^{M|M|c} \tag{4-5}$$

C is defined as the variation coefficient of the distribution of the service times, i.e. the standard deviation w_q divided by the mean value of the service time distribution $charging_q$. This formula is used with the waiting time of the original M/M/c system, given in equation (4-6):

$$W_q^{M|M|c} = \frac{1}{1-\rho} \frac{1}{c\mu} \frac{(c\,\rho)^c}{c!} \left((1-\rho) \sum\nolimits_{n=0}^{c-1} \frac{(c\rho)^n}{n!} + \frac{(c\rho)^c}{c!} \right)^{-1} \quad with\ p = \frac{\lambda}{c\mu} \tag{4-6}$$

Finally, we calculate the maximum average arrival rate λ that allows for an average waiting time w_q of 5 minutes for all possible numbers of charging points c. For each location, we compare the local average arrival rate λ_{CL_i} to the arrival rates with different c. Afterwards, we can choose the number of charging points c for each location so that the average waiting time is less than 5 minutes. Annex A.4 shows the maximum number of vehicles that can be served by a certain number of charging points. An average waiting time of less than five minutes does not mean that all vehicles wait exactly five minutes. There is a distribution of waiting times. For an exemplary arrival rate of λ = 4 trucks/hour and an average service rate of μ = 2 trucks/hour, c = 4 charging points are required to achieve an average waiting time of less than 5 minutes. The average waiting time of less than 5 min is achieved by the fact that the vast majority of trucks (~ 83%) does not have to wait at all, a few trucks (~ 8%) have to wait up to 5 minutes or 5 - 15 minutes (~ 7%), and very less (2%) have to wait longer than 15 minutes.

4.1.2 Optimized charging infrastructure network[3]

This thesis contains two types of optimized network modeling approaches. First, a Europe-wide FRLM is calculated. On the one hand, the resulting network serves as the minimum usable infrastructure for international transports outside Germany. This is essential, as otherwise, the infrastructure in the transit country Germany is overestimated. On the other hand, it represents a benchmark for Germany, to be able to assess the impact of a capacity restriction. Second, a new formulation of a CFRLM considers parking capacities. The CFRLM is limited to Germany, due to the computational effort.

4.1.2.1 Problem formulation FRLM

The FRLM without capacity restriction follows the approach presented by Capar et al. (2013) and used by Jochem et al. (2019). Whenever necessary, the assumptions by Capar et al. (2013) are slightly adjusted and new assumptions are added. In the following, italic font highlights the adjustments:

1. Traffic between an OD pair follows a single path from the center of the origin area to the center of the destination area.
2. The traffic volume for every single origin-destination path is known in advance.
3. Drivers have full knowledge of locations of charging locations along the path and recharge efficiently *to complete a single trip*.
4. Only nodes of the network are considered as possible locations of charging locations.
5. All trucks have similar driving ranges.
6. The fuel consumption is directly proportional to the distance traveled.
7. All potential recharging locations are uncapacitated.
8. *Each truck starts the trip fully charged and can be recharged at the destination.*

The first assumption corresponds to the original model. As suggested by Capar et al. (2013), the shortest paths, provided by the ETIS-U dataset, serve as input. Since only the ETISplus road network is modeled, the proposed travel distances to and from the center of the origin and destination region are also considered. The second assumption also corresponds to the original model. As indicated by the third assumption, the modeling assumes a vehicle to complete a

[3] Parts of this subchapter are based on Speth et al. (2024). This publication is still under review at the time of submission of this thesis.

single trip instead of a round trip. As explained by P. Rose (2020), a single trip better characterizes truck driving behavior than the originally assumed round trip. Assumption 4 also follows the original problem formulation, even if this is a simplified representation of reality. However, identifying real parking locations across Europe would be very complex. The following assumptions 5 to 7 are also taken from the original model. As indicated by P. K. Rose et al. (2020), waiving the assumption of a roundtrip requires an assumption regarding the charging behavior at the origin and destination of the trips. Assumption 8 assumes that charging infrastructure is available at every depot and therefore trucks can be fully charged at the origin and the destination. This also implies that trips with a distance shorter than the vehicle range do not have to be taken into account. The formulation of the uncapacitated FRLM reads (Capar et al., 2013; Jochem et al., 2019; P. K. Rose et al., 2020):

$$\min \sum_{i \in N} z_i \tag{4-7}$$

s.t.

$$\sum\nolimits_{i \in K_{i,j}^{q}} z_i \geq y_q, \qquad \forall q \in Q, a_{j,k} \in A_q \tag{4-8}$$

$$\sum\nolimits_{q \in Q} f_q y_q \geq s \sum\nolimits_{q \in Q} f_q \tag{4-9}$$

$$y_q, z_i \in \{0, 1\}, \qquad \forall q \in Q, i \in N \tag{4-10}$$

Sets and indexes

A_q	Set of all directional arcs on a shortest path q, sorted from the origin to the destination
$K_{i,j}^{q}$	Set of all potential nodes that can refuel the arc $a_{j,k}$ in A_q
N	Set of all nodes in the modeled network
Q	Set of all origin-destination pairs
i, j, k	Indices, indicating nodes
q	Index of origin-destination pairs
$a_{j,k}$	Index of a directed arc from node j to node k

Parameters

f_q	Vehicle flow at path q
s	Share of recharged vehicle flows, in this modelling always 1

Decision variables

y_q	=1 if the flow on path q is recharged, 0 otherwise
z_i	=1 if a charging station is built at node i, 0 otherwise

Equation (4-7) formulates the objective to minimize the number of charging stations (z_i) at all nodes i in the network. The constraint in equation (4-8) ensures that a path can only be recharged ($y_q = 1$), if there is a charging infrastructure for each arc in the path ($a_{j,k}$) that makes it possible to pass the arc. For this, a candidate set ($K_{i,j}^q$) is calculated for each arc ($a_{j,k}$) of a trip (q). As an example, this is shown in Figure 4-3. For example, assuming a range of 300 km, the arc $a_{4,5}$ can only be passed, if a charging station is established at one of the nodes 2, 3, or 4 ($K_{4,5}^{example} = \{2, 3, 4\}$). Equation (4-9) ensures that a certain share (s) of all vehicles flows (f_q) can be realized. In this thesis, it is assumed that all paths must be realized[4]. As shown in Figure 4-3a, four possible solutions exist for the example path, each with two stations to be built. Which solution is realized, depends on which potential stations are also located favorably for other paths.

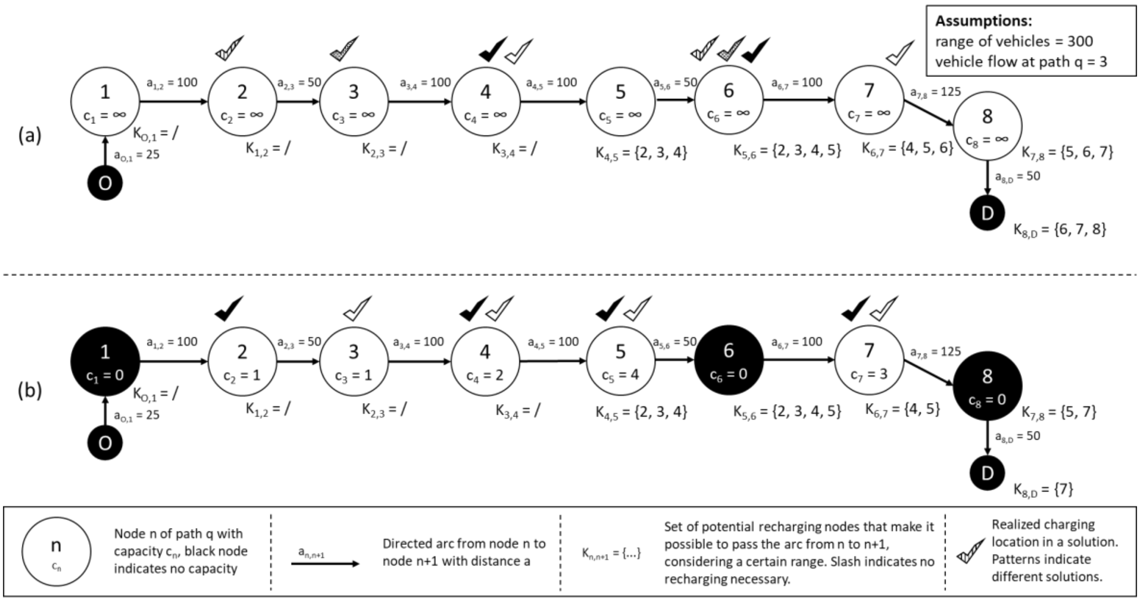

Figure 4-3: Illustration of an origin-destination path with (b) and without (a) a capacity restriction. Originally published in Speth et al. (2024).

4.1.2.2 Problem formulation CFRLM

This section presents the CFRLM to calculate the optimized German charging infrastructure network. First, new assumptions are introduced. Afterwards, the section contains the actual formulation of the mixed-integer optimization problem (MIP). Finally, the model is explained, using an example path, and special effects are addressed.

The assumptions 1, 2, 3, 5, 6, and 8 remain unchanged and are consistent with the assumptions of the FRLM in subsection 4.1.2.1. Adjustments to assumptions 4 and 7 introduce the capacity constraint. Thereby, each node in the road network receives as capacity limit. The new formulation is shown in the following:

[4] This means $y_q = 1 \; \forall q \in Q$. Thus, equation (4-9) can be omitted and equation (4-8) becomes $\sum_{i \in K_{i,j}^q} z_i \geq 1 \; \forall q \in Q, a_{j,k} \in A_q$. However, the original formulation from the literature is kept for comprehensibility.

4. *Only nodes with an assigned parking capacity are considered as locations of potential charging stations.*
7. *All potential recharging stations are capacitated.*

In the following, the new formulation is presented:

$$\min \sum_{i \in N} z_i \tag{4-11}$$

s.t.

$$\sum\nolimits_{i \in K_{i,j}^{q_s}} x_{i_{q_s}} \geq 1, \qquad \forall q_s \in Q, a_{j,k} \in A_{q_s} \tag{4-12}$$

$$\sum\nolimits_{q_s \in Q} f_{q_s} x_{i_{q_s}} \leq cap_i z_i, \qquad \forall i \in N \tag{4-13}$$

$$\sum\nolimits_{i \in N} x_{i_{q_s}} \leq l_{q_s}, \qquad \forall q_s \in Q \tag{4-14}$$

$$x_{q_s}, z_i \in \{0, 1\}, \qquad \forall q_s \in Q, i \in N \tag{4-15}$$

Sets and indexes

A_{q_s}	Set of all directional arcs on a shortest path q_s, sorted from the origin to the destination
$K_{i,j}^{q_s}$	Set of all potential nodes that can refuel the arc $a_{j,k}$ in A_{q_s}
N	Set of all nodes in the modeled network
Q	Set of all origin-destination pairs
i, j, k	Indices, indicating nodes
q_s	Index of origin-destination pairs. Extended to identical origin-destination pairs for each subset. Flows are split, if the vehicle flow exceeds the capacity of a single parking space.
s	Index, indicating a subset of a path q
$a_{j,k}$	Index of a directed arc from node j to node k

Parameters

f_{q_s}	Vehicle flow at path q_s in $peak\_hour$
cap_i	Capacity restriction in node i
l_{q_s}	Number of maximum stops to drive path q_s

Decision variables

$x_{i_{q_s}}$	=1 if the flow on path q_s is recharged at node i, 0 otherwise
z_i	=1 if a charging station is built at node i, 0 otherwise

Again, the objective function (equation (4-11)) minimizes the number of charging stations (z_i). As described by Upchurch et al. (2009) and Böhle (2021), it is not sufficient for the capacity-constrained infrastructure to ensure that every arc on a path can be traveled (equation (4-8)). Instead, it must be determined which vehicle uses which charging location. Therefore, the bivariate parameter $x_{i_{q_s}}$ indicates, if the path q_s is recharged at node i. Equation (4-12) ensures that each arc of a path is drivable by requiring the path's vehicles to recharge at least at one candidate set location. Similar to the FRLM and as shown in Figure 4-3(b), the candidate sets $K_{i,j}^{q_s}$ contain all nodes that make an arc drivable, as long as the node is a suitable charging location. The hourly maximum number of vehicles that can be served in the peak hour at node i (c_i) is calculated using queuing theory based on the methodology presented in section 4.1.1.2 and with assumptions given in 3.4.2. Equation (4-13) ensures that no more vehicles charge at a node i in the peak hour than the capacity cap_i allows. Therefore, f_{q_s} is defined as vehicle flow in the peak hour. For this purpose, the annual traffic volume on path f_{q_s} from the ETIS-U dataset is equally distributed over 250 working days and multiplied by the share of traffic in the peak hour $peak\_share$. In addition, charging is only possible, if a location is opened in node i ($z_i = 1$). Equation (4-14) limits the maximum number of charging stops on one origin-destination-tour. As shown in Figure 4-3, capacity constraints may necessitate additional stops. In the example, all vehicles need to recharge in node 7 to reach the destination. Node 7 can be reached by recharging either in node 4 or in node 5. Since the capacity in node 4 is not sufficient for all vehicles, some vehicles have to recharge in node 5 and therefore need to stop in either node 2 or node 3 to reach node 5. This means that some vehicles have to stop three times to cover 700 km, although they have a range of 300 km and start with a fully charged battery. Therefore, the model allows one additional stop and calculates the maximum number of stops l_{q_s} according to equation (4-16).

$$l_{q_s} = \left\lfloor \frac{distance_{q_s}}{range_{BET}} \right\rfloor + 1, \qquad \forall (q_s \in Q) \cap (distance_{q_s} > range_{BET}) \tag{4-16}$$

l_{q_s}	Number of maximum stops to drive path q_s
$distance_{q_s}$	Length of path q_s
$range_{BET}$	Vehicle range within one driving session of 4.5 h

Due to the increased computational effort and the incomplete Europe-wide data on available parking capacities, the CFRLM is restricted to Germany. This means that paths are taken into account, if their distance is longer than the assumed minimum range of 300 km and if they are driven at least partially in Germany. For cross-border traffic, it is assumed that vehicles can use the foreign charging stations calculated by the FRLM. Thus, the origin of the path is considered to be the last charging station before the border, and the destination is the next charging station after the border.

To solve the problems, a server with 196 GB RAM and 8 cores is used. The implementation is done in Python 3.10, integrating the solver CPLEX 12.6 via Pyomo. Depending on the parameter selection and the accepted tolerance to the theoretically possible optimum, the runtime is several days to weeks.

4.1.3 Infrastructure costs determination

As shown in equation (4-17), the total investment for public fast charging infrastructure at a time t in a scenario c_{infra}^{t} can be calculated as the sum of the investment for the single charging locations $c_{CL_i}^{t}$. The investments for the individual charging locations can be determined as a function of the number of charging points and the time of realization t, as shown in section 3.3.

$$c_{infra}^{t} = \sum\nolimits_{CL} c_{CL_i}^{t} \tag{4-17}$$

The same approach can be used for the annual costs of infrastructure.

To calculate the infrastructure costs per kWh, the annual costs can be divided by the total amount of electricity delivered by the infrastructure. The amount of energy results from the days of use of the infrastructure $days$, the daily charging events CE_{CL_i}, the recharged distance $range_{BET}$, and the energy consumption per km $cons_e$. Equation (4-18) sums up the calculation for the infrastructure costs per kWh when modeling infrastructure at regular intervals. For the optimization approach, the recharged distance depends on the previous stop and needs to be calculated for every charging event from the results of the optimization. However, the approach is identical.

$$c_{infra,annual}^{t,levy} = \frac{\sum_{CL} c_{CL_i,annual}^{t}}{\sum_{CL}(days * CE_{CL_i} * range_{BET} * cons_e)} \tag{4-18}$$

4.1.4 Discussion

As shown in subsection 2.2, a path-based FRLM is the most detailed type of modeling, given the available data. The formulation of the CFRLM used in this thesis determines the exact location for each charging event. This allows to calculate the exact amount of energy required at each location and to check the compliance with the capacity constraint highly detailed. However, this increases the computational effort. To the best of the author's knowledge, the thesis is the first to apply a (C)FRLM to a dataset with up to 375,000 OD paths. Due to the computational effort, a scenario analysis with multiple scenarios or a detailed sensitivity analysis is hardly possible. Instead, an additional approach places public fast charging infrastructure at regular intervals and estimates the local charging demand based on the local traffic. In contrast to the optimizing FRLM, this approach cannot determine the minimum number of locations required. Additionally, the approach considers any traffic that passes a location as a basis for the charging location dimensioning. This may overestimate public charging needs at locations with a high proportion of regional traffic. Compared to the FRLM, placing infrastructure at regular intervals is computationally simple and therefore well suited for sensitivity analysis. The combination of both approaches therefore allows both the analysis of minimum scenarios and the modeling of various plausible expansion paths, supplemented by sensitivity analyses. Thus, both approaches allow for the first time to estimate regionally resolved public charging infrastructure needs for BET in Europe and Germany.

4.2 Market diffusion model

As shown in chapter 2.3, agent-based modeling is particularly well suited for the purpose of this thesis. The ALADIN model - ALternative Automobiles Diffusion and INfrastructure - is a well-established agent-based simulation model for the transport sector in Germany. The aim of this chapter is to introduce a new, extended version of the ALADIN model for the diffusion of HDV. The bottom-up simulation model calculates market diffusion scenarios for passenger cars and HDV from now until 2050 in yearly steps. Geographically, the model refers to the German vehicle fleet. As shown by Plötz et al. (2019), the total mileage of German trucks is approximately equal to the total mileage of trucks in Germany. Therefore, the model also allows statements regarding the expected energy demand in Germany. Additionally, model extensions allow the consideration of the European truck fleet. Originally, the HDV diffusion model was developed to estimate the potential of overhead catenary HDV (Wietschel et al., 2017). However, the model may also consider GT, FCET, and BET as potential alternatives to DT. Most recently, the model has been widely used for market diffusion scenarios for policy, for example for the long-term scenarios of the German Federal Ministry for economic Affairs and Climate Action (Gnann et al., 2023), and industry, for example for the European Automobile Manufacturers' Association (Plötz, Link, et al., 2023). However, the model represents public charging infrastructure for BET highly simplified and requires methodological adjustments for the purpose of this thesis.

The market diffusion model presentation is divided into four steps. First, the existing model is briefly described and shortcomings are shown. Second, a model overview of the new model is given. Third, a more detailed description, including mathematical details, is presented. Finally, a brief discussion points out the advantages of the new model, but also potential for further improvements.

4.2.1 Overview of the existing model and potentials for adaptions

The ALADIN model is an agent-based model (ABM). Individual vehicles, or - even more precisely - driving profiles, are considered as agents. The vehicles recorded in the KiD dataset (WVI et al., 2012a) serve as the basis. As described in Wietschel et al. (2017) or - more recently - in Wietschel et al. (2021), the model for HDV follows a three-step procedure. As shown in Figure 4-4, the model starts with a technical analysis, followed by a TCO analysis, and a stock model. The first and the second step take place separately for each driving profile - in other words for each agent - individually. The third step aggregates the results for the whole HDV fleet.

Figure 4-4: Substeps of the existing ALADIN model for HDV.

For each driving profile, the daily mileage from the KiD dataset - approximately profiles from 2,500 HDV with a GVW higher than 12 t - is given. For the purpose of the technical analysis, it is assumed that each BET can recharge privately once a day. Taking into account the exogenously specified battery size, the depth of discharge, and the energy consumption per kilometer, the vehicle range can be calculated. From a technical perspective, the use of a BET is possible, if the vehicle range is higher than the daily mileage. In recent publications, for example Gnann et al. (2023) or Plötz, Link, et al. (2023), public charging is also considered. A ramp-up of public charging infrastructure is exogenously specified, which defines how much the infrastructure increases the vehicle range. An assumption is made that a fully developed infrastructure, based on the approach in chapter 4.1.1, can double the range of all vehicles. Implicitly, fast charging is allowed once a day. If the infrastructure is only half built, the range increases by 50%. Similar approaches are used for overhead catenary trucks. However, since overhead catenary trucks are not part of this thesis, please refer to Wietschel et al. (2017) for further information. The described approach of the technical analysis has some disadvantages: (1) The use of the daily mileage. For the usability of a BET, it is less relevant whether the vehicle stays below a certain daily mileage; it is more relevant whether the vehicle has the time and the opportunity to recharge the battery between single trips. (2) The exogenously given battery size. The specification of a battery size - typically an average of the available models in the market - means that some vehicles have significantly oversized - and therefore expensive - batteries, while in other cases the range is insufficient. (3) The exogenously given public infrastructure and its influence on the vehicle range. The given infrastructure can only represent an average case. For example, a half-built infrastructure may double the range for some vehicles, but is not usable for other vehicles.

As a second step, the TCO for each driving profile and each possible drivetrain is calculated. On the one hand, annual capital expenditures a^{capex} are considered. On the other hand, annual operating expenditures $a^{opex}$are taken into account as well[5]. As input parameters, the model considers - inter alia - vehicle prices, battery prices, fuel cell prices, but also energy carrier prices, costs for operation and maintenance, and vehicle toll. Subsidies and other policy measures can also be considered as part of the vehicle costs. Infrastructure costs are also relevant and can be taken into account, for example as part of the energy price. Finally, the cheapest drivetrain for every driving profile can be determined. Again, there is potential for improvements: The costs for infrastructure are determined exogenously and are independent of the actual need for infrastructure for the single driving profile.

[5] For an introduction into accounting, see Wöhe et al. (2020).

Finally, the stock model aggregates the single driving profiles to a market diffusion. Since ALADIN is not an integrated assessment model, the development of future registrations is based on exogenous sources. For example, the registrations in Gnann et al. (2023) are based on calculations from the AsTra model (TRT et al., 2023). The driving profiles analyzed in the previous steps serve as a cross-section of the market and are scaled so that the given number of registrations in every year can be met. In other words, every driving profile represents a certain number of vehicle registrations. Considering the results from the TCO-analysis, the cheapest drivetrain is selected. However, especially in an early market phase, demand cannot be fully met. Due to a reduced number of offered models, only some of the user decide for an alternative drivetrain, even if it is the most economic option (Wietschel et al., 2017). The remaining user represented by the driving profile choose the second best option. Taking into account the exogenously given service life, the vehicle stock can be calculated based on the annual registrations. There is also the possibility to improve the stock model. As shown in section 2.3.2, insufficient infrastructure inhibits the market diffusion of alternative drivetrains similar to unavailable vehicle models. So far, both have been modeled using a joint estimation. However, detailed infrastructure modeling allows both effects to be considered separately.

4.2.2 Model overview of the adapted model[6]

In the following, a short description of the adapted model is given. A more detailed mathematical description can be found in subchapter 4.2.3.

The ALADIN model is designed as an agent-based model (ABM). ABM is especially suitable "[...] when the population is heterogeneous, when each individual is (potentially) different." (Bonabeau, 2002, p. 7287). In the ALADIN model, the individual agents - represented by different driving profiles from the KiD (WVI et al., 2012a) - behave differently in terms of their driving behavior. The driving behavior includes the daily mileage, but also driving and parking times. Moreover, the agents interact with each other regarding the need for public charging infrastructure (Gnann, 2015). This is a second criterion for the use of agent-based simulation (Bonabeau, 2002; Hare & Deadman, 2004). However, the ALADIN model for HDV has been used a simplified agent-based approach in the past. On the one hand, each agent was defined exclusively by its daily mileage. On the other hand, the interaction between the agents, in terms of public infrastructure needs, has been modeled as an exogenous factor. The revised version of the ALADIN model for HDV presented in this thesis therefore extends the ABM both at the level of the user-centric analysis - the individual technical and economic vehicle simulation -, and on the level of the aggregated analysis - formerly the vehicle stock model.

In this thesis, the simulation covers the period from 2020 to 2050. The technical analysis, the economic analysis, and the stock analysis are performed for each year. The infrastructure

[6] Parts of this subchapter are based on Speth and Plötz (2024).

analysis is performed in 5-year-steps, starting in 2025. The fast charging infrastructure is modeled as an evolving charging infrastructure according to the CFRLM approach.

Figure 4-5 shows the structure of the adapted ALADIN model for HDV. The single parts of the model are described in the following.

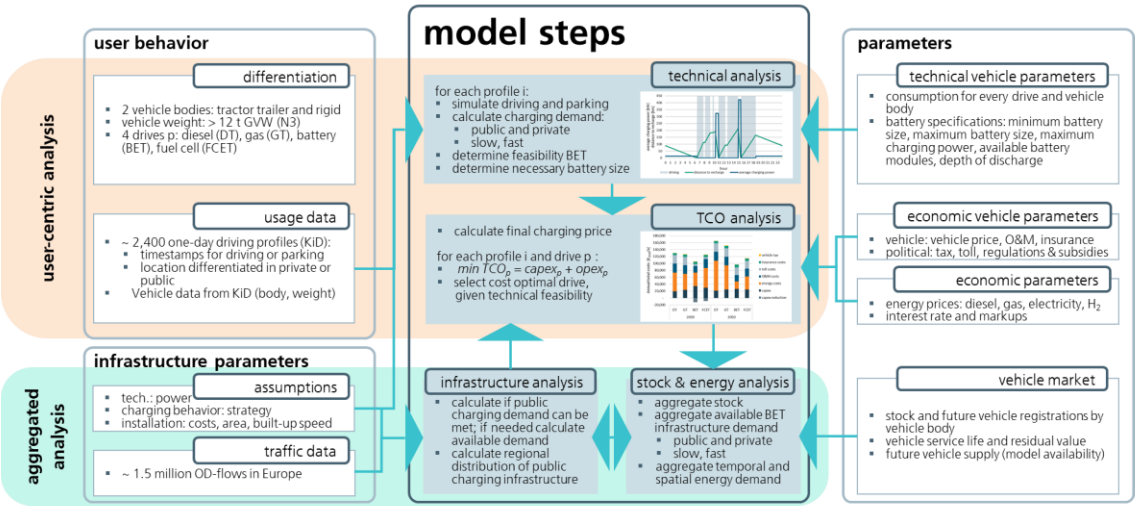

Figure 4-5: Overview of the adapted ALADIN - Alternative Automobiles Diffusion and Infrastructure - model for HDV.

The model fundamentally continues to follow the three-stage approach described in section 4.2.1 and shown in Figure 4-4. However, an infrastructure analysis is added and there are feedbacks between different model stages.

The first step of the model, the technical analysis, is especially relevant for BET. For all other drivetrains - DT, GT, and FCET-, the model assumes no technical restriction, due to higher ranges and faster refueling possibilities. The technical analysis is based on different technical vehicle parameters. For example, the average energy consumption per km and various parameters for the sizing of the battery - minimum battery size, maximum battery size, module size, and depth of discharge - are considered. Infrastructure parameters, such as the maximum available power, are also included in the technical analysis. However, the core of the analysis are approximately 2,400 driving profiles from KiD (WVI et al., 2012a), each of them describing the tours of one vehicle over one day. The continuous process of driving and parking is transformed into a discrete time simulation[7]. Based on the start and arrival times as well as the distance traveled information in the KiD dataset for each vehicle, the status of the vehicle (parking private, parking public, driving) as well as the distance traveled is considered in 5-minute-intervals[8]. If the vehicle drives more than 4.5 hours - the maximum allowed driving

[7] For an introduction into the simulation of (stochastic) systems, see for example Waldmann and Helm (2016).

[8] Buss and Al Rowaei (2010) show exemplarily that discrete-time-simulation with fixed time steps, often used in ABM, is less accurate than discrete-event-simulation with flexible time steps. At the same time, the calculation can be faster. However, due to the given accuracy of the input data, a consideration of 5-minute-steps seems appropriate.

time (EU, 2006) -, an additional break of 45 minutes is added to the driving profile after 4.5 hours of driving and the average speed is adjusted accordingly for the corresponding tour. If the end of the additional break would be later than the end of the trip, the additional break is placed in the middle of the trip. The additional breaks are considered as breaks on public area. If the vehicle is parking for at least 30 minutes and if the vehicle has reached under 25% battery state of charge or will reach that with the next trip, the vehicle will be recharged. If the current stop is shorter than 30 minutes (assumed minimum duration for charging), the vehicle is assumed to charge at the next stop of at least 30 minutes duration. The 25% state of charge threshold is equivalent to exceeding a cumulative travel distance of 75% of the BET's maximal range. For example, the maximal range assumed for rigid trucks is 450 km in 2030 and 750 km in 2050, corresponding to minimum travelled distance to initiate charging of 340 km in 2030 and 563 km in 2050. The charging process is modeled so that the vehicle is fully recharged when starting the next trip, while maintaining the maximum charging power. The vehicle is recharged as slowly as possible (see subchapter 2.1.3 for charging strategy). If the maximum charging power is not sufficient to fully recharge the vehicle in the given timeframe, the vehicle charges as much as possible. For each time step of the simulation, the kilometers to be recharged are calculated from the kilometers traveled reduced by the kilometers already recharged. After the given 24 h of a driving profile are simulated, the necessary battery size for the profile can be determined. It results from the maximum of kilometers to be recharged, taking into account the consumption and various battery framework conditions. If the necessary battery size does not exceed the maximum available battery size and if the vehicle can be fully recharged after the last trips until the first trip begins (again), the profile can be electrified. In addition, load profiles in kW are created in 5 minutes time steps for all driving profiles.

Figure 4-6 shows an exemplary driving profile of an HDV (Rigid) with 568 km daily mileage, simulated for 2030. The vehicle starts the first trip at 6:30 and reaches its first destination at 7:45 after 112 km. For 2030, the intended minimum range that must be exceeded with the next trip in order to schedule a charging event is 340 km. 340 km are reached at 13:45. However, the previous break of 25 minutes is assumed to be too short for recharging. Therefore, the charging event takes place during the next break after 403 km at 15:00 to 15:30. The charging power needed to fully recharge the vehicle within the stop duration is 798 kW on average and is assumed as charging power (following the charging strategy of lowest required charging power). At 18:30, the vehicle reaches its last destination and can be recharged overnight with 14 kW. To enable the maximum distance of 403 km to be driven with one battery charge, the vehicle is equipped with a 600 kWh battery, considering consumption, depth of discharge, and module size.

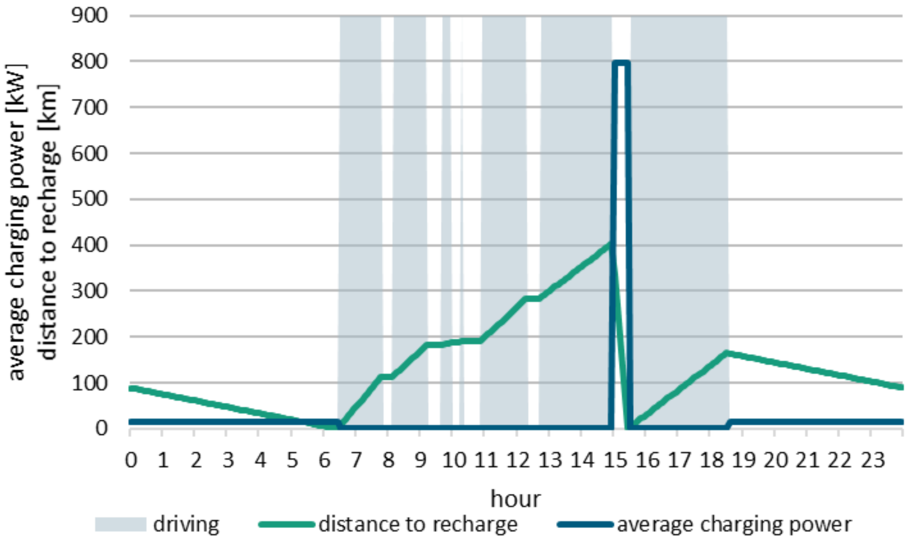

Figure 4-6: Exemplary driving profile of an HDV (Rigid) with 568 km daily mileage in 2030.

The second step of the model, the TCO analysis, remains almost unchanged, compared to Gnann et al. (2023) or Plötz, Link, et al. (2023). The annual costs for each driving profile and each drivetrain - if technically possible - are still calculated and the cheapest alternative is chosen. Economic vehicle parameters and economic general parameters, such as energy carrier prices, are still taken into account. However, the cost analysis for battery electric vehicles is more detailed, as the technical analysis allows for differentiation between public and private, and slow and fast charging. Different infrastructure costs can be derived. Finally, the cost analysis also considers the vehicle and infrastructure availability to determine the annual sales share of each drivetrain for each driving profile (Gnann, 2015; Wietschel et al., 2017). Unlike previous model versions, the adapted model calculates the availability of public fast charging infrastructure endogenously in the infrastructure analysis.

The stock and energy analysis aggregates the single sales shares of each driving profile and scales them to the total German truck registrations in the relevant year. Considering the service life of the vehicles, the entire German truck fleet with a GVW higher than 12 t is calculated for each year of the simulation[9]. In addition, based on the results of the technical analysis and the TCO analysis, the private and public charging demand for slow and fast charging infrastructure are determined. A daily load curve and an annual energy demand for the vehicle stock are calculated.

The infrastructure analysis complements the previous ALADIN Truck model. In 5-year-steps, a public fast charging infrastructure is simulated based on the CFRLM, described in subchapter

[9] To determine the stock in the first years of the simulation, new registrations for the period before 2020 are required. Simplified, nearly complete diesel registrations are assumed. Small shares of alternative drivetrains are modeled exponentially growing so that they meet the new registrations in 2020.

4.1.2.2. From an ABM perspective, the infrastructure or its operator should also be viewed as an agent (Gnann, 2015). As an agent, the infrastructure responds to the behavior of the vehicle agents by trying to meet their demand, expressed by the load curve and the energy demand provided by the stock analysis. Taking into account various infrastructure parameters, such as charging behavior and charging power, as well as the ETIS-U dataset, a public fast charging infrastructure is developed to provide the required amount of energy. The CFRLM is adjusted, so that once a location is opened, it will be used in the next period of the infrastructure analysis as well. If the CFRLM does not find a solution that can meet the demand, the demand will be reduced until it can be met. Afterwards, the annual costs of the required public fast charging infrastructure are calculated from the results of the CFRLM. Therefore, the infrastructure analysis interacts with the TCO analysis in two ways: (1) The reduced coverage of the energy demand is interpreted as limited infrastructure availability and hinders the market diffusion retroactively. This means that new registrations for the period between the last and the current infrastructure analysis are reduced accordingly. The reduction is retroactive, since the infrastructure must be built gradually during the market diffusion and the user will notice a deficient infrastructure immediately. (2) The infrastructure costs are determined from the infrastructure analysis and set the price until the next infrastructure analysis. It is assumed that the infrastructure operator will set future prices based on current costs and energy demand. This assumption seems plausible due to decreasing costs and increasing energy demand over time.

4.2.3 Mathematical description of the adapted model

In the following, the single steps of the adapted ALADIN truck model are shown in more detail, including mathematical equations.

4.2.3.1 Technical analysis

Let i be a driving profile of a BET, either a rigid truck (R) or a tractor-trailer truck (TT), in year t. Originally, the driving profile i consists of $j \in J$ single trips with defined start times $trip_{i_j}^{start}$, end times $trip_{i_j}^{end}$[10], and distances $trip_{i\_j}^{distance}$. The relevant values are directly taken from WVI et al. (2012a)[11]. The model only uses driving profiles that include information on the start and the end of each trip and where the daily mileage is equal to the sum of the individual trips. Incomplete driving profiles (R: 17.4%, TT: 9.8%) are sorted out. For further use, the driving profile is converted into a time-discrete driving profile. For every 5-minute-step ts of one day, the time-discrete driving profile contains two items: the vehicle status $status_i^{ts}$ and the totally traveled distance $distance\_total_i^{ts}$. Equation (4-19) shows the determination of $status_i^{ts}$ for every ts.

[10] For simplicity, all $trip_{i\_j}^{start}$ and $trip_{i\_j}^{end}$ are rounded to five minutes.

[11] As described in 4.2.2, if the first trip lasts longer than 4.5 h, the mandatory break is inserted after 4.5 h. If the additional break lasts longer than the original trip, the break is put in the middle of the original trip. For further trips, there are no additional breaks, since theoretically another driver may have taken over the vehicle.

$$status_i^{ts} = \begin{cases} driving^{12}, if \ \exists \ j \ \in J: (ts > trip_{i_j}^{start}) \cap (ts \leq trip_{i_j}^{end}) \\ parking, else \end{cases} \tag{4-19}$$

Dividing the $trip_{i\_j}^{distance}$ by the delta of $trip_{i\_j}^{start}$ and $trip_{i\_j}^{end}$ in minutes and multiplying the result by five returns the traveled distance in 5 minutes ($trip_{i\_j}^{distance_{5min},ts}$), for the driving profile i during trip j for $(ts > trip_{i_j}^{start}) \cap (ts \leq trip_{i_j}^{end})$. Generally, the distance for a 5-minute-step (ts) is referred to as $distance_i^{ts}$. As shown in equation (4-20), the totally traveled distance $distance\_total_i^{ts}$ for a 5-minute-step ts equals the sum of all $distance_i^{ts}$ from the beginning of the first trip to ts.

$$distance\_total_i^{ts} = \sum\nolimits_{trip_{i_{j0}}^{start}}^{ts} distance_i^{ts} \tag{4-20}$$

Figure 4-7 shows the procedure for the technical analysis of a driving profile i as a flow chart. The simulation starts with the first departure of the vehicle $trip_{i_{j0}}^{start}$. Driving is then simulated in 5-minute-steps, expressed by the variable $clock$. If the variable $clock$ exceeds the value 1435, it is reset to 0 and starts a new day[13]. The distance traveled from the battery - $dist_{recharge}^{ts=clock}$ - is the sum of the individual $distance_i^{ts}$ up to $clock$. As soon as the vehicle stops - $status_i^{ts=clock} = parking$ -, the time until the next departure - $time_{recharge}$ - is calculated in the sub-module "time for recharging". Additionally, the traveled distance without recharging after the following trip - $dist_{next}$ - is calculated in the sub-module "distance next trip". Subsequently, the sub-module "recharging necessity / possibility" determines whether a charging process takes place. A charging process takes place, if at least 30 minutes are available for recharging and if the intended charging distance - $charge_{range}{}_{BET,all}^{t}$ - is exceeded. A bypass in the "time for recharging" sub-module ensures that recharging takes place in any case after the last trip. If a charging event takes place, the recharged distance in 5 minutes - $charging$ - is determined so that charging is as slow as possible and the maximum charging rate $charging\_max_{BET,R;TT}^{t}$ is not exceeded. The charging process is simulated by reducing $dist_{recharge}^{ts=clock}$ by $charging$ in 5-minute-steps. If the charging event is over - $status_i^{ts=clock} = driving$ - and the last trip is completed - $clock = trip_{i_{j0}}^{start}$ -, the technical feasibility has to be checked. Otherwise, the next trips is simulated in the "driving" sub-module. As shown in the sub-module "feasibility", the trip can be electrified if there is no more recharging need - $dist_{recharge}^{ts=clock} = 0$ - and if the maximum possible battery range in year t - $bat_{max}{}_{BET,\,all}^{t}$- has never been exceeded.

[12] The status also allows the distinction between public and private parking, in order to allocate the charging demand for public and private infrastructure. For the sake of simplicity, this is not shown in the equation.
[13] The same applies to all clock variables, used in the modeling.

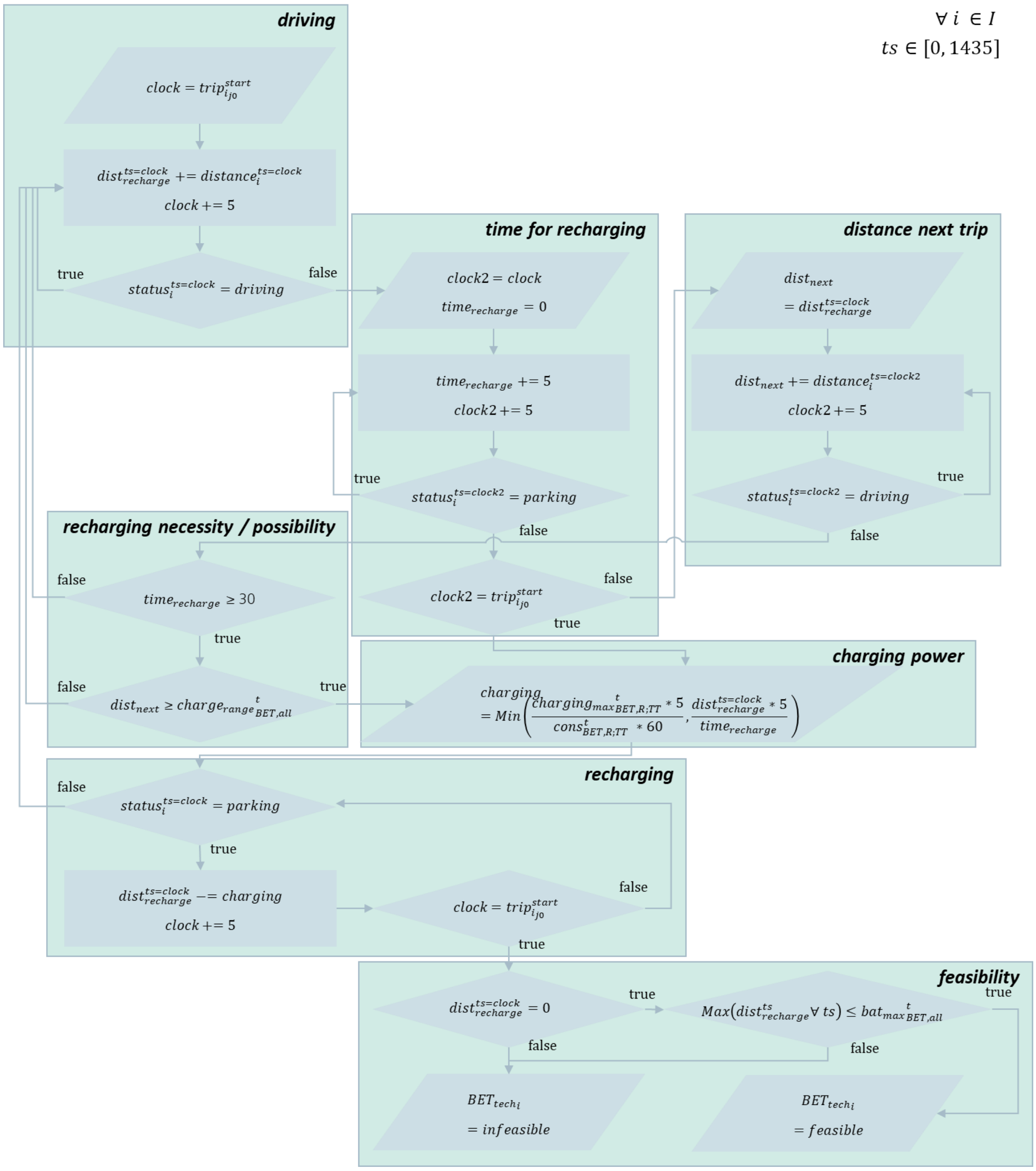

Figure 4-7: Flow chart technical analysis.

Finally, the necessary battery size for a feasible profiles i in year t is determined:

$$bat_{i,BET,all}^{t} = \left\lceil \frac{Max\left(Max\left(dist_{recharge}^{ts} \forall\, ts\right), bat_{min}{}_{BET,all}^{t}\right) * cons_{BET,R;TT}^{t}}{bat_{usable}{}_{BET,all}^{t}} \right\rceil^{bat_{pack}{}_{BET,all}^{t}} \tag{4-21}$$

First, the maximum range driven from the battery without recharging is determined over the course of the day. In addition, the model ensures that a minimum range $bat_{min}{}_{BET,all}^{t}$ is maintained. Afterwards, the energy consumption for the given vehicle type - rigid or tractor-trailer -

is considered. Taking into account the usable battery share in year t, the necessary battery size can be calculated. Finally, the value is round up to the battery module size.

4.2.3.2 Economic analysis (TCO analysis)

The economic analysis follows the technical analysis. Appendix A.3 contains all values and abbreviations. For every driving profile i and drivetrain s, an annual TCO calculation is performed. The drivetrains consider DT, GT, and FCET. BET is considered, if the driving profile i is feasible from a technical perspective. Additionally, the equation distinguishes between rigid trucks and tractor-trailers as configurations $conf$. As shown in (4-22) and following Wöhe et al. (2020), the TCO consists of annual capital expenditures and annual operating expenditures:

$$TCO_{i,s,conf}^{t} = a_{i,s,conf}^{capex,t} + a_{i,s,conf}^{opex,t} \tag{4-22}$$

The capital expenditures are calculated as shown in equation (4-23). Both, the investment $I_{i,s,conf}^{t}$ and the percentage resale value ${res_{value}}_{s,conf}^{t}$ are taken into account.

$$a_{i,s,conf}^{capex,t} = \left(I_{i,s,conf}^{t} * (1+i(t))^{life_{conf}^{t}} - I_{i,s,conf}^{t} * {res_{value}}_{s,conf}^{t}\right) * \frac{i(t)}{(1+i(t))^{life_{conf}^{t}} - 1} \tag{4-23}$$

As described in Speth, Kappler, et al. (2022), the investment calculation follows a bottom-up approach and considers various vehicle components. The single components are shown in equation (4-24). Yet, not all drivetrains s contain all components. Basically, the investment considers a chassis ${I_{body}}_{s,conf}^{t}$ for each vehicle. In addition, an investment for the engine ${I_{engine}}_{s,conf}^{t}$ is taken into account for all drivetrains. The costs scale with the performance of the vehicle $p_{s,conf}^{t}$ and are differentiated between different drivetrains s. As shown in line three of equation (4-24), the FCET is equipped with an additional fuel cell. For DT and GT, the exhaust gas aftertreatment is considered in line four. For BET and FCET, the battery system, scaled by the necessary size $bat_{i,s,conf}^{t}$, is listed in line five. For BET, the individual battery size for each driving profile i from the technical analysis is taken into account. Corresponding tank systems for FCET and GT are considered in line six. All component costs are subject to drivetrain-specific markups, to reflect the different levels of technological maturity. Finally, subsidies for alternative drivetrains are taken into account.

$$\begin{aligned} I_{i,s,conf}^{t} = {} & {I_{body}}_{s,conf}^{t} \\ & + {I_{engine}}_{s,conf}^{t} * p_{s,conf}^{t} * markup_{s,conf}^{t} \\ & + {I_{FC}}_{s,conf}^{t} * {p_{FC}}_{s,conf}^{t} * markup_{s,conf}^{t} \\ & + {I_{aftert}}_{s,conf}^{t} * p_{s,conf}^{t} * markup_{s,conf}^{t} \\ & + {I_{bat}}_{s,conf}^{t} * bat_{i,s,conf}^{t} * markup_{s,conf}^{t} \\ & + {I_{tank}}_{s,conf}^{t} * tank_{s,conf}^{t} * markup_{s,conf}^{t} \\ & - {I_{subsidy}}_{s,conf}^{t} \end{aligned} \tag{4-24}$$

According to BaLM (2023), a subsidy is considered for BET and FCET as a percentage of the additional investment compared to a DT. The calculation is shown in equation (4-25):

$$I_{subsidy}{}_{i,s,conf}^{t} = I_{red}{}_{s,conf}^{t} * (I_{i,s,conf}^{t} - I_{DT,conf}^{t}) \tag{4-25}$$

The annual operating expenditures $a_{i,s,conf}^{opex,t}$ contain energy costs, operation & maintenance costs, toll, insurance costs, and taxes:

$$a_{i,s,conf}^{opex,t} = c_{energy}{}_{i,s,conf}^{t} + c_{O\&M}{}_{i,s,conf}^{t} + c_{toll}{}_{i,s,conf}^{t} + c_{ins}{}_{i,s,conf}^{t} + c_{tax}{}_{s,conf}^{t} \tag{4-26}$$

Equation (4-27) shows the calculation of the energy costs. The fuel price $c_{fuel}{}_{s}^{t}$ in year t is multiplied by the consumption of the corresponding vehicle $cons_{s,conf}^{t}$ and extrapolated to the total annual mileage of the specific driving profile i. For this purpose, the daily mileage of the driving profile i $distance_{daily}{}_{i,s,conf}^{t}$, derived from WVI et al. (2012a), is multiplied by the working days $wd(t)$ of a single year.

$$c_{energy}{}_{i,s,conf}^{t} = c_{fuel}{}_{s}^{t} * cons_{s,conf}^{t} * wd(t) * distance_{daily}{}_{i,s,conf}^{t} \tag{4-27}$$

BET represent a special case at this point. For DT, GT, and FCET, fuel supply infrastructure costs are included in the fuel price $c_{fuel}{}_{s}^{t}$. For BET, the supply infrastructure costs are calculated separately. A distinction is made between public and private charging as well as slow charging with less than 44 kW average power and fast charging with more than 44 kW average power. 44 kW represents the maximum AC charging power with three phases. For each driving profile i, the technical analysis provides the recharged kilometers in every 5-minute-step. By considering the energy consumption $cons_{BET,conf}^{t}$, the amount of energy and the average charging power can be derived. As mentioned earlier, WVI et al. (2012a) also allows the distinction between private stops and public stops. Aggregating the 5-minutes-steps, the daily slow and fast charging demand at public and private charging infrastructure can be calculated for each driving profile i. In total, four daily energy demands are available for each driving profile i: the private slow charging energy demand $energy_{slow,private}{}_{i,BET}^{t}$, the private fast charging energy demand $energy_{fast,private}{}_{i,BET}^{t}$, the public slow charging energy demand $energy_{slow,public}{}_{i,BET}^{t}$, and the public fast charging energy demand $energy_{fast,public}{}_{i,BET}^{t}$. As shown in equation (4-28), all of them are multiplied with their respective infrastructure cost allocation. The initial values for the cost allocations are given in Table A-4 in annex A.3. The infrastructure costs for fast charging $c_{infra}{}_{fast}^{t}$ and the grid connection costs for fast charging $c_{infra}{}_{fast,grid}^{t}$ are updated in the infrastructure analysis module of ALADIN every five years. For example, the infrastructure costs from the infrastructure analysis for 2025 are used for the economic analysis from 2026 to 2030. For simplicity, it is assumed that public and private infrastructure costs are identical, only a profit markup $c_{infra}{}_{markup}^{t}$ is required for public charging.

$$c_{infra_{total}}{}_{i,BET}^{t} = (c_{infra}{}_{slow}^{t} * energy_{slow,private}{}_{i,BET}^{t} + (c_{infra}{}_{fast}^{t} + c_{infra}{}_{fast,grid}^{t}) * energy_{fast,private}{}_{i,BET}^{t}) + (c_{infra}{}_{slow}^{t} * energy_{slow,public}{}_{i,BET}^{t} + (c_{infra}{}_{fast}^{t} + c_{infra}{}_{fast,grid}^{t}) * energy_{fast,public}{}_{i,BET}^{t}) * (1 + c_{infra}{}_{markup}^{t}) \tag{4-28}$$

The calculation on energy costs for BET thus changes from equation (4-27) to equation (4-29):

$$c_{energy}{}_{i,BET,conf}^{t} = c_{fuel}{}_{s}^{t} * cons_{BET,conf}^{t} * wd(t) * distance_{daily}{}_{i,BET,conf}^{t} + c_{infra_{total}}{}_{i,BET}^{t} * wd(t) \tag{4-29}$$

The costs for operation & maintenance - $c_{O\&M}{}_{i,s,conf}^{t}$ - and toll $c_{toll}{}_{i,s,conf}^{t}$ scale with the mileage of the vehicles, as shown in equation (4-30) and equation (4-31).

$$c_{O\&M}{}_{i,s,conf}^{t} = O\&M_{s,conf}^{t} * wd(t) * distance_{daily}{}_{i,s,conf}^{t} \tag{4-30}$$

$$c_{toll}{}_{i,s,conf}^{t} = toll_{s,conf}^{t} * wd(t) * distance_{daily}{}_{i,s,conf}^{t} \tag{4-31}$$

The annual insurance - $c_{ins}{}_{i,s,conf}^{t}$ - is calculated as a percentage value of the investment (LastAutoOmnibus, 2018):

$$c_{ins}{}_{i,s,conf}^{t} = insurance_{s,conf}^{t} * I_{i,s,conf}^{t} \tag{4-32}$$

Finally, the vehicle tax - $c_{tax}{}_{s,conf}^{t}$ - is given as an annual value:

$$c_{tax}{}_{s,conf}^{t} = veh_{tax}{}_{s,conf}^{t} \tag{4-33}$$

After calculating the annual TCO for each drivetrain s, the cheapest drivetrain for each profile can be selected. Subsequently, the limited availability of alternative drivetrain vehicles and, if necessary, infrastructure is considered (Gnann, 2015; Wietschel et al., 2017):

$$sales_{share}{}_{i,s=best_{option},conf}^{t} = 1 * veh_{available}{}_{s}^{t} * infra_{available}{}_{i,s=BET}^{t} \tag{4-34}$$

As shown in equation (4-34), infrastructure availability - $infra_{available}{}_{i,s=BET}^{t}$ - is considered for BET. Given that the respective charging technology is used by the driving profile i, the infrastructure availability results from the minimum of the availabilities for private slow charging $a_{infra}{}_{private,slow}^{t}$, private fast charging $a_{infra}{}_{private,fast}^{t}$, public slow charging $a_{infra}{}_{public,slow}^{t}$, and public fast charging, $a_{infra}{}_{public,fast}^{t}$. The initial parameters are given in Table A-4 in annex A.3. For public fast charging $a_{infra}{}_{public,fast}^{t}$, the value is calculated in the infrastructure analysis module. For example, if the public fast charging infrastructure can only serve a certain share of the public charging demand in 2025, $a_{infra}{}_{public,fast}^{t}$ is reduced to this share for the previous infrastructure period, in the example from 2020 to 2025.

If the best TCO option is not fully available ($sales_{share}{}_{i,s=best\_option}^{t} < 1$), the availability for the second best option $sales_{share}{}_{i,s=2nd\_best\_option}^{t}$ is calculated accordingly. If the second best option is fully available, it can cover the remaining sales share. Otherwise, its share is multiplied by the remaining share and the third best option is considered. The diesel drivetrain always serves as backup-option with full availability.

4.2.3.3 Stock and energy analysis

The technical and economic analysis are performed for every driving profile i. To obtain the annual registrations for each drivetrain s, the analyzed driving profiles are scaled to the total number of new registrations in the relevant year reg_{conf}^{t}. There is still a distinction between rigid and tractor-trailer configuration. Subsequently, the new registrations by drivetrain are calculated by considering the previously calculated driving profile specific sales shares $sales_{share}{}_{i,s,conf}^{t}$. The calculation is given in equation (4-35).

$$sales_{s,conf}^{t} = \sum\nolimits_{i \in I} \left(\frac{reg_{conf}^{t}}{\#\, driving\ profiles_{conf}^{t}} * sales_{share}{}_{i,s,conf}^{t}\right) \tag{4-35}$$

The vehicle stock by drivetrain s is calculated as the sum of new registrations over the service life $life_{conf}^{t}$ of the vehicles[14].

$$stock_{s,conf}^{t} = \sum\nolimits_{t-life_{conf}^{t}}^{t} sales_{s,conf}^{t} \tag{4-36}$$

Similarly, the annual energy demand and the daily load profile can be scaled from the individual driving profiles and aggregated to the demand of the stock.

4.2.3.4 Infrastructure analysis

The infrastructure analysis follows methodologically the CFRLM, as described in chapter 4.1.2. However, the objective at this point is not to model an optimal network at one specific point in time, but to model the stepwise development of the public fast charging infrastructure in relation to the market diffusion of BET. Böhle (2021) suggests a multi-period CFRLM, to calculate the market diffusion of infrastructure over time. This approach is not implemented in this thesis, for two reasons: (1) The large underlying dataset, as well as the adjustments to the capacity constraint compared to P. K. Rose et al. (2020) and Böhle (2021), significantly complicate the solvability. Adding a multi-period element to the optimization would further complicate the solvability (Böhle, 2021). (2) The multi-period FRLM suggests a central planner's perspective with full knowledge of all future developments (Böhle, 2021). Due to the interaction of the infrastructure ramp-up and the BET diffusion, full knowledge is not available. Therefore, a CFRLM is used that, if available, takes into account the results of a previous simulation

[14] To determine the stock in the first years of the simulation, new registrations for the period before 2020 are required. Simplified, nearly complete diesel registrations are assumed. Small shares of alternative drivetrains are modeled exponentially growing so that they meet the new registrations in 2020.

in an earlier year *t-1*. In this thesis, CFRLM runs are performed in 5-years-steps, starting with the year 2025. The new requirements are briefly listed below:

1. The maximum range may change between t and t-1.
2. The recharged energy in the CFRLM in year t corresponds to the identified public fast charging energy demand in the stock analysis in year t.
3. A predefined minimum number of locations in year t is available.
4. A predefined maximum number of locations in year t is not exceeded.
5. A location opened in $t-1$ is also available in t.
6. A fraction of the OD-pairs q_s that charged at a specific location in t-1 also charge at the same location in t, if the profile still needs to be recharged.

The mathematical formulation is shown in the following. A description of the individual aspects is given below.

$$\min \sum_{i \in N} z_i \tag{4-37}$$

s.t.

$$\sum\nolimits_{i \in K_{i,j,t}^{q_s}} x_{i_{q_s}} \geq 1, \qquad \forall q_s \in Q, a_{j,k} \in A_{q_s} \tag{4-38}$$

$$\sum\nolimits_{q_s \in Q} r_t f_{q_s} x_{i_{q_s}} \leq cap_i z_i, \qquad \forall i \in N \tag{4-39}$$

$$\sum\nolimits_{i \in N} x_{i_{q_s}} \leq l_{q_s}, \qquad \forall q_s \in Q \tag{4-40}$$

$$\sum_{i \in N} z_i \geq z_{min,t} \tag{4-41}$$

$$\sum_{i \in N} z_i \leq z_{max,t} \tag{4-42}$$

$$z_i = 1 \qquad \forall i \in I_{true,t-1} \tag{4-43}$$

$$\sum\nolimits_{q_s \in Q} r_t f_{q_s} x_{i_{q_s}} \geq 0.7 * \sum\nolimits_{q_s \in Q} r_{t-1} f_{q_s} x_{i_{q_s,t-1}} \qquad \forall i \in I_{true,t-1} \tag{4-44}$$

$$x_{q_s}, z_i \in \{0,1\}, \qquad \forall q_s \in Q, i \in N \tag{4-45}$$

Sets and indexes

A_{q_s}	Set of all directional arcs on a shortest path q_s, sorted from the origin to the destination
$K_{i,j,t}^{q_s}$	Set of all potential nodes that can refuel the arc $a_{j,k}$ in A_{q_s} in year t
N	Set of all nodes in the modeled network
Q	Set of all origin-destination pairs
$I_{true,t-1}$	Set of all nodes with a realized charging location in year $t-1$
i, j, k	Indices, indicating nodes
q_s	Index of origin-destination pairs. Extended to identical origin-destination pairs for each subset. Flows are split, if the vehicle flow exceeds the capacity of a single parking space.
s	Index, indicating a subset of a path q
$a_{j,k}$	Index of a directed arc from node j to node k

Parameters

r_t	Rescaling factor in year t
r_{t-1}	Rescaling factor in year $t-1$
f_{q_s}	Vehicle flow at path q_s in $peak\_hour$
cap_i	Capacity restriction in node i
l_{q_s}	Number of maximum stops to drive path q_s
$z_{min,t}$	The minimum number of charging locations in t
$z_{max,t}$	The maximum number of charging locations in t
$x_{i_{q_s},t-1}$	=1, if the flow on path q_s was recharged at node i in $t-1$ and if $x_{i_{q_s}}$ exists

Decision variables

$x_{i_{q_s}}$	=1 if the flow on path q_s is recharged at node i, 0 otherwise
z_i	=1 if a charging station is built at node i, 0 otherwise

As described in the technical analysis, the range of the vehicles changes over time. To obtain the best possible match between the technical analysis and the simulated infrastructure, the range in the CFRLM is also adjusted. When calculating the candidate sets $K_{i,j,t}^{q_s}$, the CFRLM ensures that a given maximum distance between two stops is not exceeded. In the technical simulation, the charging range ${charge_{range}}_{BET,all}^{t}$ determines the range at which the vehicles have usually been recharged[15]. Therefore, ${charge_{range}}_{BET,all}^{t}$ is used to calculate the candidate sets in year t. The calculation of the candidate sets still follows the description in sub-chapter 4.1.2.

[15] In some cases, if there is no sufficient driving break, higher distances can be covered.

As described in the second new requirement, the recharged energy in the CFRLM needs to equal the recharged energy at public fast charging infrastructure in the stock analysis. However, the amount of energy is not directly given in the CFRLM, but can be determined after the calculation by following each path q_s and calculating the energy demand for each possible charging event $x_{i_{q_s}}$. The scaling factor r_t is therefore initially set so that the daily mileage in the CFRLM corresponds to the daily mileage of all driving profiles with public fast charging share in the stock model. As described in subchapter 4.1.2, the CFRLM calculates the charging infrastructure for the peak hour. The peak hour share is derived from the load profile of the stock analysis. After solving the CFRLM, the energy demand in the CFRLM is calculated and compared to the energy recharged at public fast charging infrastructure in the stock analysis. If the deviation is higher than 10%, the scaling factor r_t is adjusted accordingly and a new run for year t is started.

In contrast to the modeling in subchapter 4.1.2.2, the ALADIN truck model aims to calculate a realistic market diffusion for the vehicles and the infrastructure, not a theoretical optimum. Therefore, framework conditions regarding the minimum number of charging locations $locations^t_{min}$ and the maximum number of charging locations $locations^t_{max}$ in year t are defined. The new equations (4-41) and (4-42) ensure these constraints by using $locations^t_{min}$ as $z_{min,t}$ and $locations^t_{max}$ as $z_{max,t}$. Information on specifying these parameters can be found in subchapter 3.5.1.3 or in Table A-4 in the appendix. Additionally, the maximum number of charging points at one location cap_i is no longer based solely on the available parking lots, but also considers a realistic location size $plug^t_{max}$ from an electricity grid perspective in year t.

The last two new requirements concern the multi-period application of the model. Since the electricity grid connection is typically depreciated over 40 years (Kippelt et al., 2022), a location opened in $t-1$ will be also in operation in t. Equation (4-43) implements this requirement. The CFRLM used here does not directly determine the location size, but considers a maximum size for each location. Therefore, the shifting of traffic from one charging location to another is limited between two periods. Equation (4-44) ensures that 70% of the traffic using a charging location in $t-1$ will also use the same location in t, as long as the underlying paths q_s are still able to charge at the given location. Some flexibility is provided to allow for changes in the charging behavior due to increasing ranges. The exact value represents the result of an iterative process in which different values were tested.

If the model is unable to find a solution for year t, due to the capacity constraint and the limited number of locations, the mileage in the CFRLM is reduced in ten percentage point steps until a solution is found. The reduction is passed to the economic analysis as reduced infrastructure availability ${infra_{available}}^t_{i,s=BET}$, for example 90% for a one-time reduction. The limited availability applies to the years between the infrastructure analysis in year t and the previously performed infrastructure analysis $t-1$. For example, a reduction calculated for 2030 would affect the years 2026 to 2030.

Finally, the annual infrastructure costs for fast charging infrastructure are calculated. The costs consist of the actual infrastructure costs $c_{infra}{}^{t}_{fast}$ and the costs for the grid connection $c_{infra}{}^{t}_{fast,grid}$. To determine the costs for the grid connection $c_{infra}{}^{t}_{fast,grid}$, the necessary grid connection is calculated for each location i opened in the CFRLM in year t based on the charging events $x_{i_{q_s}}$ at the node i and their weighted traffic flow $r_t f_{q_s}$. The assumptions regarding the simultaneity factor, the power factor, and the efficiency correspond to chapter 3.3. Due to the depreciation period of 40 years (Kippelt et al., 2022), a grid connection required in year t is taken into account for the entire time horizon considered, even if a smaller grid connection would be adequate at a later point in time. However, an extension of the network connection is possible at any time. The annuity is calculated as shown in chapter 3.3. To determine the costs for the charging infrastructure $c_{infra}{}^{t}_{fast}$, the necessary number of charging points for each location i in year t is also calculated based on the charging events $x_{i_{q_s}}$ at the node i and their weighted traffic flow $r_t f_{q_s}$. Once established, charging points are depreciated and operated over 15 years, even if they would not be needed in one of the following periods. This means that any expansion at one location only takes place, if the location does not have enough charging points from a former period. As described in section 3.3, newly installed charging points are calculated at costs valid in year t and depreciated over 15 years (Kippelt et al., 2022). Finally, for both the grid connection and the actual infrastructure, the costs per kWh - $c_{infra}{}^{t}_{fast,grid}$ and $c_{infra}{}^{t}_{fast}$ - are calculated by dividing the sum of the annual costs across all installed locations by the total amount of energy delivered by the infrastructure in year t. The costs determined in t are passed to the economic analysis and apply to all subsequent year until the next infrastructure analysis in period $t + 1$.

4.2.4 Discussion

This thesis presents an updated and adapted version of the ALADIN - ALternative Automobiles Diffusion and INfrastructure - market diffusion model for HDV with a GVW of more than 12 t[16]. As shown in Table 4-1, the adaption mainly focusses on five aspects. Two of them relate to the technical analysis: (1) The new model no longer uses the daily mileage as proxy for the technical feasibility of BET, but simulates 2,400 driving profiles over one day. (2) The battery size is no longer exogenously defined, but can be derived from the technical analysis. Three adaptions relate to the integration of public fast-charging infrastructure: (1) Public fast charging infrastructure is no longer defined exogenously, but a regionally resolved infrastructure model defines the market ramp-up based on framework parameters. (2) The costs for using fast charging infrastructure are no longer exogenously determined, but are calculated based on the actual charging demand. (3) The charging infrastructure availability is no longer exogenously defined; instead, the model verifies whether the actually needed public fast charging infra-

[16] As part of this thesis, the existing model was newly programmed. However, the basic structure still corresponds to the original model.

structure can be built, considering ramp-up boundaries. The approach is well suited to account for long-distance traffic in the regional distribution of charging locations, providing deeper insights than a node-based approach. However, due to the definition of the minimum values of the objective function, the solution represents one possible solution and not a unique optimum.

Table 4-1: Improvements of the ALADIN model for the market diffusion of HDV.

Previous ALADIN model	**Adapted ALADIN model**
Daily mileage as indicator for feasibility of BET	Simulation of 2,400 driving profiles for one day
Single battery size exogenously defined	Selection of the appropriate battery size based on driving profile analysis
Public charging infrastructure exogenously defined	Public fast charging infrastructure development within framework parameters based on the model-endogenous charging demand
Costs of charging infrastructure exogenously and independently of actual use defined	Costs of fast charging infrastructure based on actual use of public fast charging infrastructure
Infrastructure availability exogenously defined	Infrastructure availability endogenously determined, considering a ramp-up scenario

Nevertheless, there is potential for further improvements. Regarding the technical analysis, the observation period of one day is comparatively short and may therefore overestimate the technical feasibility of BET. However, the question raised by logisticians about reliability in use (see subchapter 2.3.2) is significantly increased by the detailed simulation compared to the previous model. Regarding the charging strategy, a plausible strategy is implemented. Future studies could investigate other charging strategies and their impact on the infrastructure needs. Even more detailed findings would be possible, especially if an extensive source of spatially and temporally resolved driving profiles were available. The focus of this thesis is on public fast charging infrastructure. The model developed allows to simulate a regionally distributed fast charging infrastructure that interacts with the market diffusion of BET. Since the focus is on public fast charging infrastructure, slow charging infrastructure costs are estimated on literature values. Additionally, private fast charging costs are estimated to be equal to the public fast charging costs reduced by a price premium for the infrastructure provider. Without detailed data on individual logistics locations, this appears to be a plausible estimate, which should be verified in the future. For computational reasons, the infrastructure was simulated in five year steps. A shorter interval could further detail the results.

In summary, the model adaption improved the accuracy with regard to the logistics concerns in subchapter 2.3.2: reliability (technical analysis), costs (economic analysis), and infrastructure (infrastructure analysis). However, there is still a demand for further research.

5 Results

The chapter is divided into two parts. In the first part, the results of pure infrastructure modeling are shown. Afterwards, the results of the joint market diffusion of public fast charging infrastructure and the BET vehicle fleet are described.

5.1 Fast charging infrastructure distribution and dimension

The following sections present the results of pure infrastructure modeling. Section 5.1.1 contains the results of infrastructure modeling at regular intervals. Subsequently, section 5.1.2 shows the optimized charging infrastructure network.

5.1.1 Charging infrastructure at regular intervals[1]

This chapter first presents the charging infrastructure at regular intervals for the EU27, Norway, Switzerland, and Great Britain. Second, the charging infrastructure network for Germany is presented in more detail.

5.1.1.1 Charging infrastructure at regular intervals in Europe

Public fast charging locations

Figure 5-1 shows the distribution of charging locations in the scenarios *Startup2025*, *Wide2030*, *Dense2030,* and *Dense2045*. For the scenarios *Startup2025* and *Wide2030* with a distance of 100 km between charging locations, the model calculates 917 charging locations spread over Europe. A summary table can be found in Appendix A.5. For the scenarios *Dense2030* and *Dense2045* with a distance of 50 km between charging locations, the number of charging locations increases to 1,701. The number of charging locations does not exactly double, since short sections as well as peripheral areas already receive charging locations in the wide network and do not need densification. At highway junctions, the distance can be closer than the distance given by the scenario definition, since the model treats highways independently. This can be seen clearly in areas with a dense road network, such as Central Europe, or urban areas, like Greater London. Additionally, highways without any charging infrastructure exist. These roads are not part of the E-road network or the road section is too short for electrification, for example in eastern Spain.

[1] Parts of this subchapter are based on Speth, Plötz, et al. (2022) and Speth, Sauter, and Plötz (2022).

With regard to the geographical distribution of charging points, there is a concentration in Central Europe, for example France, Germany, Belgium, and the Netherlands. The traffic generated by the ports in the Netherlands, Belgium, and Germany is of great interest for the dimensioning of the charging locations. The surrounding countries - for example Norway, Sweden, Finland, Greece, Italy, and Spain - are equipped with smaller locations that cover the whole area.

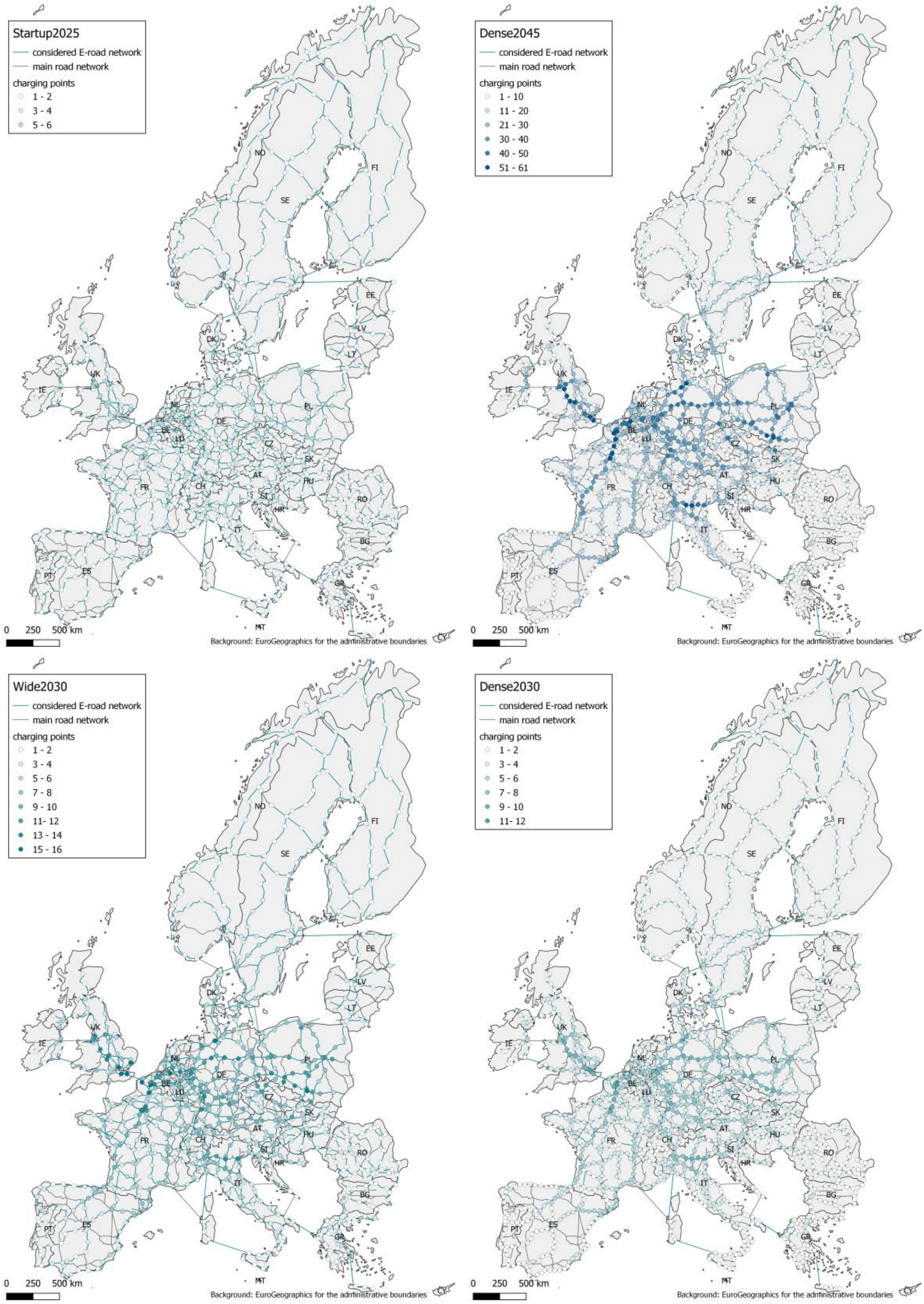

Figure 5-1: Charging infrastructure at regular intervals in Europe in the scenarios Startup2025, Dense2045, Wide2030, and Dense2030.

Number of charging points per location

Figure 5-2 shows an overview of the distribution of charging points in the scenarios *Startup2025, Wide2030, and Dense2030*.

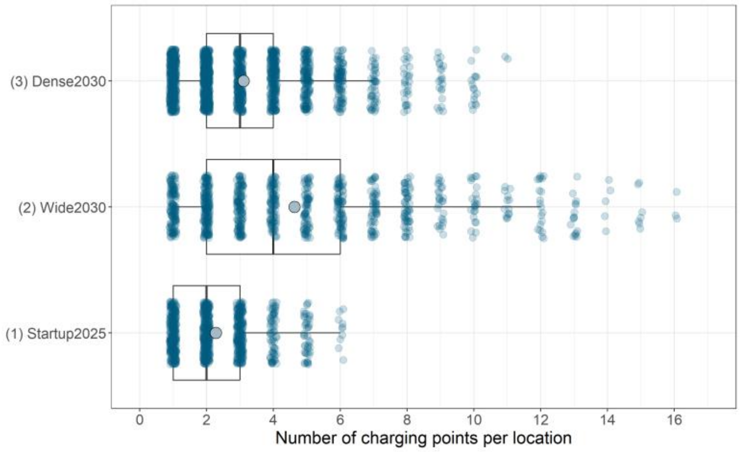

Figure 5-2: Box plot of charging points per location in the scenarios Startup2025, Wide2030, and Dense2030. Gray dot indicates mean value.

The *Startup2025* network consists of 2,090 charging points at 917 locations. Therefore, an average charging location in 2025 could include two to three charging points (mean = 2.3, median = 2, σ = 1.2). While there are 271 charging locations with one charging point to cover the area, the largest ten stations include six charging points. The modeled public fast charging infrastructure serves 27,100 charging events per day. Assuming a tripling of the share of battery electric trucking (BET_{share} 5% versus 15%) and an increase of the traffic volume by 13% in the scenario *Wide2030*, the average charging location doubles the number of charging points per location (mean = 4.6, median = 4, σ = 3.3). However, the variation between individual locations also increases. The three largest locations include 16 charging points, while there are still 131 locations with one charging point to cover the area. In total, 4,250 charging points are needed. Alternatively, the distance d_{avg} between the locations can be reduced. In the scenario *Dense2030*, the average distance becomes 50 km instead of 100 km. The average location comprises three charging points in the *Dense2030* scenario (mean = 3.1, median = 3, σ = 2.0). However, the total number of charging points increases to 5,290. This is an increase of 24%, compared to the scenario *Wide2030*. Due to queuing theory, large locations are more efficient and can serve more vehicles per charging point than small locations (see Figure A-4 in Appendix A.4). In both scenarios for 2030, 92,275 charging events are performed daily at the modeled infrastructure. Figure 5-3 shows the change in the required number of charging points from the scenario *Startup2025* to the scenario (a) *Wide2030* and (b) *Dense2030*. In case (a), 19% of the locations built in the *Startup2025* scenario can also be operated unchanged in the *Wide2030* scenario. At all other locations, up to ten charging points must be added. In case (b), 41% of the locations remain unchanged. Up to five charging points expand 54% of the locations. At 5% of the locations, a deconstruction of up to three charging points takes place.

These are typically locations nearby areas with high traffic, such as ports, where a new charging location is opened closer to the high traffic location. Since the identified locations are merely a representation of a highway section of 50 or 100 km and do not specify an exact location, this effect would likely be considered in the detailed infrastructure planning and the deconstruction would likely not be implemented in reality.

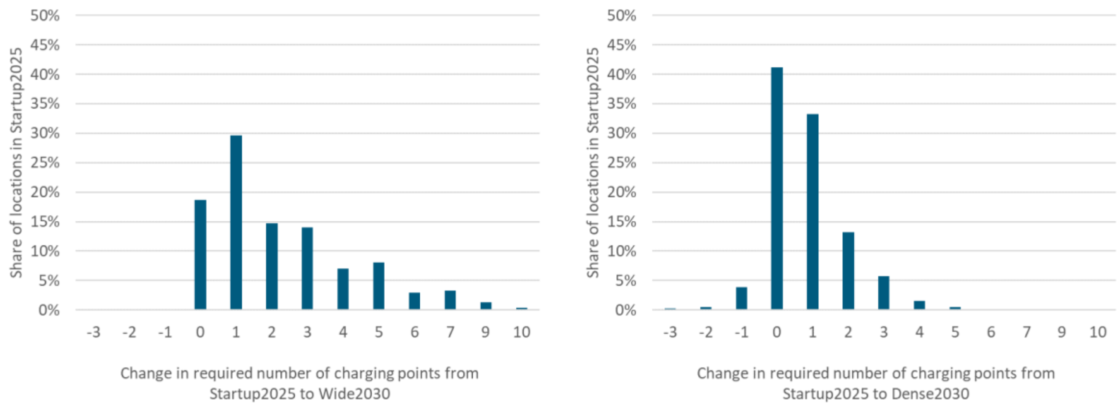

Figure 5-3: Change in number of charging points from (a) Startup2025 to Wide2030 and (b) Startup2025 to Dense2030.

The *Dense2045* scenario shows the infrastructure to convert the entire HDV fleet to BET. 1,701 locations comprise 21,804 charging points, 4,771 of them are in Germany. An average location contains approximately ten charging points (mean = 12.8, median = 9, σ = 11.7). Figure 5-4 illustrates the distribution of charging points in the *Dense2045* scenario. In total, the public charging infrastructure serves 615,225 charging events per day, 144,245 of them are in Germany.

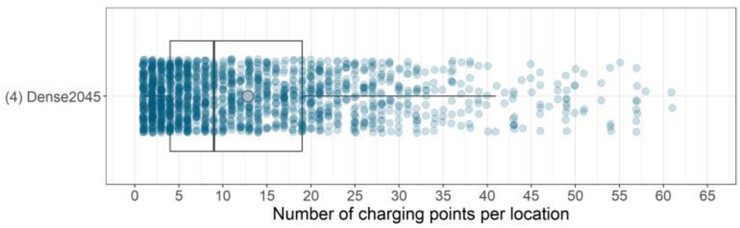

Figure 5-4: Box plot of charging points per location in the scenario Dense2045. Gray dot indicates mean value.

Sensitivity analysis

As shown in section 3.4.1, the modeling of charging infrastructure at regular intervals depends on various parameters. Since BET for long-haul trucking are not yet available, the calculations come with some uncertainties and estimates. Originally, the modeling assumes 15% battery electric trucking (BET_{share}), 25% public charging (CE_{public}), 6% of the daily charging events in the peak hour ($peak\_hour$), and a typical range of 300 km ($range_{BET}$) in 2030. To assess the influence of BET_{share}, CE_{public}, $peak\_hour$, and $range_{BET}$, the parameters are varied by +/- 50% (original value * 1.5 or original value * 0.5) in the *Wide2030* scenario. Figure 5-5 shows the results of the sensitivity analysis. Please note that the variations of BET_{share}, CE_{public}, and $peak\_hour$ lead to the same result and are therefore identical.

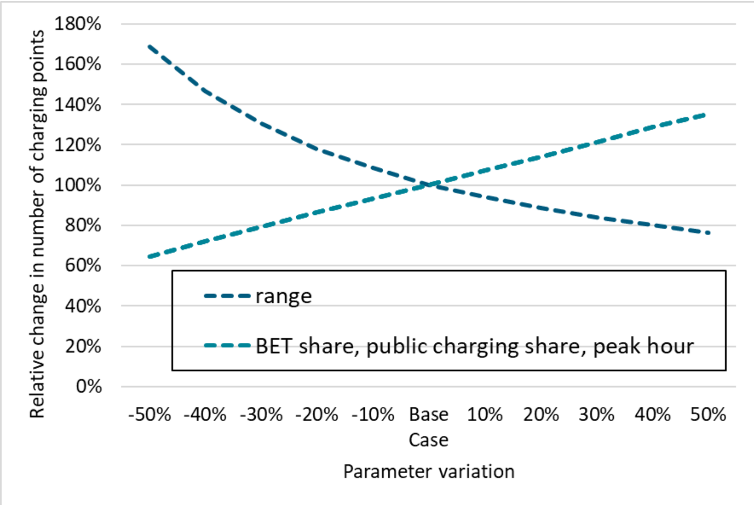

Figure 5-5: Variation of parameters BET_{share}, CE_{public}, $peak\_hour$, and $range_{BET}$ in the scenario Wide2030.

An increase in BET_{share}, CE_{public} or $peak\_hour$ by 50% increases the number of charging points from 4,250 to 5,739. This means the number of charging points increases by 35%. Similarly, a reduction in BET_{share} or CE_{public} results in a 35% reduction in charging points. A reduction of the vehicle range $range_{BET}$ by 50% increases the number of charging points by 69%, from 4,250 to 7,175. An increase of the vehicle range $range_{BET}$ results in a decrease of the necessary charging points by 23%.

The charging time $charging_q$ also represents a critical parameter, as recharging within 30 minutes requires the MCS standard, which is still under development. In addition, the regulation on driving time needs to be slightly adjusted so that the vehicles can release the charging point after 30 minutes. Doubling the charging time to one hour, leads to 7,678 charging points in the *Wide2030* scenario. This fits to the charging power of the current CCS standard with up to 350 kW. The increase in the number of charging points due to doubling the charging time corresponds to 81%.

5.1.1.2 Charging infrastructure at regular intervals in Germany

This thesis refers in particular to road freight transport in Germany. Therefore, Figure 5-6 plots the distribution of charging points in the *Wide2030_GER_ETIS-U* scenario and the *Wide2030_GER_M-TCD* scenario for Germany. The *Wide2030_GER_ETIS-U* scenario shows the German part of the *Wide2030* scenario for Europe. The *Wide2030_GER_M-TCD* scenario is subject to the same framework assumptions. This includes 15% battery electric trucking (BET_{share}), 25% public charging (CE_{public}), and a distance (d_{avg}) of 100 km between charging locations. However, the scenario is based on the manual traffic count data in Germany (M-TCD) instead of the European ETIS-U dataset. As explained in section 3.4.1, this also changes the annual mileage considered (AM_{total}) and the road network considered for electrification.

Public fast charging locations

As defined in section 3.4.1, the *Wide2030_GER_ETIS-U scenario* defines an infrastructure installation along the E-road network (UN, 2016). This network does not include all single- and double-digit highways in Germany, as the network in the *Wide2030_GER_M-TCD* scenario does. As shown in Table 3-4 in section 3.4.1, the considered E-road network is shorter by about 3,000 km. For example, the eastern route form Rostock to Berlin is not included. The route between Dortmund and Leipzig in the north of Erfurt is also not part of the modeling in the *Wide2030_GER_ETIS-U* scenario. In total, the *Wide2030_GER_ETIS-U* scenario includes 101 charging locations. The broader *Wide2030_GER_M-TCD* scenario includes 142 charging locations. As the model treats highways independently, the distance between two charging locations can be shorter than 100 km. In addition, as described in section 4.1.1.1, the beginning and the end of a highway are treated differently to ensure connectivity between highways and countries. For example, the *Wide2030_GER_M-TCD* scenario creates a location at the A5 highway near the city of Freiburg, 50 km before the end of the highway at the Swiss border. At the same time, the model has positioned a charging location 10 km further north. This location is about 100 km away from the next charging location, near Karlsruhe. Since the highway A5 is electrified from North to South, this effect occurs at the southern end of the highway. This effect does not occur in the *Wide2030_GER_ETIS-U* scenario, since E-roads are defined across borders. However, a similar effect occurs at highway junctions.

Overall, the restriction to the E-road network represents a minimum requirement and does not necessarily enable all routes to be covered. The network on single- and double-digit highways is more comfortable. However, more locations must also be built.

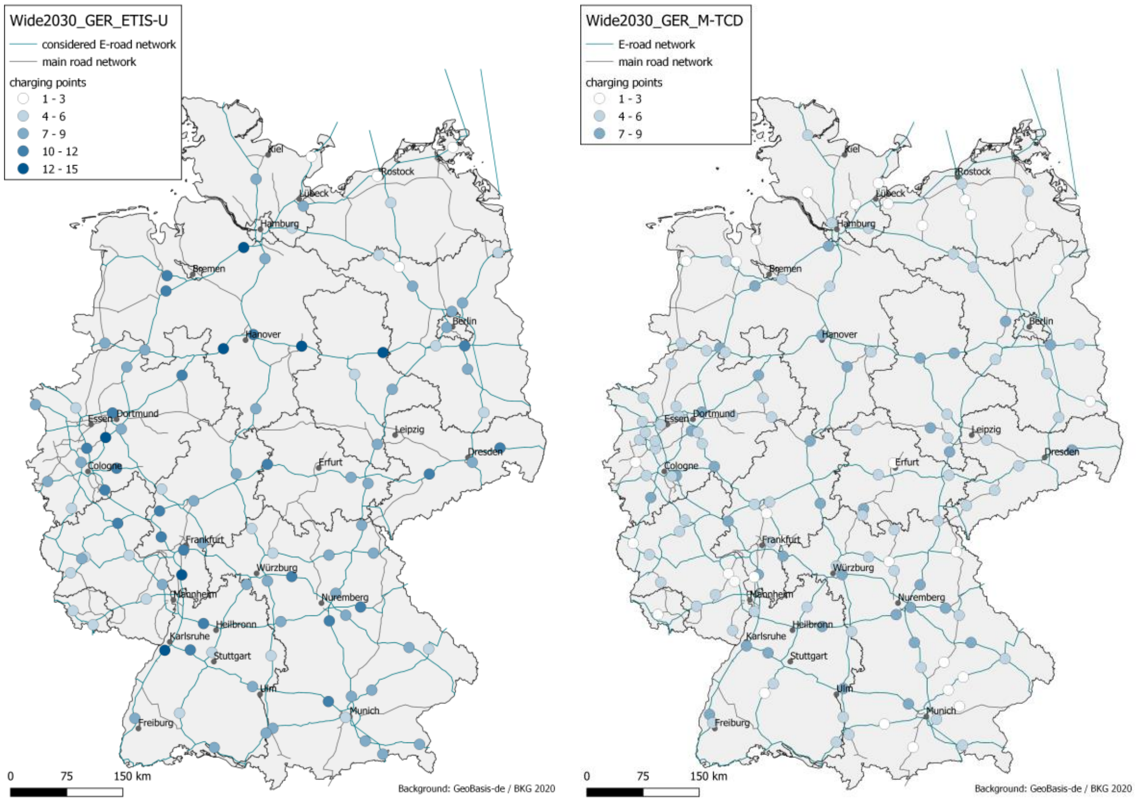

Figure 5-6: Charging infrastructure at regular intervals in Germany in the scenarios Wide2030_ETIS-U and Wide2030_M-TCD.

Number of charging points per location

As shown in section 3.4.1, the considered annual mileage AM_{total} in the *Wide2030_GER_ETIS-U* scenario is higher than in the *Wide2030_GER_M-TCD* scenario. Therefore, the number of daily public fast charging events $CE_{total,public}$ in Germany also differs between the scenarios. The *Wide2030_GER_ETIS-U* scenario assumes 20,691 charging events, while the scenario *Wide2030_GER_M-TCD* calculates 16,250 charging events per day. Due to the lower number of charging locations, the individual charging locations in the *Wide2030_GER_ETIS-U* scenario are also significantly larger than in the *Wide2030_GER_M-TCD* scenario. On average, one charging location consists of eight charging points (mean = 8.0, median = 8, σ = 2.6). This corresponds to twice the size of charging locations in the Europe-wide *Wide2030* scenario.

In contrast, the average charging location in the *Wide2030_GER_M-TCD* scenario includes only five charging points (mean = 5.2, median = 5, σ = 2.0). Figure 5-7 shows the distribution of charging points per location in both scenarios. Although the *Wide2030_GER_ETIS-U* scenario records 27% additional charging events, the number of charging points only increases by 9% from 741 to 809, compared to the *Wide2030_GER_M-TCD* scenario. Again, the higher efficiency of larger locations is evident.

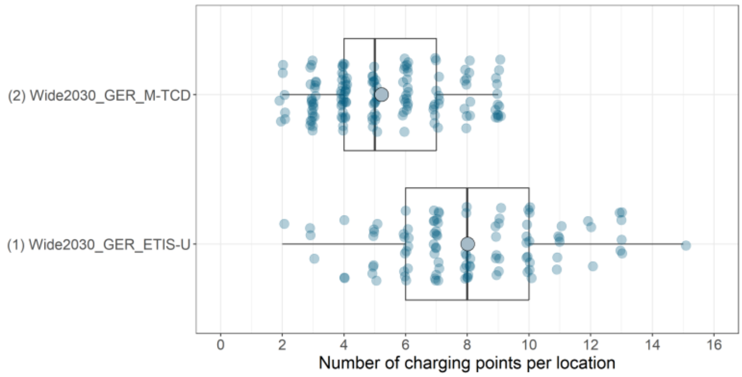

Figure 5-7: Box plot of charging points per location in the scenarios Wide2030_GER_ETIS-U and Wide2030_GER_M-TCD. Gray dot indicates mean value.

5.1.1.3 Discussion

The discussion of charging infrastructure modeling at regular intervals contains two major topics. The first topic refers to the necessary assumptions and input parameters. The second topic deals with the method itself and its limitations.

Assumptions and input parameters

As shown in chapter 2.2.1 and 3.1.1, counting station data or other types of node-based data are easy to understand and easily accessible. However, this approach comes with relevant limitations. The actual mileage of the relevant population needs to be estimated from additional sources. When using synthetic datasets, counting station data and traffic volume are congruent. However, the dataset is no longer based on real-world measured data. Furthermore, the comparison of the two scenarios for Germany shows that the selection of the database regarding the underlying network influences the number of charging locations. Against this background, the total number of charging points is more relevant than the number of charging locations.

Additionally, the model relies on assumptions regarding the future share of battery-electric trucking BET_{share}, the range of the vehicles $range_{BET}$, the share of public charging CE_{public}, and the charging demand in the peak hour $peak\_hour$. As shown in the sensitivity analysis in subchapter 5.1.1.1, the mentioned parameters have a relevant impact on the results. Within the plausible range of the parameters, at least a deviation of +/- 35% is possible, per parameter. For example, the share of public charging CE_{public} is estimated by the share of high-mileage vehicles. However, if vehicles with a daily mileage less than 500 km also regularly require public charging infrastructure, for example due to difficulties in the ramp-up of private charging infrastructure, a remarkable increase of the public charging demand seems plausible. Conversely, even vehicles with a high daily mileage might be able to charge exclusively at private depots, if the stopovers allow for it. Peak hour traffic $peak\_hour$ estimates also vary between different data sources, as shown in chapter 3.1.2.

The charging time $charging_q$ and the waiting time w_q are also subject to uncertainty, since they rely on the MCS standard and on the willingness to stop longer than 45 minutes in very rare cases. As shown in the sensitivity analysis in subchapter 5.1.1.1, doubling the charging time would almost double the number of charging points.

Against this background, the results of the infrastructure modeling at regular intervals should be interpreted as a plausible order of magnitude, not as exact values.

Methodology

In addition to data limitations, the model itself also comes with some limitations. First, the selection of locations does not take into account the suitability of the location for a charging area. Aspects such as parking area availability or the power grid connection are not part of the analysis. The locations are intended as representatives for the particular highway section, not as a defined location. However, the model gives a good impression of the general distribution of charging locations as well as the total number of charging points required. As part of the model development, location details could be integrated up to a certain level in the future. However, a planner will evaluate the local conditions in the targeted area in detail.

Second, as a node-based model, the coverage approach does not consider traffic flows. Vehicles are counted several times for different subsections, they pass. It is plausible that vehicles recharge evenly distributed throughout the road network according to the local traffic volume. However, special effects may occur. As an example, the ETIS-U dataset contains extensive port-hinterland-traffic. This traffic leads to a high traffic volume locally. As shuttle transports, these vehicles are probably charged at private depots. The model tends to overestimate the required public charging infrastructure in these sections. The assumption that charging processes are distributed equally to traffic volumes should be verified in the future, for example with driving logbooks or with data from parked vehicles. To overcome the underlying problem, the use of path- or tour-based models can also improve the results.

Third, the differentiation between public fast charging in the mandatory break and public slow charging is highly simplified and can only be modeled as part of CE_{public} At this point, path-based or tour-based models are better suited. However, these models are associated with significantly higher computational effort and a high demand on data availability.

Unlike an optimization model, the modeling of infrastructure at regular intervals cannot guarantee the minimum number of charging stations. Nevertheless, it has other advantages: (1) The input data requirements are comparatively low. While an FRLM requires a complete set of transport flows, modeling of infrastructure at regular intervals works with counting station data. (2) The modeling of infrastructure at regular intervals is not computationally demanding, while the optimization approach for the entire vehicle fleet of a country relies on significant simplifications to render the problem solvable. (3) The modeling of infrastructure at regular intervals meets the user’s demand to reach a charging station quickly at any time. This is even more valid for trucks, where detours or additional recharging stops beyond the usual mandatory breaks are unlikely to be accepted.

5.1.2 Optimized charging infrastructure[2]

The following sections present the results of the optimization scenarios *Optimziation2045*, *Optimization2045_Ger*, and *Optimization2045_Ger_C*. The results for the EU27, Norway, Switzerland, and Great Britain are presented first, followed by the results for Germany. While the results for Europe in subchapter 5.1.2.1 are based on an uncapacitated FRLM, the results for Germany contain an uncapacitated and a capacitated approach.

5.1.2.1 Optimized charging infrastructure in Europe

Figure 5-8 shows the distribution of 339 charging stations in the *Optimization2045* scenario, according to the FRLM. Especially along roads with few junctions, for example Norway or Sweden, charging stations are placed at the maximum possible distance of 300 km. To serve traffic of several streets with one station, stations are often built at intersections. For every road section in the ETIS-U dataset, the average daily traffic volume of the relevant origin-destination paths (> 300 km, ≥ 50 trucks/a) is plotted in the background. It can be clearly seen that the traffic volume does not affect the charging infrastructure density. Highly trafficked routes, for example from North Spain via France to Belgium, also have charging stations with about 300 km distance. The number of charging stations required per country is thus essentially defined by the density of the road network. Appendix A.5 shows the number of charging stations per country.

In order to maintain a reasonable computation time, the presented solution of the FRLM accepts a maximum tolerance of the MIP of 5%. This means the optimal solution could theoretically be 323 charging stations.

The FRLM does not assign an exact charging location to vehicles, but simply ensures that each OD path is drivable. Additional assumptions would therefore have to be made, in order to calculate the number of charging points at each location (compare for example Jochem et al. (2019)). However, since the results of the infrastructure modeling at regular intervals already show that no realistic location size can be expected with such a small number of charging locations, this is not done at this point.

[2] Parts of this subchapter are based on Speth et al. (2024). This publication is still under review at the time of submission of this thesis.

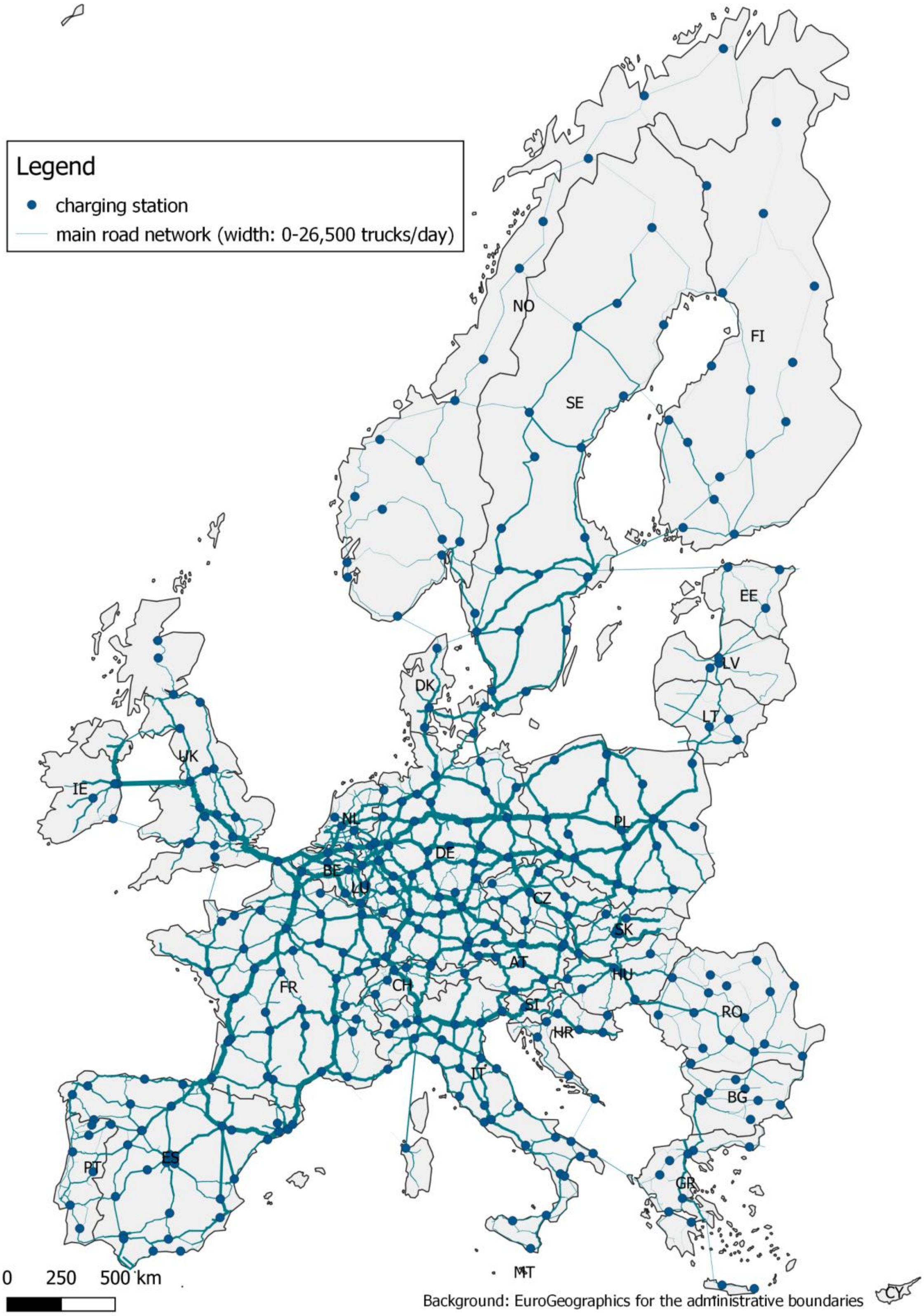

Figure 5-8: Optimized charging infrastructure in the scenario Optimization2045, based on FRLM. Originally published in Speth et al. (2024).

5.1.2.2 Optimized charging infrastructure in Germany

Public fast charging locations

In the *Optimiziation2045_Ger* scenario without any capacity restriction, Germany receives 42 charging locations. With 14,000 km of roads in Germany in the ETIS-U dataset, this corresponds to one charging location per 333 km. However, the locations are often placed at intersections, so the real distances are smaller. Long distance sections, for example from Denmark to the charging location near Hamburg or on the heavily traveled east-west highway A2, are usually shorter than 200 km. However, intersections in particular are typically unsuitable as locations for infrastructure (P. Rose, 2020). Therefore, the results of the *Optimization2045_Ger_C* scenario, which considers available parking spaces, are of particular interest.

Figure 5-9 shows the distribution of 124 charging locations in Germany, according to the CFRLM. To keep the computation time reasonable, the solver tolerance is set to 15%. Using IBM CPLEX on a virtual machine with 8 processors (AMD EPYC 7742) and 256 GB RAM, the computation time is still several days. The theoretically possible best solution would therefore be 106 charging locations. This shows the importance of the capacity restriction. Even if the theoretical lower bound could be reached, 2.5 times as many stations as in the *Optimiziation2045_Ger* scenario without capacity restriction would be needed. In the network shown, the demand triples.

As shown in Figure 5-9, there are still sections with long distances between two charging locations. This includes, for example, the section from Denmark to Hamburg. The positioning of the first charging location in Germany, located in the north of Hamburg, is quite similar in the scenarios *Optimiziation2045_Ger* and *Optimiziation2045_Ger_C*. Simultaneously, location density increases on highly frequented long-haul sections. A good example is the transit route from the Netherlands - via Essen, Hanover, passing Berlin - to Poland. As part of this route, the A2 highway connects major European ports (Amsterdam, Rotterdam and Antwerp) to Eastern Europe. To sum this up, the CFRLM does not distribute stations evenly, but places large stations with close distances along highly trafficked long-haul routes.

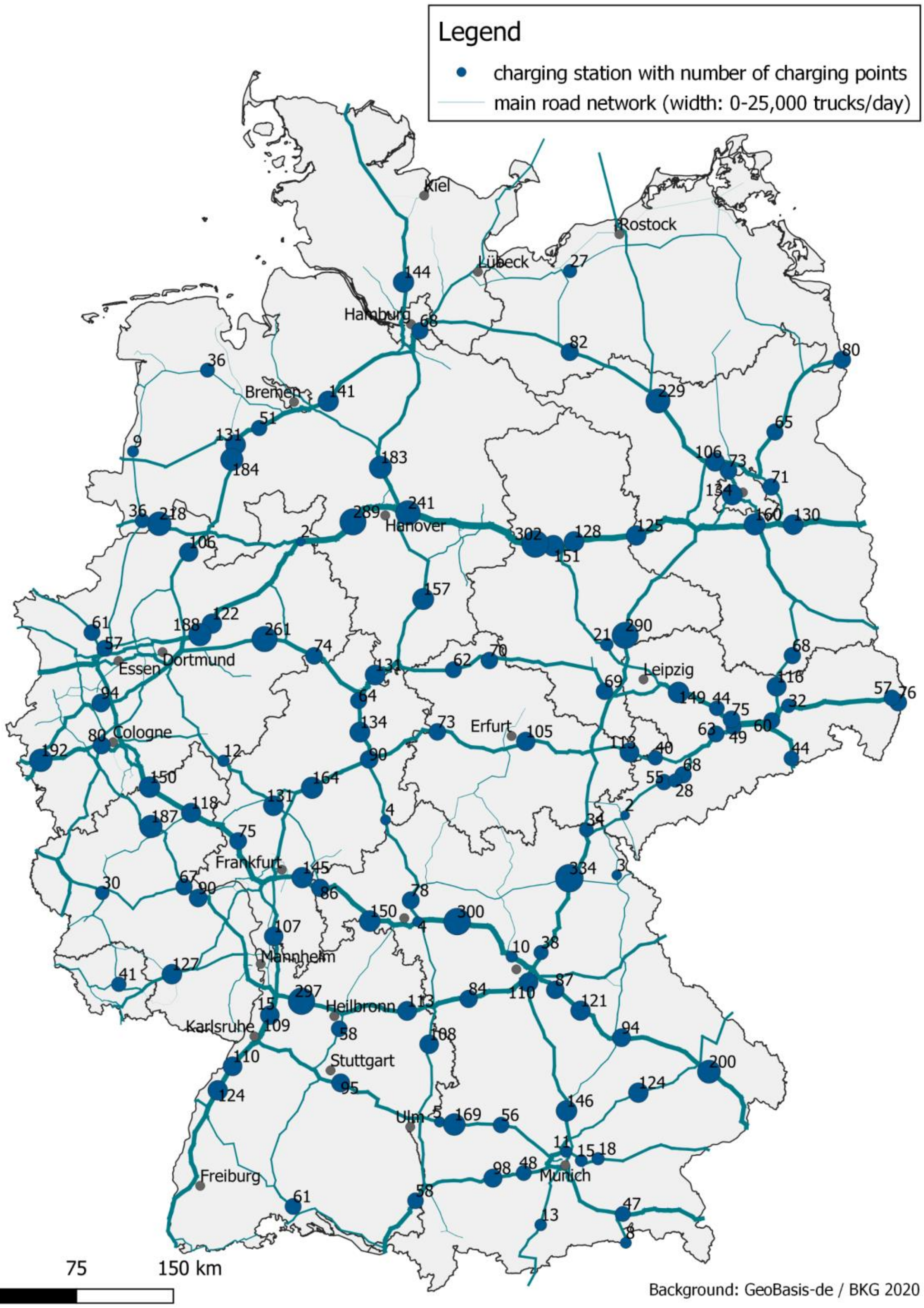

Figure 5-9: Optimized German charging infrastructure in the scenario Optimization2045_C, based on CFRLM. Originally published in Speth et al. (2024).

Number of charging points per location

In total, the *Optimiziation2045_Ger_C* scenario contains 12,323 charging points. The charging points serve 388,000 charging events per day, of which 23,000 are in the peak hour. Despite the capacity restriction, minimizing the number of charging locations still results in large locations. As shown in Figure 5-10a, locations with up to 334 charging points are built. However, a single location can comprise several parking areas. For example, 334 charging points at the largest location cover four separate charging areas within a radius of 2 km from the relevant node in the highway network. On average, one location contains 99 charging points (mean = 99, median = 83, σ = 71.9). Figure 5-10b indicates that the individual locations are typically almost fully developed, meaning that almost every available parking space receives a charging point. This is also due to minimizing the number of charging locations, which favors large, fully developed locations.

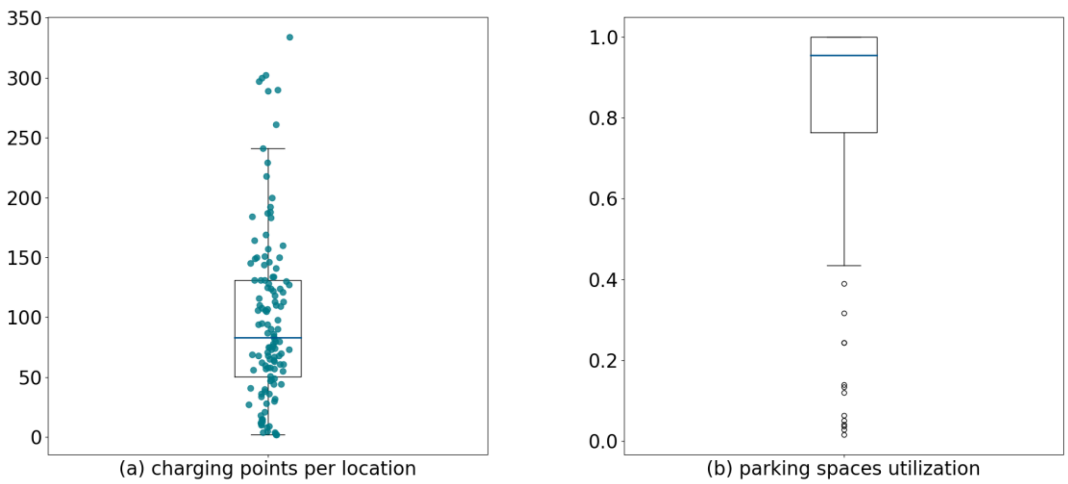

Figure 5-10: (a) Number of charging points per charging location and (b) utilization of available parking spaces at charging locations in the Optimiziation2045_Ger_C scenario. Originally published in Speth et al. (2024).

Utilization of charging infrastructure

The assignment of individual charging events to charging locations in the CFRLM allows an evaluation of the utilization of the infrastructure. As shown in Figure 5-11a, the average charging location in the *Optimiziation2045_Ger_C* scenario is occupied 43% of the day (mean = 0.43, median = 0.45, σ = 0.06)[3].

[3] $$u_{temporal,node\ i} = \frac{charging\ events_i\left[\frac{vehicle}{h}\right]* \frac{charging_q\left[\frac{min_{charging}}{vehicle}\right]}{60\left[\frac{min_{charging}}{h_{charging}}\right]}* \frac{1}{peak\_hour\left[\frac{d}{h}\right]}* 250\left[\frac{d}{a}\right]}{8760\left[\frac{h_{charging\_possible}}{a}\right]*charging\_points_i\ [\#]}$$

The utilization rate is lower for smaller stations, since fluctuations in the arrival rate have stronger influence and make oversizing necessary.

Since the trucks usually do not need to charge at the maximum power of 1 MW, the energetic utilization is lower than the temporal utilization. As shown in Figure 5-11b, the average charging station provides 23% of the theoretically maximum possible amount of energy (mean = 23, median = 23, σ =3.9)[4].

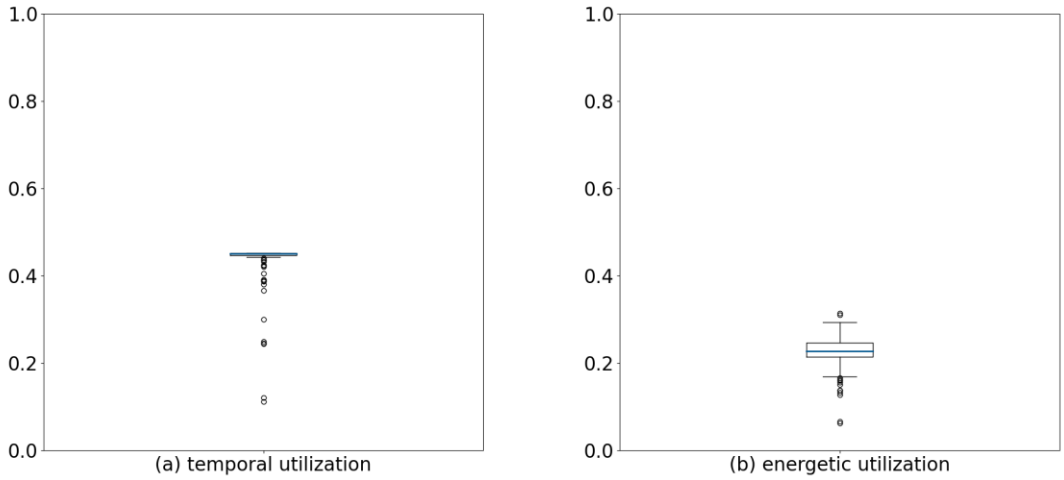

Figure 5-11: (a) Temporal and (b) energetic utilization of charging locations in the Optimiziation2045_Ger_C scenario. Originally published in Speth et al. (2024).

Energy demand

Finally, the assignment of individual charging events to charging locations allows calculating the distance traveled since the last recharging event. Taking into account the average consumption, the amount of energy recharged can be calculated. At vehicle level, an average of 263 kWh is recharged per charging stop (mean = 263, median = 282, σ = 76.2). This corresponds to a range of 219 km (mean = 219, median = 235, σ = 63.5). As shown in Figure 5-12a, there are charging events that nearly exhaust the demand of 360 kWh resulting from the maximum range of 300 km. However, other stops take place after short driving distances and result in low charging demands. Nevertheless, they are necessary to make all paths drivable. In total, trucks charge 25 TWh annually at the modeled CFRLM infrastructure. Figure 5-12b shows that large locations count for more than 0.6 TWh per year.

[4] $u_{energetic,node\ i} = \frac{\sum_{q_s}(x_{i_{q_s}} * f_{q_s}\left[\frac{vehicle}{h}\right] * recharge_{x_{i_{q_s}}}[km]) \frac{1}{peak\_hour\left[\frac{d}{h}\right]} * 250\left[\frac{d}{a}\right] * cons_e\left[\frac{kWh}{km}\right]}{8760\left[\frac{h}{a}\right] * p_{peak}\left[\frac{kW}{\#}\right] + charging\_points_i\,[\#]}$, with $recharge_{x_{i_{q_s}}}$ as the amount of km driven at path q_s since the last charging event on the route. All other parameters are defined in section 3.4.2 or 4.1.2.2.

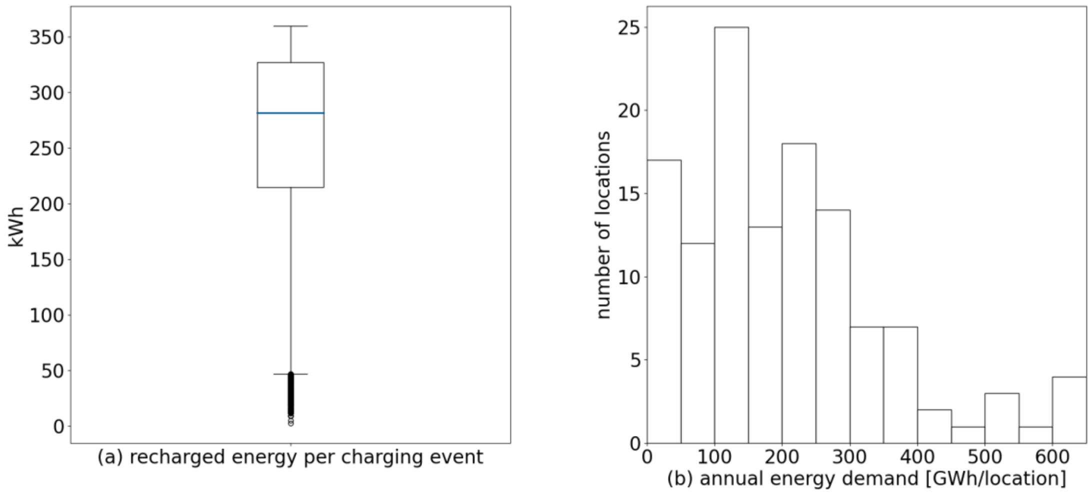

Figure 5-12: (a) Recharged energy per charging event and (b) annual energy demand of charging locations. Originally published in Speth et al. (2024).

5.1.2.3 Discussion

To the best of the authors' knowledge, this thesis is the first attempt to apply a capacity-constrained FRLM (CFRLM) to a dataset with more than 200,000 traffic flows and real-world parking capacities. The results show that the capacity constraint more than doubles the required number of charging stations compared to a traditional FRLM. Furthermore, the distinct assignment of each charging event to one charging location allows additional evaluations with regard to the amount of energy required locally. However, the results presented here are also dependent on methodological framework conditions and the underlying data. Therefore, both aspects will be discussed in more detail.

The literature review shows that optimization methods are very popular for location planning from a methodological point of view. However, the optimality of the solution often comes with significant simplifications, to keep the problem solvable. The integration of required charging locations by the introduction of a capacity constraint shows that the result of an uncapacitated, large-scale FRLM are of limited relevance in practical applications. However, this additional accuracy comes with a significant additional computational effort - in this case several days.

Another methodological aspect is the integration of cross-border traffic. Unlike previous studies, cross-border traffic is integrated into the model in high resolution. Yet, the assumption of charging events at charging stations of the unrestricted FRLM in foreign countries is a simplification. The simplification results in less stations being built in the border area. More restrictive assumptions could further improve the results.

Finally, minimizing the number of charging stations results in a solution that includes few but large stations. In this case, the objective function was chosen to keep CFRLM and FRLM comparable. Future studies could focus even more on real-world relevance. On the one hand, this can be done by adapting the objective, for example by integrating a cost function. On the other hand, additional restrictions, for example restrictions derived from the power grid, could also be taken into account.

In terms of the data used, the ETIS-U dataset represent a broad database. However, the dataset is also a simplification. In particular, it does not represent driving profiles. This means that a trip with multiple stops is reflected as multiple independent paths. The charging behavior may differ as a result. Especially, long parking periods cannot be distinguished from short parking periods. Therefore, all public charging events are modeled as fast charging events. In combination with the fact that long routes are modeled as one long trip, although the vehicles may stop several times at depots on the route to fulfill other OD-paths within the same trip, this leads to an overestimation of the fast charging infrastructure demand. If available, future studies could build on extensive real-world driving profiles including time stamps. The analysis presented covers 85% of the traffic volume in the dataset. Some OD-flows with a low traffic volume are ignored, to keep the problem solvable. However, in their German section, these flows typically correspond to other flows included in the analysis. So, in principle, they are drivable. Due to their low traffic volume, they would have only minor impact on the infrastructure demand. Yet, future analyses may converge parallel flows to include them.

The assumed range represents a central parameter, which is conservatively estimated as 300 km. A higher range would reduce the need for charging infrastructure. In contrast to the modeling of infrastructure at regular intervals, the range of the vehicles serves as an upper limit rather than an average. This means that there are more charging events in total to fulfill the same total mileage.

Finally, the optimization approach benefits from the low requirements regarding additional assumptions. Thus, in contrast to the modeling of charging infrastructure at regular intervals, no assumptions on the share of public charging are needed.

5.1.3 Costs for public fast charging infrastructure

To assess the potential of a future public fast charging infrastructure for HDV, costs play a relevant role. Table 5-2 sums up the investment, the annual costs, and the infrastructure levy per kWh in all modeled infrastructure scenarios. The infrastructure levy is defined as the costs of the infrastructure per kWh of electricity supplied by the infrastructure. The calculations follow the methodology in chapter 4.1.3 and include the input data from chapter 3.3.

In the scenarios modeled, the conversion of the European HDV fleet to battery electric vehicles necessitates an investment in the high single-digit billion €$_{2020}$ range. The *Dense2045* scenario reaches an investment required of almost 10 billion €$_{2020}$. The scenarios *Startup2025*, *Wide2030*, and *Dense2030* represent intermediate steps. For instance, the *Startup2025* scenario shows that investments of over 1 billion €$_{2020}$ are necessary in the short term.

The indicated investments do not include replacements, but represent the one-time investments to build the infrastructure. Since replacement investments are already being made in the period under consideration, the annual costs caused by the infrastructure are even more relevant than the investment. The *Dense2045* scenario, as steady-state system, shows 1.3 billion €$_{2020}$ annually.

In terms of infrastructure levies per kWh, it can be seen that the infrastructure surcharge is well below 10 ct$_{2020}$/kWh in all scenarios. In highly utilized networks with an adequate demand even at small locations, the levy can drop to as low as 2 ct$_{2020}$/kWh. It should be noted that the modeling does not estimate any costs for land-use, as it is uncertain whether the infrastructure providers can use areas that they already own. However, the high energy consumption at the infrastructure allows for low infrastructure levies.

It can be seen that almost 20% of the investment in the *Wide2030* scenario applies in Germany. According to the modeling of infrastructure at regular intervals, investments of almost half a billion €$_{2020}$ is expected for public fast charging infrastructure for HDV in Germany until 2030. The results of the of the optimization approach show a contrast to the results presented. For the fully developed charging infrastructure in the *Optimization2045_Ger_C* scenario, investments amounting to 5.8 billion €$_{2020}$ are required. Thus, the investment in this scenario is more than 50% of the investment in the *Dense2045* scenario for Europe. Due to the non-exogenously determined share of public charging events, significantly more charging events take place at the optimized charging infrastructure. However, the infrastructure levies are almost similar. For comparison, annual truck toll in Germany in 2019, before the COVID-19 pandemic, was 7.5 billion €$_{2020}$ (BAG, 2021). Wietschel et al. (2017) calculated almost 9 billion €$_{2015}$ for 4,000 km of overhead catenary lines in Germany, resulting in 0.7 billion €$_{2015}$ annually.

Table 5-1: Investment, annual costs, and infrastructure levy in all charging infrastructure scenarios. Six scenarios are based on charging infrastructure at regular intervals, one scenario is based on optimization (CFRLM).

Scenario	**Investment [Mio. €$_{2020}$]**	**Annual costs [Mio. €$_{2020}$/a]**	**Infrastructure levy [€$_{2020}$/kWh]**
Startup2025	1,388	182	0.06
Wide2030	2,429	323	0.03
Wide2030_Ger_ETIS-U	449	60	0.03
Wide2030_Ger_M-TCD	416	56	0.03
Dense2030	3,099	410	0.04
Dense2045	9,934	1,299	0.02
Optimization2045_Ger_C	5,808	754	0.03

5.1.4 Summary

Chapter 5.1 shows a possible public fast charging infrastructure for HDV in five European and four German scenarios. Table 5-2 contains the most relevant results of all scenarios. For better comparability, the German share of the *Dense2045* scenario is additionally given as *Dense2045_Ger.*

Table 5-2: Overview on the number of required charging locations and charging points in all infrastructure scenarios

Scenario	Events [thou./d]	Locations	Charging points Total	Mean	Min	Max	Investment [Mio. €$_{2020}$]
Charging infrastructure at regular intervals:							
Startup2025	27	917	2,090	2.3	1	6	1,388
Wide2030	92	917	4,250	4.6	1	16	2,429
Dense2030	92	1,701	5,290	3.1	1	11	3,099
Dense2045	615	1,701	21,804	12.8	1	61	9,934
(Dense2045_Ger)	144	190	4,771	25.1	2	57	2,207
Wide2030_Ger_ETIS-U	21	101	809	8.0	2	15	449
Wide2030_Ger_M-TCD	16	142	741	5.2	2	9	416
Optimized charging infrastructure:							
Optimization2045		339					
Optimization2045_Ger		42					
Optimization2045_Ger_C	388	124	12,323	99.0	2	334	5,808

The scenarios *Startup2025*, *Wide2030* / *Dense2030*, and *Dense2045* can be interpreted as expansion stages. They show that a demand for several thousand public fast charging points could arise across Europe in the short term. Even converting 5% of HDV traffic to BET, as in the *Startup2025* scenario with 27,000 charging events per day, will require more than 2,000 charging points. With the parameters considered in this thesis, a full fleet conversion would require 22,000 charging points across Europe. The comparison between the *Wide2030* and the *Dense2030* scenarios shows that the number of charging points, due to the lower efficiency at smaller locations, increases when reducing the distance between the locations. However, the increase is smaller than the increase in the number of charging locations. The number of charging locations in the network depends on the desired convenience and the considered road network. Regarding the European network, the 339 charging location in the *Optimization2045* scenario represent a minimum number to make all paths drivable. However, to keep the location size feasible at full fleet conversion, the 50 km distance proposed in the *Dense2045* scenario seems appropriate. Large locations contain more than 60 charging points. Taking into account the parameters assumed in this thesis, the investment for a full-scale expansion in Europe amounts to 10 billion $€_{2020}$.

From a German perspective, the scenarios show a need for 800 charging points in the medium term, for example until 2030. Assuming a full fleet conversion to BET, the coverage approach results in slightly less than 5,000 charging points. The charging points are distributed to 190 locations with a distance of approximately 50 km. By 2030, the calculated investments are less than half a billion $€_{2020}$ in Germany. For the 2045 network, the investments increase to more than 2 billion $€_{2020}$. However, looking at the results of the optimization approach, the need for charging points and investments, could be twice as high. The difference reflects the high uncertainty regarding various input parameters concerning the actual driving behavior. The uncertainty includes the lack of tour-based driving information, the distribution of traffic volumes throughout the day connected to the daily peak traffic, the maximum accepted recharging time, the necessary network density, and technical parameters such as the expected future vehicle range. A deeper understanding can be gained by the detailed analysis of individual vehicle driving profiles as well as the integration of the market diffusion of BET in relation to the infrastructure. These two aspects are covered in the second part of this thesis.

Finally, the first research question is answered at this point:

Q1: Taking into account the locally resolved demand for freight transport, how can a station-based public charging infrastructure for battery electric heavy-duty vehicles in Germany look like and which costs arise due to the infrastructure installation?

A public charging infrastructure for battery electric heavy-duty vehicles in Germany can consist of charging locations that provide vehicles with a peak charging power of at least one megawatt. An infrastructure that is capable to cover the whole German heavy-duty vehicle traffic requires investments in the single-digit billion $€_{2020}$ range.

Q1a: Where could a public fast charging infrastructure for battery electric heavy-duty vehicles be spatially located?

High demand arises particularly on highly traveled long-distance corridors, for example the highway A2 as connection between ports in the Netherlands and Eastern Europe. Along such routes, particularly large charging locations with a small distance should be built. The network has to fulfill two conditions. First, the locations must enable all tours in the German highway network. Even when taking into account existing parking areas, this is possible with a maximum of 124 locations. Second, the network must provide a minimum level of convenience and reliability by covering highways at regular intervals. This requires more locations, for example nearly 200 locations for a desired coverage of 50 km per location.

Q1b: How should the public charging infrastructure be technically dimensioned in terms of charging points and charging power?

Based on the scenarios examined, a public fast charging network for heavy-duty vehicles could comprise between 4,500 and 12,000 charging points. However, the analysis shows that different input parameters are subject to high uncertainty, which necessitates further research. Each charging point should deliver up to 1 MW power. Due to the slope of the charging curve with increasing charging level and the simultaneity of different charging processes, the total power of all charging locations is less than the sum of the peak power of the charging points.

5.2 Market diffusion of battery electric trucks

The results for the joint market diffusion of public fast charging infrastructure and the market diffusion of alternative fueled vehicles is shown in the following. First, the results of the individual model steps are presented. The results are then discussed and summarized.

5.2.1 Technical analysis regarding feasibility, battery dimensions, and charging behavior

The following section presents relevant results of the first model step of the market diffusion model, the technical analysis. The results are based on the analysis of 2,410 driving profiles of rigid trucks and tractor-trailer trucks of the KiD (WVI et al., 2012a) with a GVW higher than 12 t. At this point, the results include the technical feasibility of electrification from a technical perspective, the required battery sizes, and the energy demand in combination with the load profile.

5.2.1.1 Technical feasibility

One important component is the technical possibility to electrify the individual driving profiles, given framework conditions. Figure 5-13 shows the number of stops required depending on the battery size and the daily mileage of the individual driving profiles for 2020, 2025, 2030, and 2050. The given battery sizes indicate the total capacity of the battery, not the usable battery size. The figure for 2020 shows that, due to the limited battery capacity of 500 kWh maximum, mainly driving profiles with a below-average daily mileage can be electrified. Higher mileages can be electrified, if the individual driving profiles allow for intermediate stops for recharging. Therefore, there are also driving profiles in 2020 with more than 1,000 km daily mileage that can be electrified with up to eight stops. Due to increasing efficiency as well as improvements in the battery technology, the required battery size for the driving profiles decreases over time. Increasing the available battery size, for example up to 700 kWh in 2025, enables electrification of more driving profiles. The number of charging events per driving profile decreases, due to the modeled driving behavior that foresees longer distances between two charging events. Interestingly, smaller batteries are used for short-range vehicles in 2030 than in previous years. This is due to battery improvements as well as increasing efficiency that allows for the required minimum range with smaller batteries. In 2050, batteries with up to 900 kWh are available. The minimum range between to charging events further increases, so that a maximum of three charging events is required per driving profile. Nonetheless, a small number of driving profiles cannot be electrified in 2050. In particular, these are driving profiles with a high daily mileage, potentially driven by multiple drivers. Either the batteries are too large or the charging breaks are too short to recharge the batteries[5].

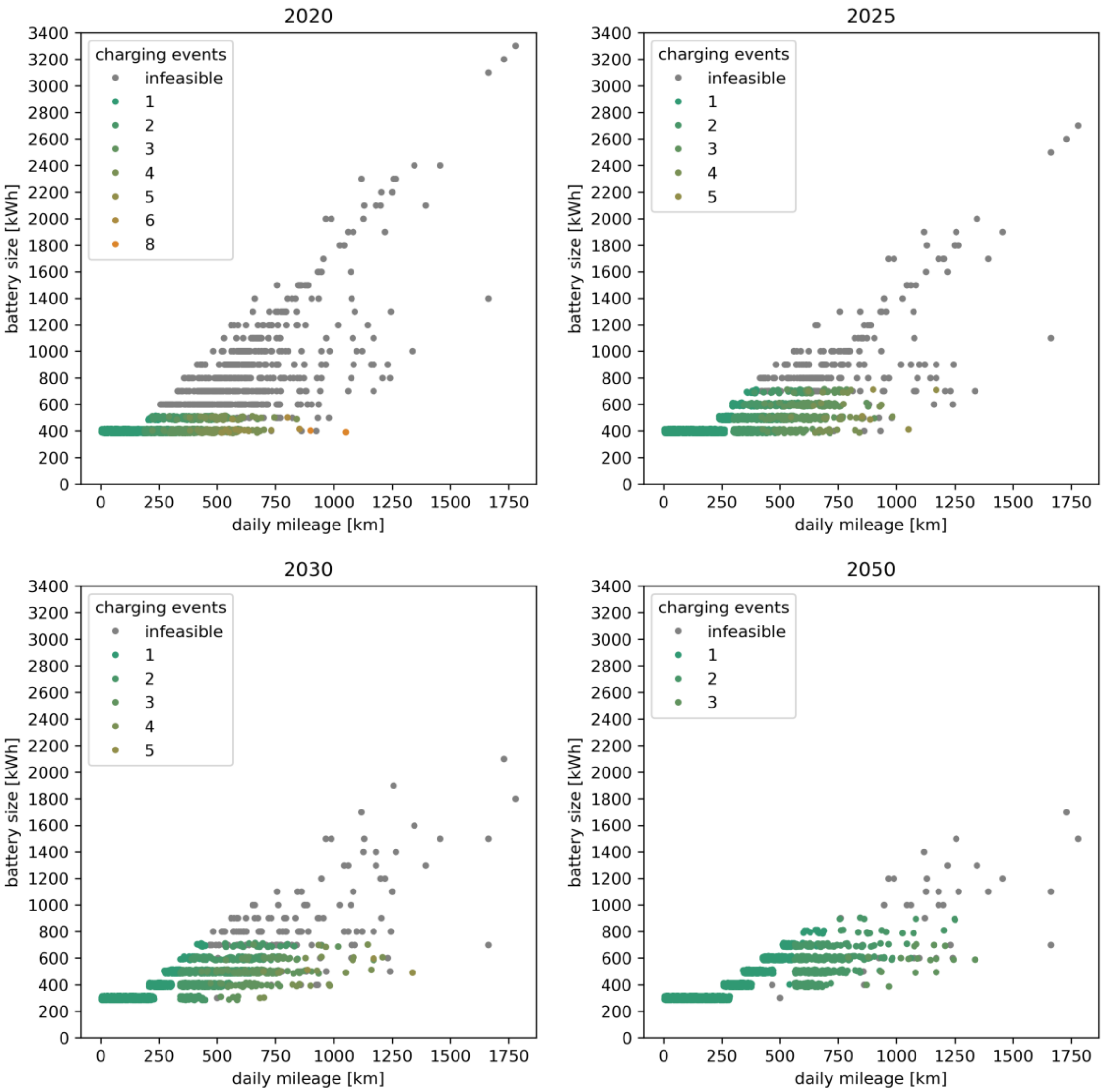

Figure 5-13: Technical feasibility of driving profiles in 2020, 2025, 2030, and 2050, considering daily mileage, battery size, and the number of charging events. All profiles refer to vehicles with a GVW of more than 12 t.

[5] Please note that there are also some driving profiles with comparatively low daily mileage that are not feasible. Typically, these driving profiles cannot be recharged due to short parking periods over night. This is a limitation of the methodology, which requires full charging after the last trip and assumes the same driving profile at all days. A more comprehensive database over several days could strengthen the analysis. With the current data, these driving profiles should be considered primarily as a model phenomenon.

As shown in Figure 5-14, 70% of all driving profiles in 2020 can be electrified from a technical perspective. However, since these driving profiles are typically profiles with a below-average daily mileage, only 44% of the daily mileage can be electrified. In addition, it can be recognized that a maximum of four charging events is usually sufficient. In 2020, there are driving profiles with up to 8 charging events. However, they are neither relevant for the share of driving profiles nor for the share of daily mileage that can be electrified. With an increasing battery capacity, rising charging power and decreasing consumption, the potential for electrification rises significantly by 2025. From a technical perspective, almost 90% of the driving profiles and 75% of the daily mileage can be electrified. In 2050, the electrification potential increases to 97% of the driving profiles. Due to the high mileage of non-electrified driving profiles, the share of electrified mileage is again slightly lower at 93%. However, the analyses show two relevant aspects: (1) There is a high technical potential for BET in the short term, and (2) in the long term, an almost complete conversion of the HDV fleet with a GVW of more than 12 t to BET is technically possible.

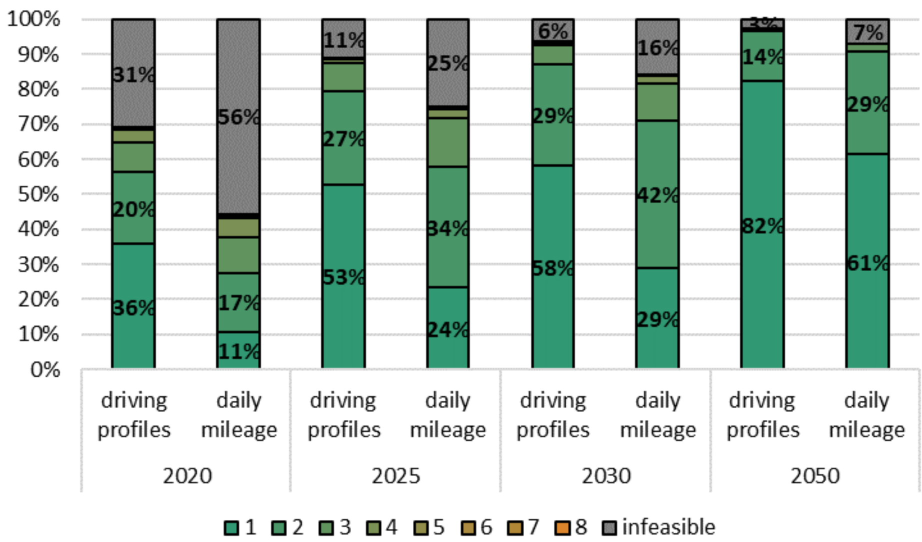

Figure 5-14: Technical electrification potential from 2020 to 2050, including the number of daily charging events. Not feasible profiles with the assumed maximal battery ranges and the modeled charging behavior are shown in grey. All data refers to vehicles with a GVW > 12 t.

5.2.1.2 Battery size

Figure 5-15 shows the necessary gross battery size for technically feasible driving profiles in 2020, 2025, 2030, and 2050 as boxplots. In 2020, the majority of the vehicles require 400 kWh battery gross capacity. The median, the lower quartile, and the upper quartile are identical. 11% of the driving profiles, shown as outliers in the boxplot, require 500 kWh. Over time, the median remains constant at 400 kWh. The maximum battery size is limited by the maximum vehicle range assumed for the different simulation years. A large share of the fleet can meet its daily mileage with just 400 kWh and one stop, as shown in Figure 5-13. Large batteries with up to 900 kWh are needed for high-mileage driving profiles in the long-term. In a purchase decision, larger batteries and ranges could be purchased for convenience or to compensate for underdeveloped charging infrastructure. However, the focus in the present analysis is on technically required battery sizes and charging power.

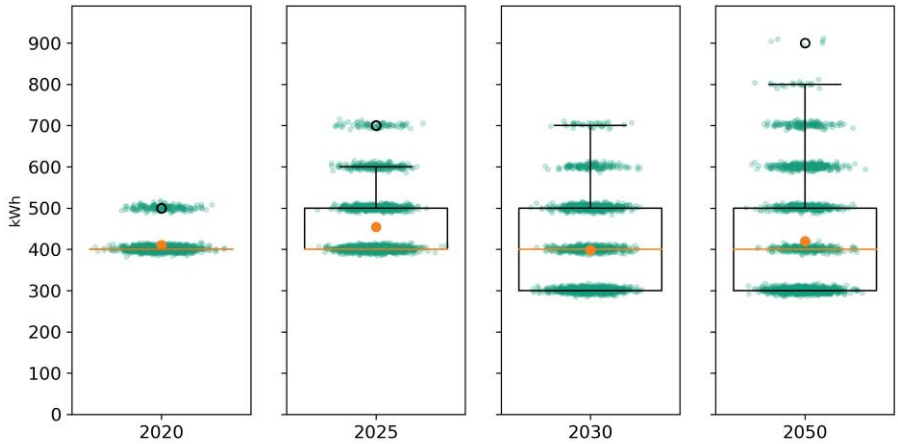

Figure 5-15: Necessary gross battery size for technically feasible driving profiles in 2020, 2025, 2030, and 2050 (both tractor-trailer and rigid vehicles > 12 t GVW). Orange dots mark the average and horizontal orange line the median, horizontal black lines the first and the third quartile. Green dots show individual driving profiles and are slightly varied for better visibility. Batteries are assumed in 100 kWh steps.

Due to the limited battery capacity, it is particularly easy to electrify driving profiles with below-average mileage. Higher mileages can be electrified in early years, if the individual driving profiles contain intermediate stops that allow recharging.

5.2.1.3 Charging behavior

The driving and charging behavior determines the future infrastructure requirements, since the infrastructure is designed to serve the daily charging demand. Figure 5-16 shows the driving and charging behavior of technically feasible HDV as BET on a daily basis for the years 2025, 2030, and 2050 (columns in Figure 5-16) differentiated by daily driving distance of the HDV (rows in Figure 5-16). In each case, the new vehicle fleet is shown, assuming that all technically feasible vehicles are electrified. It is clearly evident that the majority of the charging time occurs at private locations. Private charging is shown in green shades in the figure, public charging is shown in blue[6]. Almost constant over the years, a maximum of 11% of all vehicles simultaneously use a public charging infrastructure. In comparison, during the peak hour - at night - between 75% and 80% of all vehicles charge at private infrastructure, depending on the year. The detailed analysis shows that the need for public charging infrastructure is higher for driving profiles with more than 500 km daily mileage. However, private charging dominates also for vehicles with more than 500 km daily mileage. In 2030, 73% of all technically feasible

[6] For approximately 3% of all vehicles, the location cannot be determined in the dataset. Corresponding charging events are counted as public charging events.

driving profiles only use private infrastructure (2050: 80%), i.e., 27% of BET need public charging.

Additionally, the charging behavior is divided into different power levels. A distinction is made between three levels: (1) charging with up to 44 kW, as this level can be met with AC charging, (2) charging with up to 350 kW, as this level can be covered today with the CCS standard from an infrastructure perspective, and (3) charging with more than 350 kW, as this level will be probably served by the MCS standard[7]. Charging with more than 350 kW is assumed to be available after 2025. Please note the average power within one group is smaller than the upper limit, for example average power in the 45 - 350 kW group is below 350 kW, typically around 200 kW in the simulation. Fast charging, and in particular MCS charging with more than 350 kW, primarily takes place in the midday hours and in the afternoon for intermediate charging. In the long term, the curve is more evenly distributed throughout the day, due to larger batteries. However, never more than 6% of the fleet charge simultaneously at a fast charging infrastructure with more than 44 kW. MCS charging with more than 350 kW is never required by more than 1.5% of the vehicles at the same time. Public MCS charging is used by 1% of the vehicles at the same time in 2030. By 2050, the share decreases to 0.5% of the fleet. If charging with more than 44 kW is also taken into account, up to 1.6% (2030) and 1.3% (2050) of the fleet are charged publicly in parallel. In 2030, 62% of all technically feasible driving profiles exclusively rely on slow charging (2050: 80%). Again, it can be seen that the demand for fast charging is higher for the vehicle fleet with more than 500 km daily mileage. With regard to public fast charging infrastructure, it can be estimated from the technical analysis that it should be designed for up to 1.6% of the fleet simultaneously in 2030 and for up to 1.3% of the fleet in 2050. However, since the technical analysis assumes a complete fleet conversion, further analyses are carried out in combination with the modeled market diffusion in the following subchapters.

[7] The analysis relies on the average charging power. However, due to the large battery capacity compared to passenger cars, it can be assumed that the charging curve for trucks will be almost constant at charging powers below 350 kW. Technically, charging with less than 350 kW could also be done with the MCS standard.

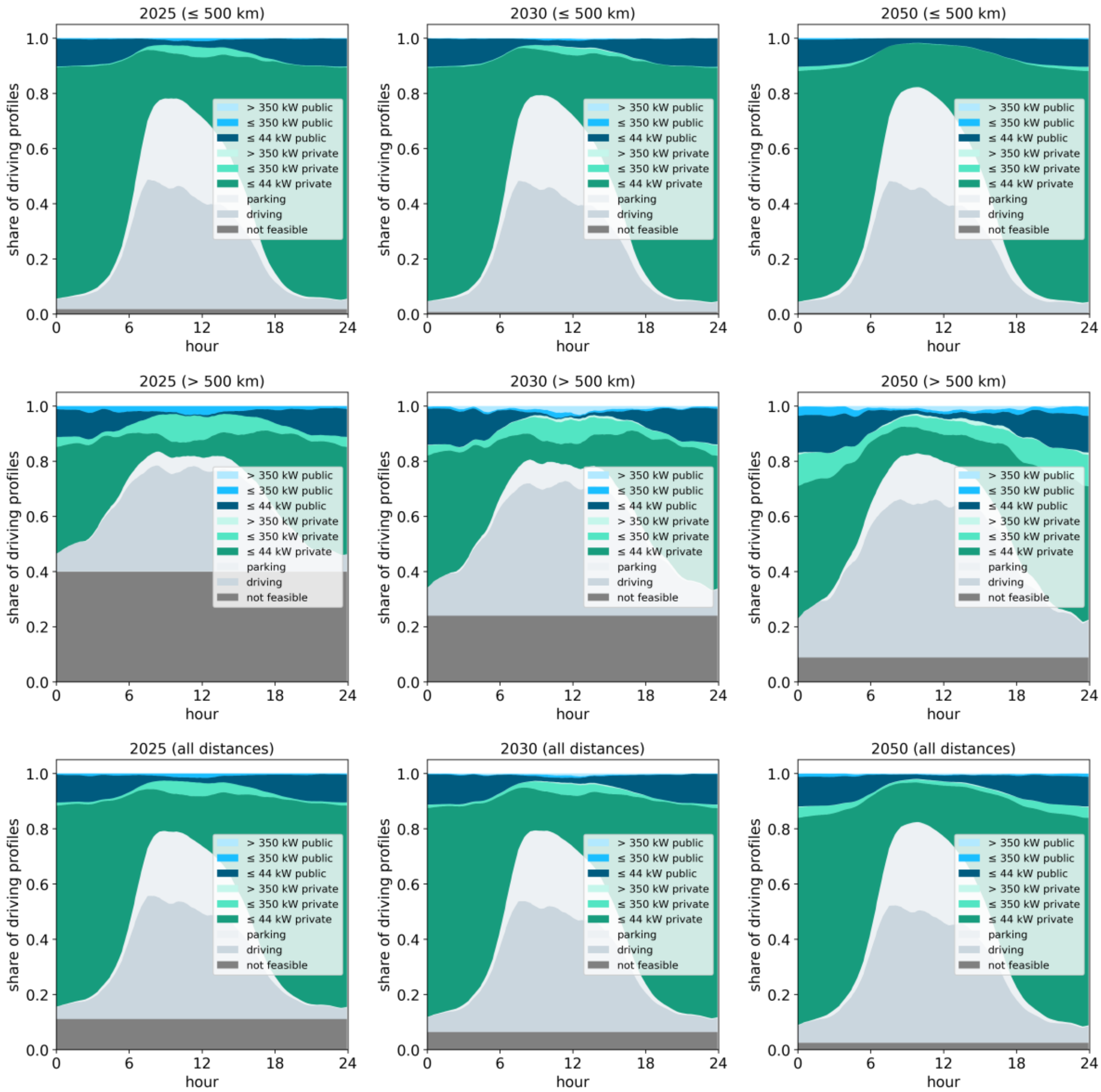

Figure 5-16: Driving and charging behavior of technically feasible BET diving profiles in 2025, 2030, and 2050. Top row: HDVs with ≤ 500 km per day, middle row: HDVs > 500 km per day, bottom row: All HDVs. All HDVs with >12 t GVW. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise.

Figure 5-17 shows the aggregated load profiles of the technical analysis for 2025, 2030, and 2050. Since the absolute power demand can only be determined by considering the market diffusion of BET, the values are normalized so that the total demand over one day equals 100%. The magnitude of the curve can be interpreted as the percentage hourly demand. Interestingly, the increasing efficiency of the vehicles as well as the increasing share of electrified driving profiles offset each other with less than 2% deviation for the years considered, so that the normalization is almost identical for all years and therefore a comparison of the individual figures is permissible. As shown in Figure 5-16, the share of fast charging vehicles is in the single-digit percentage range. In combination with the comparatively small sample of

2,410 driving profiles, this leads to fluctuations in the load curve. However, fundamental effects are discernible: (1) There is a high power demand for charging with up to 44 kW overnight with over 85% of it at private infrastructure. (2) Charging with 44 kW to 350 kW is required at night for driving profiles with an energy demand that cannot be fulfilled with 44 kW, but is also used during the day for intermediate charging. (3) Increasing battery sizes lead to a decrease in the need for intermediate charging until 2050, while the need for overnight charging with higher power increases. Despite the small number of driving profiles that charge simultaneously at high charging power, a generally flat charging profile with a dip between 6:00 and 10:00 and a slight midday peak results for 2025 and 2030. In the analysis for 2050, the demand in the midday hours is significantly reduced, while the demand in the early evening hours and at night increases. The effect occurs due to the higher usable battery capacities, the lower energy consumption and a higher minimum driving range until the first charging stop. In summary, the effect is due to technical assumptions as well as the implemented charging strategy. (4) Fast charging with more than 350 kW is almost exclusively used for intermediate charging in the midday hours. Again, the demand decreases over time due to increasing battery sizes.

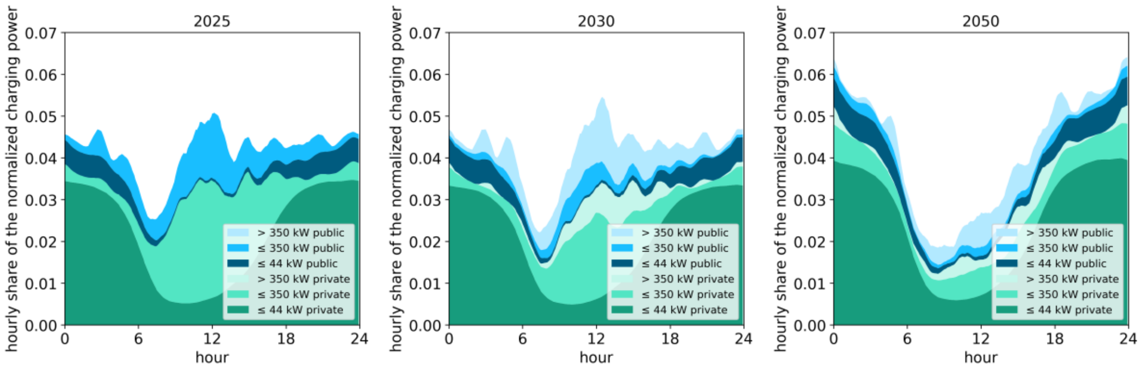

Figure 5-17: Normalized daily load curve of technically feasible BET driving profiles in 2025, 2030, and 2050. The indicated charging power refers to the average power of the charging process. All data refers to vehicles with a GVW of more than 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise.

5.2.2 Economic analysis

In the following, key results from the economic analysis are presented. To generate a general understanding, the TCO calculation of all drivetrains is shown for one exemplary driving profile. Afterwards, the aggregated TCO results for the whole fleet are shown. A special focus is on the economic efficiency of BET compared to DT.

5.2.2.1 Exemplary TCO calculation for one specific driving profile

Figure 5-18 shows an exemplary TCO calculation of a rigid truck with a daily mileage of 568 km for 2030 and 2050. As electric vehicle, the vehicle stops twice a day for charging at a public location in both years. The driving profile for 2030 is shown in subchapter 4.2.2 in Figure 4-6.

In 2030, the vehicle is equipped with 600 kWh battery. In 2050, 500 kWh are sufficient. It is shown that operational costs - especially energy costs, operation & maintenance costs, and toll costs - dominate for all drivetrains. Costs for the driver are assumed to be identical for all drivetrains and are therefore not part of the investigation. The BET represents the most cost-effective alternative in 2030 and 2050. It should be noted that a part of this effect, especially in 2030, is due to political measures, for example purchase price premiums, toll reductions, and an increasing national CO_2 price for diesel and methane. However, these measures are in line with the politically set goal of climate neutrality (see subchapter 1.1). An assessment of policy designs is beyond the scope of this thesis, but it is shown that a significant cost advantage for BET can be achieved already in 2030.

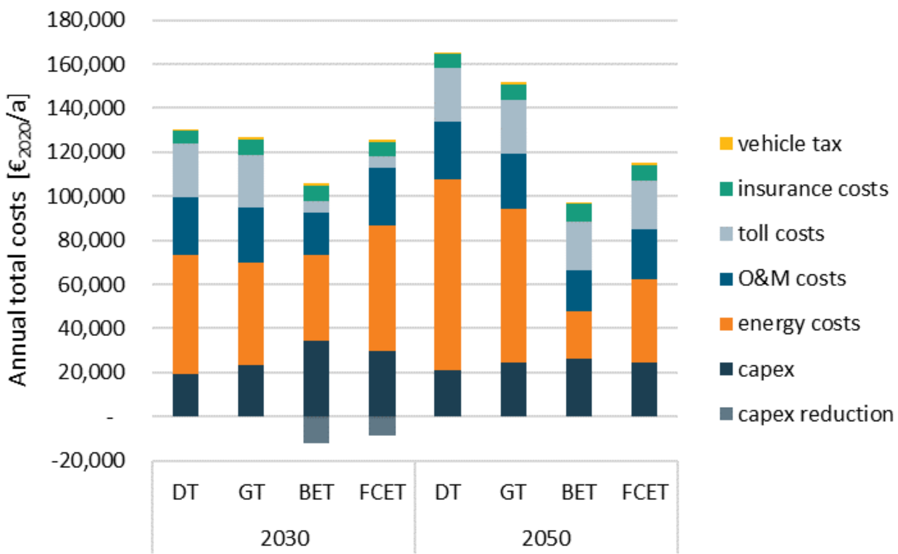

Figure 5-18: Exemplary annual costs of a rigid truck with a daily mileage of 568 km (140,000 km/a).

5.2.2.2 Cost-effectiveness of different drivetrain options in the vehicle fleet

Figure 5-19 shows the TCO delta between DT and BET for all technically feasible driving profiles in 2026, 2030, 2031, and 2050. In 2026, the model determines the infrastructure costs per kWh for public fast charging endogenously for the first time. These costs are also assumed for private fast charging, taking a price reduction due to the price premium of the charging point operator into account. Green dots represent driving profiles that purely rely on slow charging with less than 44 kW. The model does not calculate endogenous infrastructure costs for these driving profiles. The variance for profiles with the same daily mileage is due to different battery sizes as well as different shares of public slow charging with price premiums for the infrastructure provider. Yellow dots represent driving profiles that rely, at least partially, on fast charging with an average charging power of more than 44 kW. It can be seen that these BET driving profiles have a cost advantage compared to DT already in 2026. Taking into account the energy demand of the vehicles, the electricity price can - ceteris paribus - increase by 0.06 $€_{2020}$/kWh until the first driving profile - the driving profile with the lowest mileage of 202 km - reaches a cost advantage as a DT. With increasing mileage, the cost advantage per kWh also increases. The variance between driving profiles with similar mileage is again due to different battery sizes as well as different usage of different charging infrastructures. In 2030, the cost advantage per kWh for the driving profile with the lowest cost advantage increases to 0.16 $€_{2020}$/kWh. The termination of the purchase price premium in 2031 reduces the cost advantage to 0.10 $€_{2020}$/kWh. In addition, the impact of different vehicle battery sizes on the cost advantage is more apparent. Due to smaller batteries, driving profiles with a fast charging share can achieve higher cost advantages than driving profiles with a similar mileage and purely slow charging, despite higher charging costs. In 2050, the cost advantage compared to DT increases to a minimum of 0.48 $€_{2020}$/kWh for the driving profile with the least per kWh cost advantage and a fast charging share.

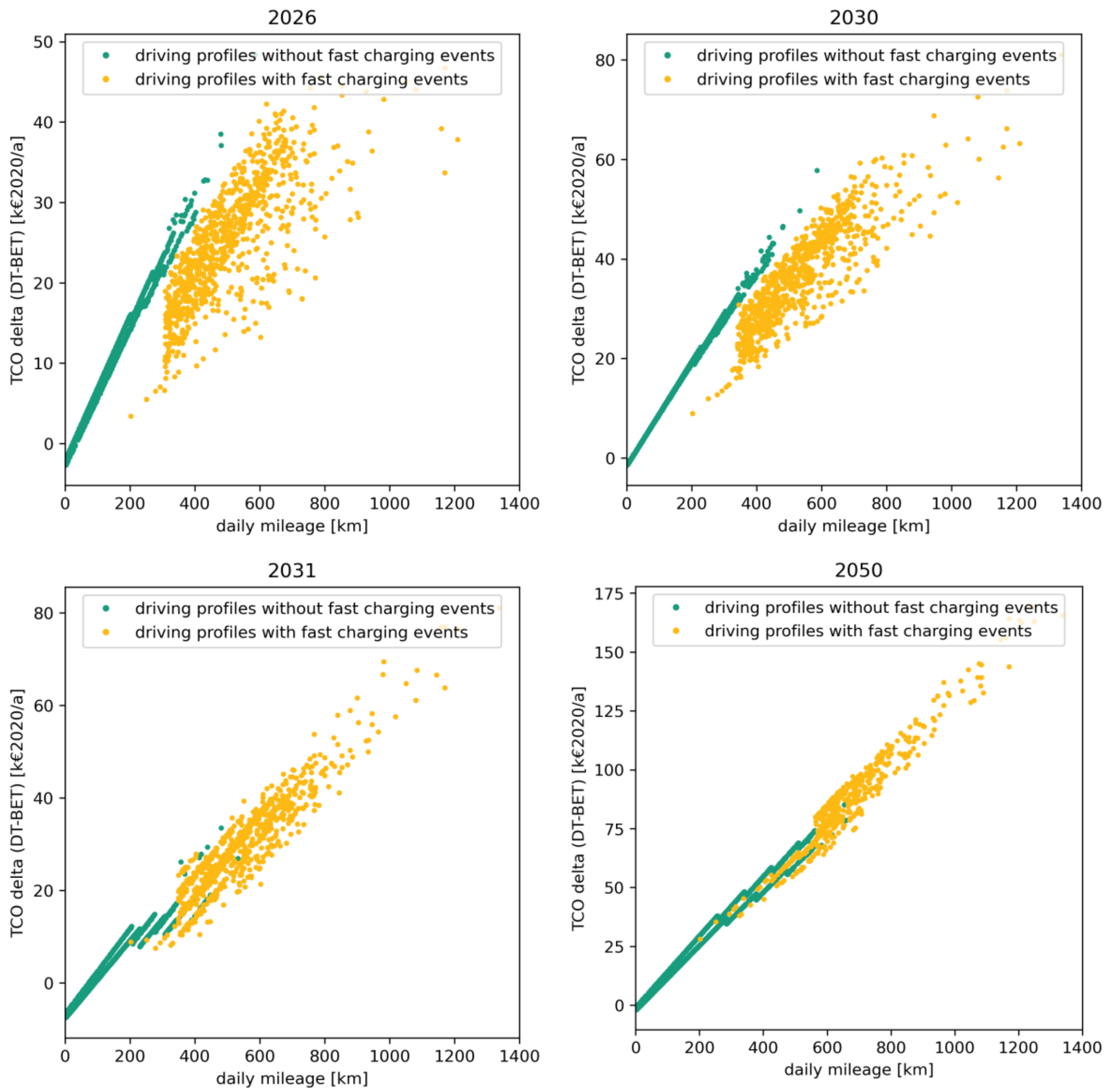

Figure 5-19: TCO delta between DT and BET for all technically feasible driving profiles in 2026, 2030, 2031, and 2050. Please note the different y-axes.

Finally, Figure 5-20 shows the best TCO option for every driving profile from 2020 to 2050. Please note that technically not feasible BET driving profiles are treated as infinite costs. DT are particularly competitive for driving profiles with low daily mileage. When the mileage increases, other drivetrains become more economical, due to the lower operational costs. In the first years of the simulation, in particular GT are more economical than DT at higher mileage. One exception is the year 2022, when the methane gas price rises sharply, due to war in the Ukraine. Due to technical and economic improvements, BET are increasingly the cheapest solution for a large proportion of the driving profiles. For long distances, GT are initially used, followed by FCET from 2027 onwards. For 2030 to 2035, DT for low mileage and GT for high mileage again gain some relevance. The reason is the decrease in subsidies for BET and FCET, especially purchase price premiums and toll reductions. In the perspective up to 2050, DT are the best option only for vehicles with very low mileages. FCET, similar to BET, are competitive with DT as TCO decreases over time (see Figure 5-18). Additionally, they profit from fast refueling. For driving profiles with a high daily mileage or with an unfavorable trips distribution throughout the day, FCET are used. In the given scenario, FCET are always more expansive than BET, as long as BET are technically feasible. However, for more than 95% of the driving profiles, BET are the most cost-efficient solution in 2050 and technically feasible.

Figure 5-20: Best TCO option from 2020 to 2050 for HDV with a GVW > 12 t. Dots are slightly varied on the x-axis for better visibility.

In summary, it can be concluded that BET achieve clear economic advantages over the other drivetrains for a large proportion of the driving profiles. Accordingly, the market diffusion of BET is limited less by the economic efficiency than by the technical feasibility and the vehicle and infrastructure availability. FCET, as a further new technology, can be used in particular for driving profiles with high mileage or unfavorable trip combinations. However, their share is likely to remain limited from an economic perspective.

5.2.3 Market diffusion of alternative drivetrains

The fowling presents the new registrations as well as the HDV stock until 2050.

5.2.3.1 Vehicle registrations

Figure 5-21 shows the development of new registration shares for HDV with a GVW higher than 12 t by drivetrain from 2020 to 2050. As already evident from the technical and economic analysis, BET dominate for large parts of the fleet, displacing DT. The share of new BET registrations in both 2025 and 2030 is less than five percentage points below the maximum share set by the vehicle availability curve in subchapter 3.5.1.2. The share of BET on the registrations in 2025 is 9%, increasing to 55% in 2030. In the given scenario, more than 95% of new registrations are BET in 2050.

GT continue to play a small role for driving profiles with a high mileage until the second half of the decade. For these profiles, BET are inititally technically not feasbile and DT are more expensive. However, the cost advantage is small, as shown the increasing number of DT registrations between 2022 and 2025 due to high methane gas prices and the removal of subsidies. Given the small market share, it remains uncertain whether manufacturers will continue to offer GT. In particular, the assumed costs reductions potentials may not be achievable.

Starting in 2027, FCET are used for driving profiles with high daily mileage and replace GT. In 2031, new FCET rgistrations decline due to the expiry of subsidies, but stabilize again in the following years. FCET reach their maximum registrations share, 7%, in 2035. They thus represent a bridging technology that is used in particular for driving profiles that are difficult to electrify. Again, it is uncertain whether the assumed costs reductions for vehicles and infrastructure - represented as part of the hydrogen costs - can be achieved.

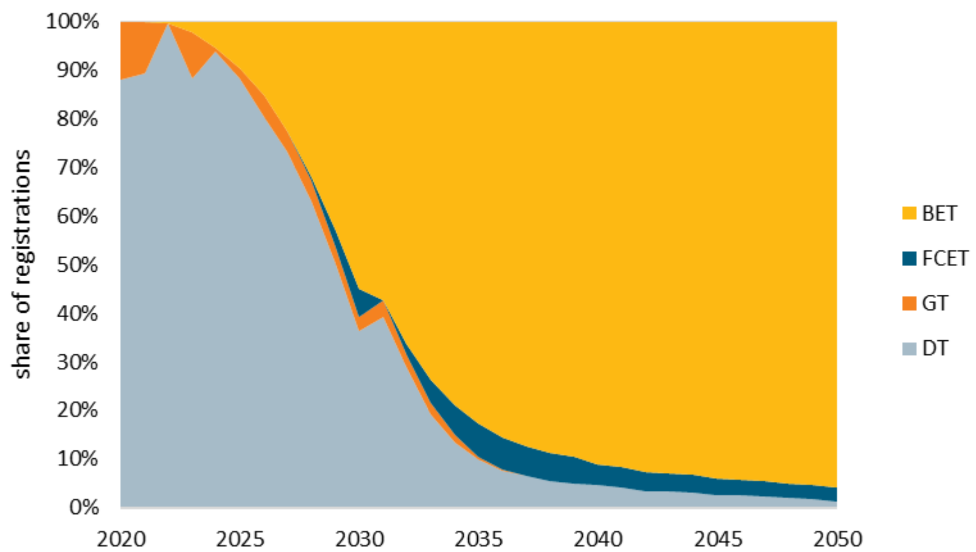

Figure 5-21: Annual share of new registrations of HDV with a GVW > 12 t by drivetrain from 2020 to 2050.

5.2.3.2 Vehicle stock

In this subchapter, the HDV stock and the total annual mileage by drivetrain are presented.

Figure 5-22 shows the stock share of the different drivetrains from 2020 to 2050 for the given scenario. The stock follows the new registrations. In 2025, 3% of stock are BET. The BET share rises to 30% by 2030. By 2045, the year of targeted climate neutrality, the BET share increases to 93%. Another 4% of stock are FCET. The remaining 3% are DT that must be fueled with GHG neutral fuels. By 2050, the share of BET increases even further, reaching nearly 95% of stock.

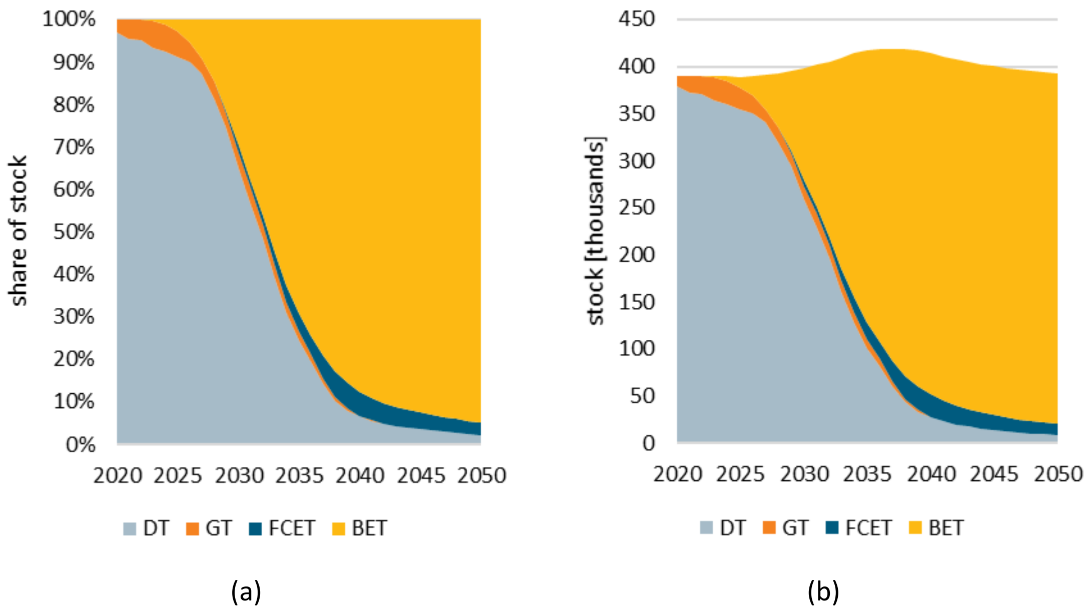

Figure 5-22: Annual (a) stock share and (b) stock of HDV with a GVW > 12 t by drivetrain from 2020 to 2050.

Figure 5-23 compares the share of each drivetrain regarding the total stock and the total mileage of the fleet. Due to limited technical feasibility of very high daily mileage, BET mileage share is always slightly smaller than BET stock share. The German government aims to electrify one third of the HDV mileage directly or with electric fuels by 2030 (Deutsche Bundesregierung, 2019). BET contribute 27% to the target, FCET 2%. If the planned blending of 4% synthetic fuel can be achieved, the overall target can be approximately reached.

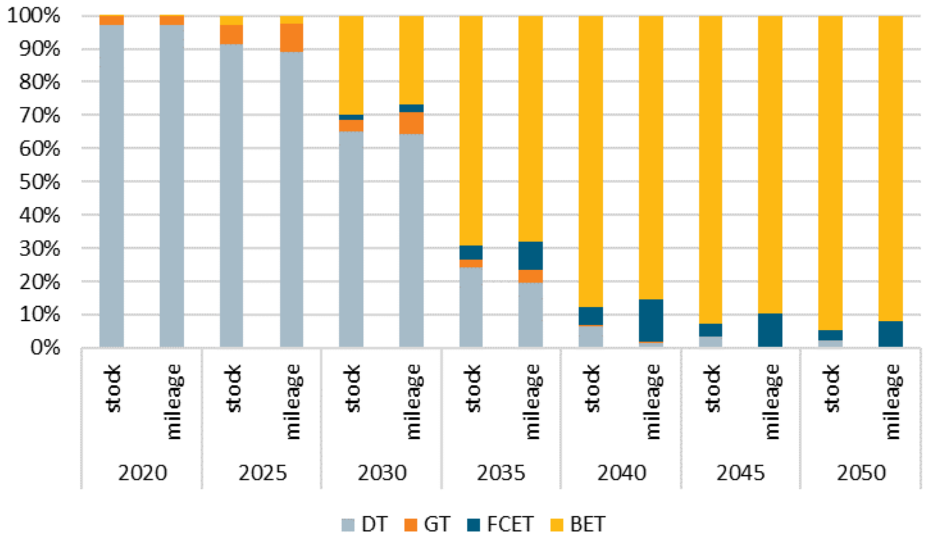

Figure 5-23: Stock share and mileage share of HDV with a GVW > 12 t by drivetrain from 2020 to 2050.

5.2.4 Energy demand

This subchapter first shows the annual final energy demand of the entire simulated HDV fleet from 2020 to 2050. Next, the electricity demand of BET at different infrastructures are shown in more detail. Finally, the daily load curve of BET is presented.

5.2.4.1 Annual total energy demand of the vehicle fleet

Figure 5-24 shows the final energy demand of all HDV with a GVW higher than 12 t in Germany from 2020 to 2050. Conventional, synthetic, and biogenic fuels are reported as a total. Diesel demand decreases from 2020 to 2030 from 109 TWh to 66 TWh. After 2040, the annual demand drops to less than 1 TWh per year. Simultaneously, the demand for electricity and hydrogen is increasing. Electricity demand increases to 11 TWh by 2030 and is mostly stable between 30 and 33 TWh after 2035. Hydrogen demand increases to 2 TWh by 2030 and reaches the maximum demand of 11 TWh in 2039. Afterwards, the demand decreases to 6 TWh by 2050.

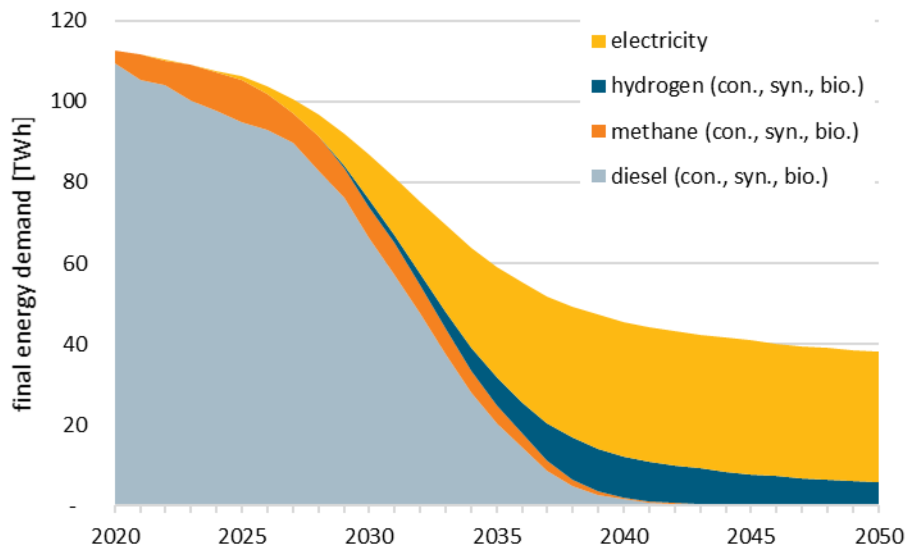

Figure 5-24: Annual final energy demand of HDV with a GVW > 12 t from 2020 to 2050.

5.2.4.2 Annual electricity demand of the BET fleet

To even better understand BET charging behavior and infrastructure needs, Figure 5-25 presents the electricity demand broken down by charging power and charging location. Electricity demand increases to 33 TWh by 2040 and remains almost constant afterwards, due to efficiency improvements and a nearly constant total vehicle fleet[8].

Overall, private charging is almost constantly responsible for about three quarters of the energy demand from 2025 onwards. It can be seen that the highest energy demand comes from private slow charging with up to 44 kW average power. In 2030, the share amounts to almost 50% and rises to 56% by 2050, due to increasing battery ranges. Approximately one quarter of the electricity demand is charged publicly from 2025 onwards[9]. For public charging, fast charging with more than 44 kW average charging power is more relevant than for private charging. By 2030, the share of fast charging on public charging in terms of electricity volumes increases to 70%, remains almost constant until 2040, and drops to 62% by 2050. The majority of public fast charging energy is charged at more than 350 kW average charging power.

[8] For comparison: According to BNetzA (2023a), Germany's net electricity demand was slightly less than 500 TWh in 2022. Sensfuß et al. (2022) assumed an annual electricity production of 1,200 TWh by 2045.

[9] Please note that due to increasing ranges and the inclusion of local traffic in the market diffusion model, the total demand for publicly charged electricity in the market diffusion model is smaller than in the CFRLM described in 5.1.2.2

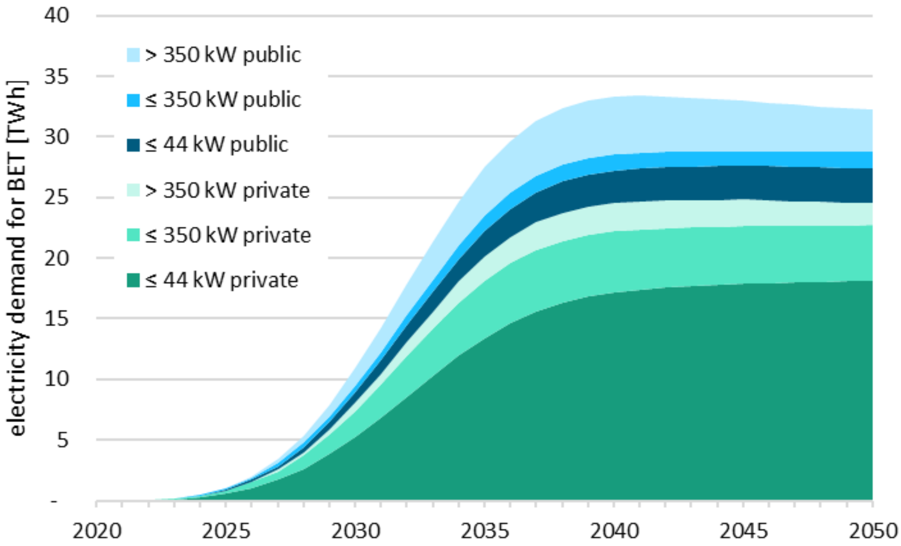

Figure 5-25: Annual electricity demand of BET with a GVW > 12 t by charging power and charging location from 2020 to 2050.

5.2.4.3 Daily charging behavior of the BET fleet

In the following, the daily charging behavior of the BET fleet is presented. Figure 5-26 shows in 5-year-steps from 2025 to 2050 how many vehicles use a charging infrastructure at each time of the day. The figures thus also allow conclusions about the need for charging infrastructure. It is obvious that the majority of the charging events takes place overnight at private charging locations with less than 44 kW average charging power. Public slow charging overnight is also relevant. Fast charging with an average charging power of more than 44 kW initially takes place primarily in the midday hours and, in the long term, increasingly shifts to the evening and night hours due to increasing vehicle range. This is in line with findings of the technical analysis in subchapter 5.2.1.3. However, the stock simulation allows additional conclusions regarding the order of magnitude. For better comprehensibility, Table 5-3 summarizes the maximum number of simultaneously charging BET. The calculation of the required public fast charging infrastructure does not distinguish between BET with a charging power between 44 kW and 350 kW (in figures: ≤ 350 kW) and BET with an average charging power above 350 kW (in figures: > 350 kW). Therefore, it should be noted that the maximum number of charging vehicles in both classes does not occur at the same time. A corresponding analysis is shown in the Appendix A.6 in Figure A-6. Due to the comparatively low number of driving profiles that need fast charging, these values are also subject to higher fluctuations.

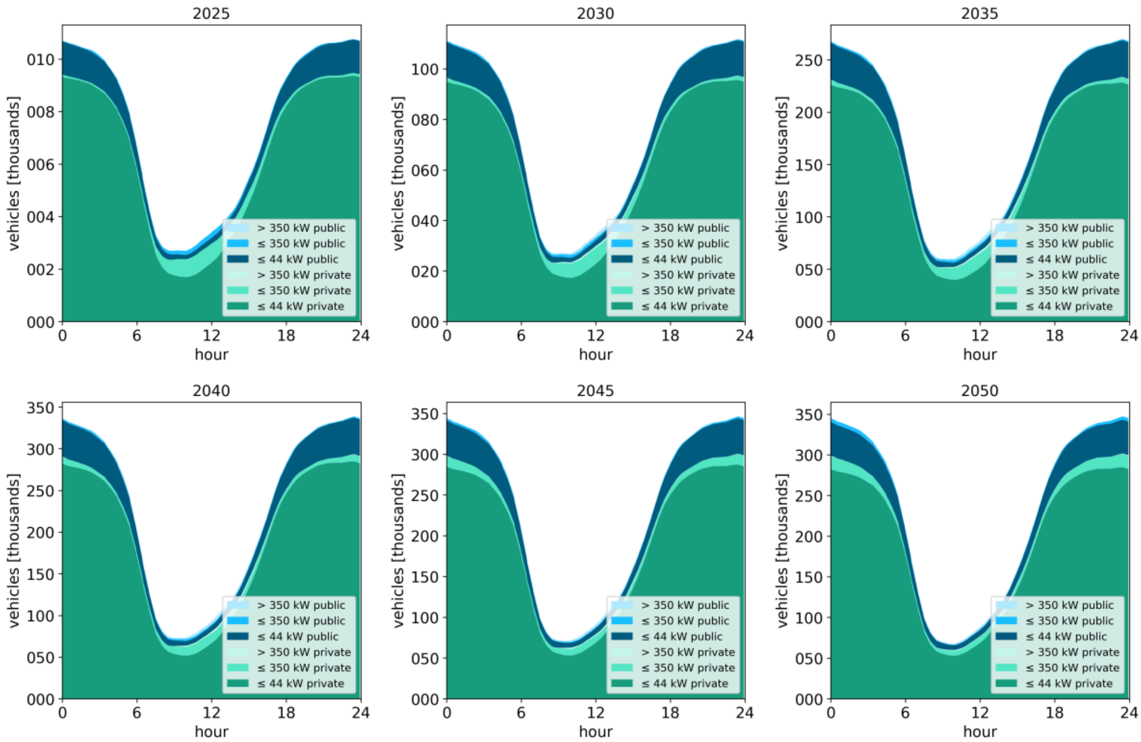

Figure 5-26: Charging behavior of the simulated BET fleet from 2025 to 2050. The indicated charging power refers to the average power of the charging processes. All data refers to vehicles with a GVW > 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise. Please note the different y-axes.

Table 5-3: Maximum number of simultaneously charging BET in thousands from 2025 to 2050.

	2025	2030	2035	2040	2045	2050
≤ 44 kW private	9.4	95.6	228.3	284.9	287.3	284.6
≤ 350 kW private	0.8	6.5	14.1	12.7	13.0	16.4
> 350 kW private	0	0.7	2.6	3.0	2.5	1.9
≤ 44 kW public	1.3	14.0	35.0	44.0	43.6	41.5
≤ 350 kW public	0.2	1.3	2.5	2.6	3.2	5.0
> 350 kW public	0	1.5	4.0	4.3	3.7	2.8

Figure 5-28 shows the daily load profile of the simulated HDV BET fleet from 2025 to 2050 in 5-year-steps. For direct comparability, the y-axis was kept fixed for each year. For better visibility, Figure 5-27 additionally shows the load profiles for 2025, 2030, and 2035 with a variable y-axis.

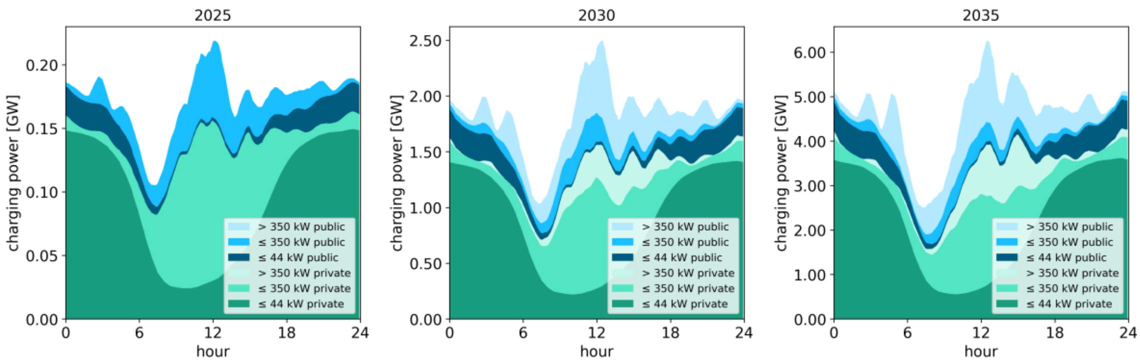

Figure 5-27: Daily load curve of the BET fleet in 2025, 2030, and 2035. The indicated charging power refers to the average power of the charging process. All data refers to vehicles with a GVW > 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise.

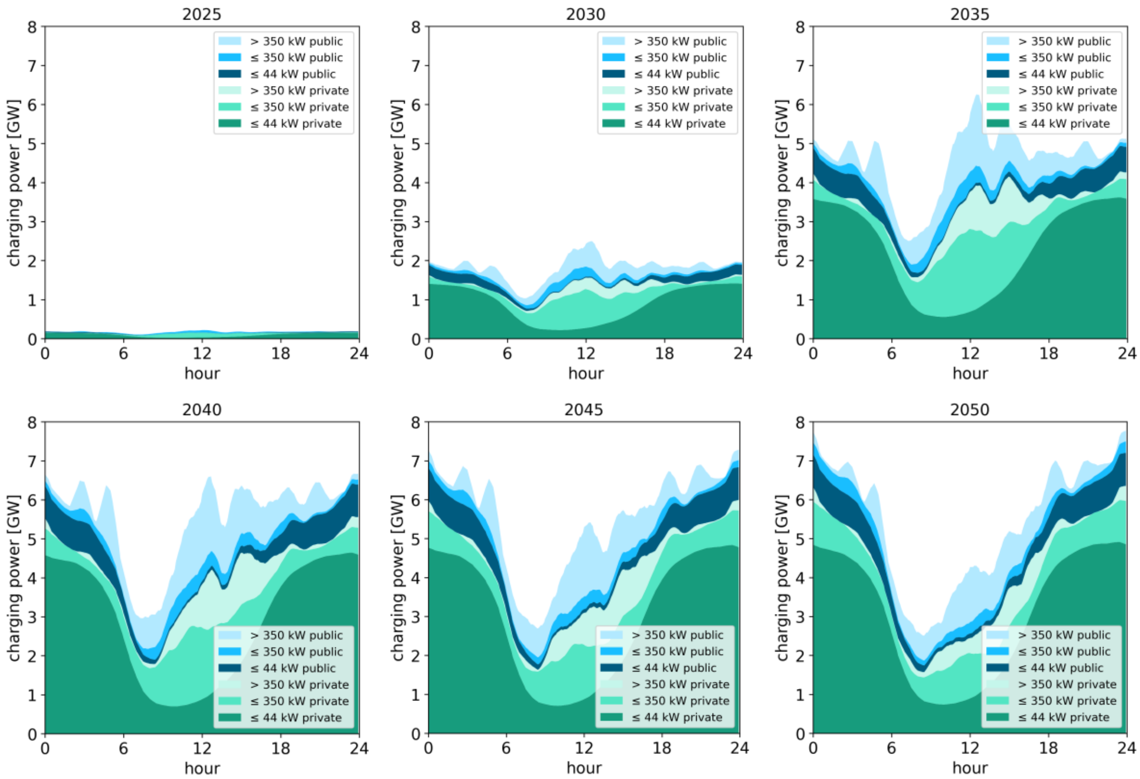

Figure 5-28: Daily load curve of the BET fleet from 2025 to 2050. The indicated charging power refers to the average power of the charging process. All data refers to vehicles with a GVW > 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise. Unified y-axis for all years.

The peak power for the BET fleet increases to nearly 2.5 GW by 2030. Afterwards, the peak power doubles to more than 6 GW by 2035. Until 2050, there are comparatively moderate increases to almost 8 GW peak power. According to (BNetzA, 2023c), the maximum peak load in Germany in 2021 was 81.4 GW. (Sensfuß et al., 2022)) assumed a daily peak load in the order of up to 250 GW in 2045. Due to the high charging power, the comparatively few fast charging processes initially generate a clear midday and afternoon peak. In the long term, demand shifts to the evening and night hours due to increasing vehicle ranges. Due to the comparatively small share of fast-charging vehicles with more than 44 kW average power in the sample - 22% of all 2,410 driving profiles rely on fast charging in 2050 -, the load curve contains visible peaks. Individual spikes should therefore not be over-interpreted, the load curve rather shows the general trend. Regarding public fast charging, a substantial midday peak, approximately 0.8 GW in 2030 and 2 GW from 2035 onwards, is calculated. In the perspective up to 2050, there is a drop to approximately 1.6 GW. For better understanding, Figure A-7 in the appendix shows a separate analysis of public fast charging. It should also be noted that in public charging, the midday peak, which is almost exclusively due to fast charging, is higher than the slow charging peak. Therefore, the grid connection at public rest areas is probably dominated by the fast charging demand at most locations.

The load curves shown are also the results of the implemented charging strategy (charging as slow as possible). The high share of charging with less than the maximum charging power also shows that trucks are potentially suitable for load shifting, especially in afternoon and in nighttime hours. This may lead to further potential costs reductions in energy costs. However, this is beyond the scope of this thesis.

In summary, BET generate an electricity demand of more than 30 TWh in the long term. In the modeled scenario, the highest increase occurs between 2030 and 2035. More than half of the energy can be recharged at private charging infrastructure with an average power of less than 44 kW. In the load profile, a midday peak caused by intermediate fast charging can be expected. Due to an increasing vehicle range, the peak load shifts to the evening and night hours by 2050.

5.2.5 Public fast charging infrastructure in the market diffusion model for BET

The following sections present the public fast charging infrastructure modeled as part of the BET market diffusion. First, the influence of public infrastructure on the market diffusion of BET is presented. Then, the charging locations and the required charging points are shown. The following subchapter deals with the utilization and the average charging power of the modeled fast charging infrastructure. Finally, the costs of the infrastructure are discussed.

5.2.5.1 Influence of public charging infrastructure on the market diffusion of BET

Figure 5-29 shows the share of the BET fleet that relies at least partly on public charging infrastructure in the modeled market diffusion scenario[10]. Additionally, the corresponding share of the mileage is shown. Public fast charging with more than 44 kW average power is required by 15% of the vehicles after 2035, slightly fluctuating. Those vehicles provide 25% to 30% of the mileage of the entire fleet.

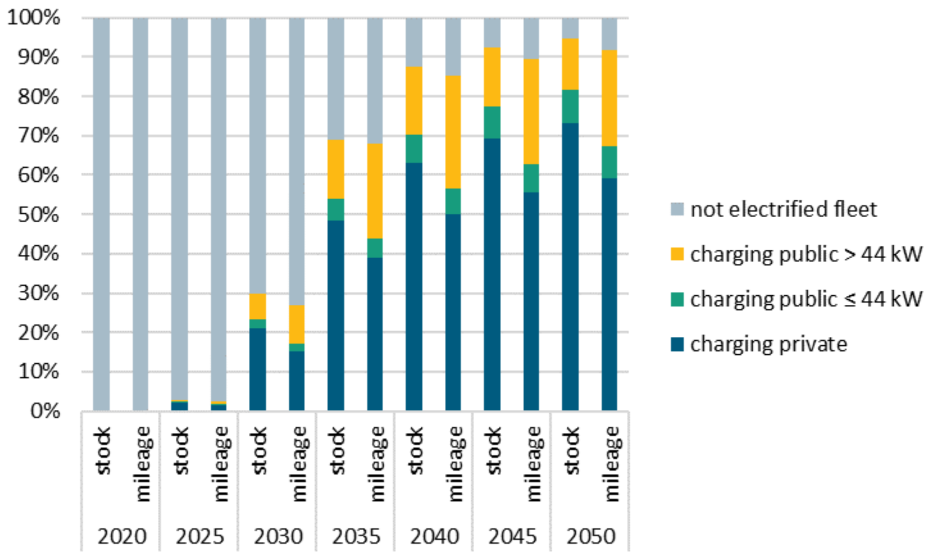

Figure 5-29: Electrified stock and mileage share for the modeled market diffusion by the public infrastructure needed from 2020 to 2050. "Charging public ≤ 44 kW" may also contain "charging private". "Charging public > 44 kW" may also contain "charging public ≤ 44 kW" and "charging private".

Additionally, a sensitivity analysis on a delayed public fast charging infrastructure (> 44 kW) was deployed. For this purpose, the parameters $locations_{max}^{t}$, $locations_{min}^{t}$, and $plug_{max}^{t}$ were shifted by five years. This means that initially only smaller and less locations are possible. The infrastructure ramp-up starts between 2025 and 2030 (first simulation of public fast charging infrastructure for 2030), instead of between 2020 and 2025. Due to lack of infrastructure, the model has reduced the market diffusion of BET relying on public fast charging infrastructure by 25% between 2025 and 2030 compared to the baseline scenario. No further reduction took place thereafter. Regarding the entire fleet, this corresponds to a reduction in BET stock of two percentage points (30% BET in the baseline scenario versus 28% BET in the delayed scenario in 2030). Regarding mileage, the reduction amounts for three percentage points.

5.2.5.2 Public fast charging locations

The following section focusses on the realized fast charging locations. The modeling shows that the specified minimum number of locations is always sufficient to cover the demand for

[10] The results refer to the modeled scenario. A removal of the public charging infrastructure could be partially compensated by larger batteries and a modified charging strategy. However, this is beyond the scope of this thesis.

charging events. Table 5-4 summarizes the required number of charging locations in three size categories from 2025 to 2050. The size categories are based on the critical number of charging points in relation to the required grid connection, as shown in subchapter 3.3. According to the assumptions, medium locations with up to 30 charging points may not be built before 2030, and large locations with up to 45 charging points may not be built before 2035. It can be seen that after 2040, due to the declining demand for public fast charging, large locations are reduced. However, once established, each charging point is in operation for 15 years. Thus, the deconstruction is partially delayed.

Table 5-4: Number of charging locations for the modeled market diffusion of BET.

	2025	**2030**	**2035**	**2040**	**2045**	**2050**
small (max. 12 charging points)	120	93	106	88	98	103
medium (max. 30 charging points)	0	67	56	49	53	72
large (max. 45 charging points)	0	0	58	83	69	45
total	120	160	220	220	220	220

Figure 5-30 illustrates the regional distribution of public fast charging infrastructure in Germany for the modeled BET diffusion in 2025, 2030, and 2045. Location sizes are presented in the three introduced classes. The initial network rollout is distributed all over Germany. The increase in network density through additional and larger charging locations takes place primarily on long-distance corridors. These corridors include the transit route from the Netherlands - via Essen, Hanover, passing Berlin - to Poland. As part of this route, the A2 highway connects major European ports (Amsterdam, Rotterdam and Antwerp) to Eastern Europe. As a second long-haul route, the highway A3 connects the Netherlands to Austria via Cologne, Frankfurt, and Nuremberg. The parallel highways A61 and A45 in the south of Cologne and the highway A8 between Karlsruhe and Munich, which runs in the south of the A3, are also among the routes that are densified. Other locations with less transit traffic, for example the highway A20 from Lübeck via Rostock to Poland, are being less expanded. They primarily serve to provide area coverage. The detailed maps in Appendix A.7 show the expansion steps for each individual location in 5-year-steps.

Due to increasing vehicle range and the associated shift in charging demand to long-haul routes, some charging locations are oversized from 2040 onwards. Oversizing affects 63 locations in 2040, 49 locations in 2045, and 48 locations in 2050. In 2045, slightly more than one third of the locations are oversized by 5 charging points (mean = 6.5, median = 5, σ = 6.2). The effect diminishes in 2050, as charging points built as part of the major expansion in 2035 are removed from service. A more detailed analysis of the number of charging points follows in subchapter 5.2.5.3.

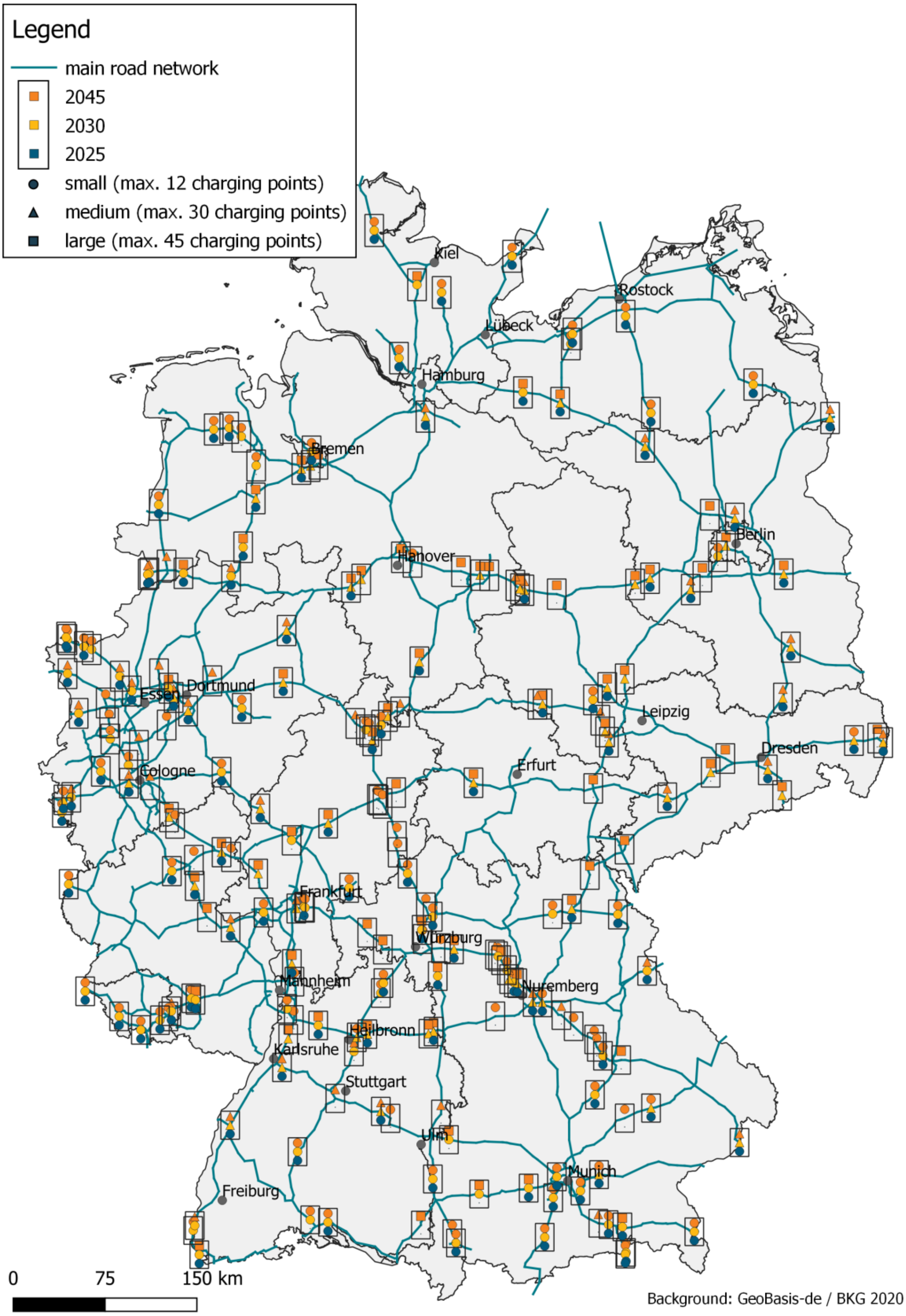

Figure 5-30: Corresponding public fast charging infrastructure in Germany for the modeled BET diffusion in 2025, 2030, and 2045.

5.2.5.3 Number of public fast charging points

The initial public fast charging network consists of 302 charging points in 2025[11]. By 2030, the stock increases to almost 2,000 charging points and more than doubles to nearly 4,200 charging points 2035. By 2030, there is still a small increase to nearly 5,100 charging points. Simultaneously, overcapacities are emerging, due to increasing vehicle range and shifting charging demand. Almost 320 charging points are no longer needed, but still installed. In 2045 and 2050, the infrastructure is reduced to approximately 4,300 and 3,800 charging points. Figure 5-31 shows the total number of public fast charging points installed in Germany from 2025 to 2050. In addition, the number of newly installed charging points is shown. In contrast to the stock, newly installed charging points increase in the period between 2045 and 2050, as charging points built between 2030 and 2030 that are still needed must be replaced.

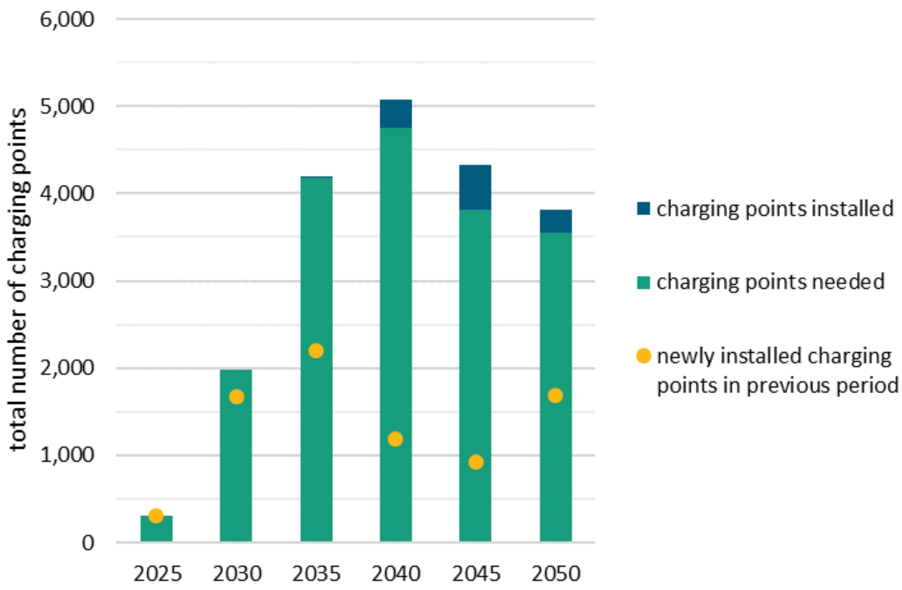

Figure 5-31: Corresponding total number of public fast charging points in Germany for the modeled BET diffusion from 2025 to 2050.

In addition, Figure 5-32 shows the number of charging points per charging location from 2025 to 2050 as boxplots. While the maximum of 12 charging points specified by the model is not used in 2025, the maximum of 30 charging points in 2030 and 45 charging points from 2035 onwards is used at some locations. Overall, a wide spread of location size can be seen. Small locations cover the area and result from the requirement of a minimum number of locations. Large locations serve highly trafficked highways.

[11] For comparison: From March 2022 to March 2023, 4,537 new fast charging points (> 50 kW) for passenger cars were built in Germany. By March 2023, 13,714 fast charging points had been established. The stock of fast charging points with at least 300 kW power increased by 1,565 charging points to 3,540 charging points from 2022 to 2023. (BNetzA (2023b)).

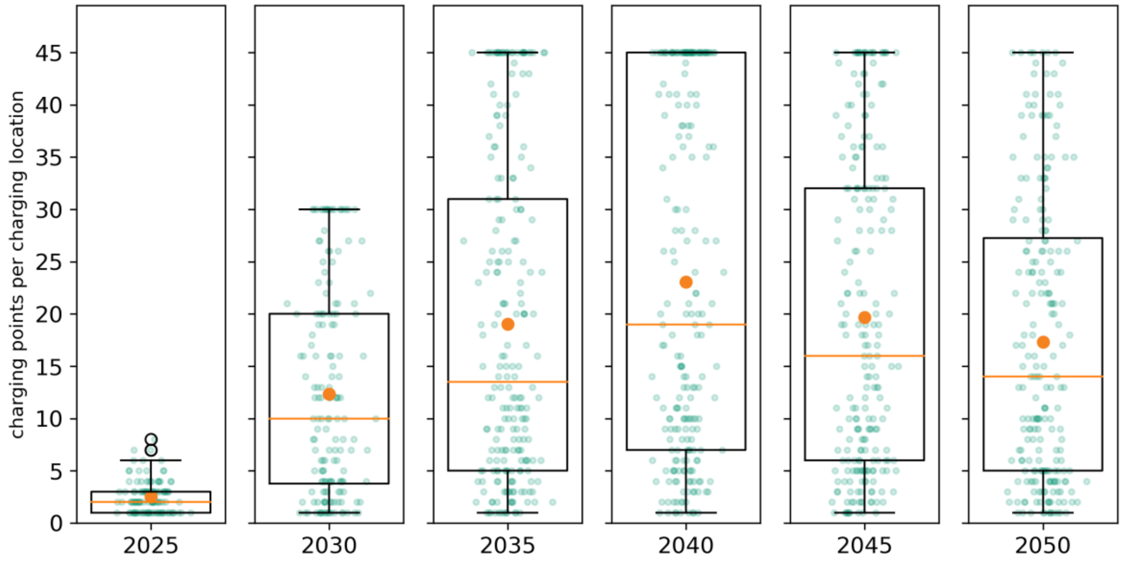

Figure 5-32: Boxplot for corresponding number of charging points per public fast charging location for the modeled BET diffusion from 2025 to 2050. Orange dot indicates mean value. Green dots show individual values.

Overall, the specified infrastructure parameters are consistently sufficient, both in terms of the maximum number of charging locations and the maximum number of charging points per location, so that the infrastructure ramp-up does not inhibit the market diffusion of BET.

5.2.5.4 Utilization and average charging power

The utilization of a charging location depends on the characteristics of the traffic volume in the peak hour. The more prominent the peak hour is, the more the location is oversized during other hours of the day. Table 5-5 sums up the peak hour traffic at public fast charging infrastructure derived from the simulated load curves. It can be seen that the daily peak is higher than the assumed daily peak of 6% in the first part of this thesis. As a result, the utilization in this section is lower than in the optimization scenario without fleet simulation. Nevertheless, the daily peak is declining over time. The location size, which is limited to 45 charging points, also leads to a lower utilization, since large locations are more efficient according to queuing theory.

Table 5-5: Peak hour traffic at public fast charging infrastructure for the modeled market diffusion.

	2025	2030	2035	2040	2045	2050
peak hour traffic [%]	11.4	10.2	9.5	9.1	9.5	8.5

Figure 5-33 shows the temporal utilization of public fast charging infrastructure from 2025 to 2050. The average utilization increases from 8 % (mean = 0.08, median = 0.09, σ = 0.05) in 2025 to 23% (mean = 0.23, median = 0.26, σ = 0.08) in 2035 and is almost stable at this level except for a small decrease in 2045 to 20% (mean = 0.20, median = 0.22, σ =0.08). This means that in the medium term, the charging location are occupied for about one quarter of the day. Thus, the average utilization is 18 percentage points lower than in the *Optimiziation2045_Ger_C* scenario in subchapter 5.1.2.2. Reasons area higher peak hour traffic, smaller locations, and the minimum number of locations that also leads to a higher number of locations. The highest utilized location of fast charging infrastructure for the modeled BET diffusion reaches 32% utilization in 2050, the year with the lowest peak hour traffic.

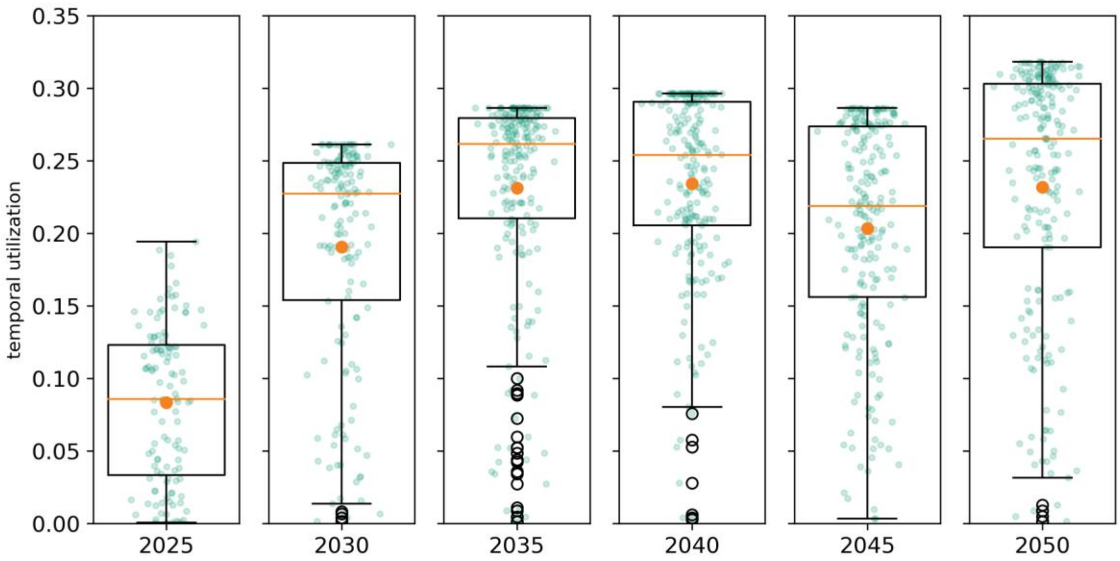

Figure 5-33: Boxplot of corresponding utilization per fast charging location for the modeled BET diffusion from 2025 to 2050. Orange dot indicates mean value. Green dots show individual values.

Figure 5-34 shows the average charging power for charging events at each location. Interestingly, despite the increasing vehicle range, the average charging power only increases from 458 kW (mean = 458, median = 432, σ =81) in 2025[12] to 575 kW (mean = 575, median = 548, σ = 165) in 2050. According to the assumptions, vehicles charge so that they are fully recharged within 30 minutes. If the required number of stops on an OD path does not change and if the same charging locations are selected in different years, charging power also remains constant or slightly decreases due to efficiency improvements. Additionally, the spread of average charging power increases over time, since stops can be made more flexible due to longer ranges. For example, vehicles can recharge shortly after starting or shortly before arriving at their destination.

[12] Please note that the charging strategy in the public fast charging infrastructure modeling always assumes recharging within 30 min, while this is the case in the technical analysis from 2030 onwards. Therefore, the average charging power of the 2025 infrastructure modeling is higher than the maximum value of the technical analysis. At this point, the technical analysis is a conservative estimate.

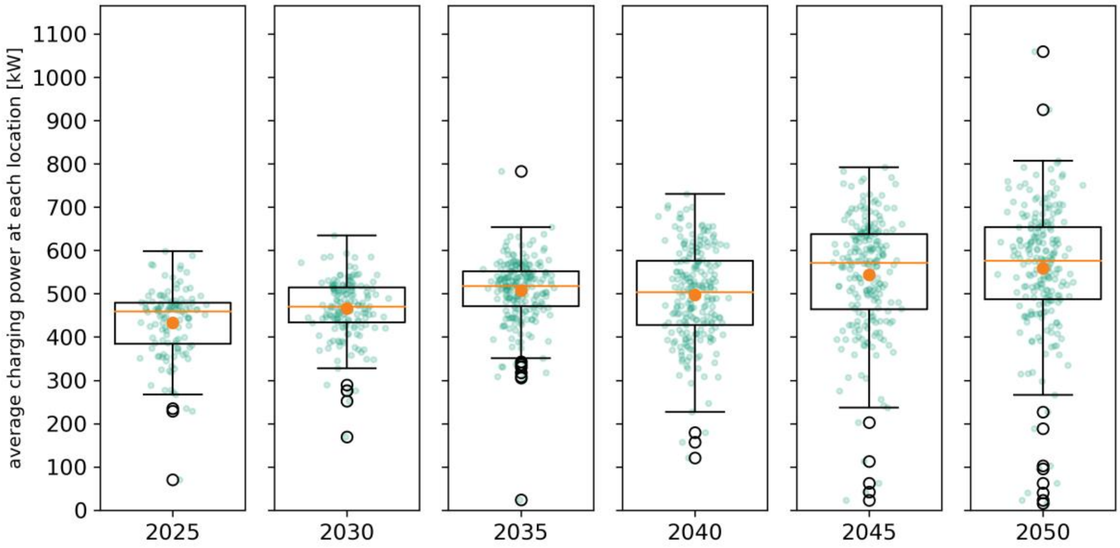

Figure 5-34: Boxplot of average charging power for charging events at each public fast charging locations for the modeled BET diffusion from 2025 to 2050. Orange dot indicates mean value. Green dots show individual values.

5.2.5.5 Costs for public fast charging infrastructure

Table 5-6 sums up the annuities for the modeled public fast charging infrastructure and the corresponding infrastructure levies per kWh.

The annuity of the grid connection increases continuously until 2040, the year of maximum expansion of the public fast charging infrastructure. After 2040, it remains constant due to the depreciation period of up to 40 years. As a levy, the connection generates costs of less than 0.01 €$_{2020}$/kWh and is thus less relevant.

The annuity of the charging infrastructure increases to a third of a billion €$_{2020}$/a by 2040 and drops to 200 million €$_{2020}$/a by 2050. The comparatively short depreciation period of 15 years allows for quick changes. The levy falls clearly from 0.18 €$_{2020}$/kWh in 2025 to 0.07 €$_{2020}$/kWh in 2030, due to the increasing utilization of the infrastructure. Afterwards, the levy falls considerably lower due to the continued slight increase in utilization and the assumed cost reduction of 2% per year for new public fast charging infrasctructure. The levies are close to the initial assumptions, so that, taking into account the high economic benefits of BET in subchapter 5.2.2.2, there are no changes in new registrations due to the internally calculated charging infrastructure costs.

As an initial comparison, annual truck toll in Germany in 2019, before the COVID-19 pandemic, was 7.5 billion €$_{2020}$ (BAG, 2021). Wietschel et al. (2017) calculated almost 9 billion €$_{2015}$ for 4,000 km of overhead catenary lines in Germany, resulting in 0.7 billion €$_{2015}$ annually. Due to different framework assumptions, the costs are not directly comparable; for example, different requirements of depot infrastructure are not taken into account.

At this point, is should be pointed out that the levies include costs of the hardware, its construction, its maintenanace, and a profit-based interest rate, but not the costs of the landscape. The clandscape costs can vary widely. In this thesis, it is assumed that public fast charging infrastructure is built on parking areas and that no additional costs occur. However, this can vary depending on the charging point operator.

Table 5-6: Modeled annuity for public fast charging infrastructure for the modeled BET diffusion from 2025 to 2050.

	2025	**2030**	**2035**	**2040**	**2045**	**2050**
grid connection [Mio. $€_{2020}$/a]	2.3	8.4	25.4	32.2	32.2	32.2
grid connection [$€_{2020}$/kWh]	0.017	0.004	0.005	0.005	0.006	0.006
charging infrastructure [Mio. $€_{2020}$/a]	23.9	143.4	285.7	331.6	260.9	199.1
charging infrastructure [$€_{2020}$/kWh]	0.176	0.071	0.055	0.053	0.052	0.038

5.2.6 Discussion

The market diffusion model for alternative drivetrains for HDV used in this thesis builds on an established model logic and extends the modeling with regard to the integration of public fast charging infrastructure for BET. On the data part, previously used input data is integrated into the model at a substantially higher temporal resolution. Additionally, spatially resolved traffic flows are taken into account for the infrastructure modeling. However, methodological and data assumptions still influence the results. Therefore, methodological and data-driven influences are discussed in the following. The discussion follows the structure of the model.

The technical analysis is strengthened by considering individual trips instead of the daily mileage. Unfortunately, only a short observation period of one day is available. Therefore, the electrification potential can be overestimated. Yet, even for early years, the technical analysis shows a high potential for electrification for a wide range of daily mileage. Nevertheless, large-scale driving data surveys over several days should be carried out in the future to improve the data quality. The technical analysis models a charging strategy that foresees charging with lowest possible power. Implicitly, controlled charging is assumed. Thus, despite the small sample of 2,410 driving profiles, a load profile can be generated that is not characterized by individual outliers. Even though general trends can be seen, additional fluctuations due to the small sample size are obvious. Therefore, future analyses could further examine the effects of other charging strategies, especially if a larger data sample is available.

The economic analysis shows clear cost advantages for BET for almost all driving profiles. Since this finding is consistent with the results of the literature review in subchapter 2.1.2, a sensitivity analysis was not performed, but the economic advantage of the BET compared to the DT for all driving profiles was determined. Even in 2026, the analysis shows that the electricity price for fast charging needs to increase by 0.06 $€_{2020}$/kWh to have an impact on the drivetrain choice. This corresponds to one third of the infrastructure levy and increases rapidly over time. Against this background, the economic analysis can be considered very stable. This makes the restriction of the vehicle availability one of the most important parameters. Availability was updated as part of this thesis based on manufacturer information. The resulting market diffusion of BET is in line with the goal of the German government in terms of electrified mileage (Deutsche Bundesregierung, 2019). Against this background, the market diffusion appears ambitious, but feasible. It can be assumed that a corresponding market ramp-up will be supported politically. The measures assumed in this thesis are exemplary; the goal can also be achieved with other measures. All in all, the modeled market diffusion provides a good basis for the infrastructure analysis.

The adapted optimization model for the infrastructure analysis uses the strengths of the CFRLM approach, especially the consideration of relevant individual OD paths and the capacity restriction for each potential location. In the version used in this thesis, all paths must be drivable. This is in line with the assumption that BET must be able to be deployed at each route, but prevents high-resolution modeling of the very initial network setup. Future modeling approaches could instead maximize the share of electrified traffic, especially for an early market phase. Multi-period optimization would also be a topic for future research, to reduce the installation of charging points that are no longer needed in future periods. However, the implicit assumption that charging point operators do not have perfect foresight and that a decline in public fast charging demand leads to reduced infrastructure utilization seems realistic.

Finally, the coupling between the market diffusion model for BET and the public fast charging infrastructure modeling should be addressed. In this thesis, two different datasets are used for the modeling parts and linked based on the amount of energy to be recharged. For future modeling, a dataset should be provided that is both sufficiently detailed to daily driving profiles and extensive enough to simulate a countrywide infrastructure deployment. This could prevent differences between the market diffusion model and the infrastructure model, for example regarding the modeled charging behavior.

5.2.7 Summary

Chapter 5.2 presents the results of the market diffusion modeling of alternative drivetrains for vehicles with a GVW of more than 12 t in Germany from 2020 to 2050. BET's regionally and temporally resolved energy demand and the required public fast charging infrastructure are of particular interest.

The technical analysis within the market diffusion modeling demonstrates that almost 90% of all driving profiles and 75% of all daily mileage can be directly electrified in 2025. In 2050, the electrification potential increases to 97% of all driving profiles and 93% of the total mileage.

From an economic perspective, BET also show advantages compared to other drivetrains in the modeled scenario. Even substantial increases in costs, for example by 0.05 €$_{2020}$/kWh of electricity, would only minimally change the results of the market diffusion scenario. Therefore, the market diffusion is characterized by the availability of BET vehicles as well as the corresponding infrastructure. The modeled scenario projects a BET stock share of 30% by 2030. Additionally, the scenario is in line with the German government's target to electrify one third of HDV road transport by 2030 (Deutsche Bundesregierung, 2019). By 2050, the BET share rises to 95% of the stock.

FCET can be used in particular for driving profiles with high mileage or unfavorable trip combinations. However, their share is likely to remain limited from an economic perspective. The modeling shows shares less than 10% of total vehicle stock. It is uncertain whether assumed economies of scale can be achieved and an infrastructure can be operated economically.

After an initial market ramp-up from 2035 onwards, the modeled BET fleet requires between 30 TWh and 35 TWh of electricity per year. More than half of the electricity is recharged at private charging infrastructure with an average charging power of less than 44 kW. Public fast charging with more than 44 kW average power is responsible for 15% to 20% of electricity demand after 2035. Considering the lowest possible charging power strategy modeled, public fast charging is relevant, but not dominant. The per day analysis shows that during the daily peak, less than 6,000 vehicles use a public fast charging infrastructure with more than 44 kW average power at the same time across all years considered. During the daily peak at private charging infrastructure with less than 44 kW average charging power, up to 290,000 vehicles use the infrastructure in parallel. The daily load profile reaches between 6 GW and 8 GW total charging power in the peak hour from 2035 onwards. The daily peak is initially reached in the midday and afternoon hours and is caused in particular by fast intermediate charging. However, nighttime slow charging also requires more than 4 GW in 2035. In the long term, midday intermediate charging is eliminated for many driving profiles due to increasing range, so that the daytime peak shifts to the nighttime hours.

Public fast charging infrastructure is initially built up across the country. Afterwards, additional charging locations are built and existing charging locations are enlarged, especially along transit routes. The maximum demand for public fast charging points with assumed peak power of 1 MW is reached in 2040 with almost 5,100 charging points in Germany. After 2040, due to increasing range of vehicles, a partial deconstruction of the infrastructure takes place. The specified maximum infrastructure expansion is always sufficient so that the public fast charging infrastructure does not inhibit the BET market diffusion. Table 5-7 sums up the corresponding infrastructure ramp-up for the modeled BET diffusion. Additionally, the results from the previous infrastructure scenarios are shown for comparison. The comparison reveals that the market diffusion of BET, and thus the public fast charging infrastructure demand, develops about twice as fast by 2030 as assumed in the scenarios. However, in the 2045 perspective, the *Dense2045_Ger* scenario is similar to the results from the market diffusion modeling approach. Due to the assumed range of 300 km, the *Optimization2045_Ger_C* scenario clearly overestimates the demand for charging points, also compared to the results of the market diffusion modeling. The market diffusion modeling does not achieve the infrastructure levies calculated in the pure infrastructure modeling, which is due to higher peak utilization as well as necessary deconstruction.

Table 5-7: Overview on the number of required charging locations and charging points for the modeled market diffusion of BET.

Scenario	Locations	Charging points				Infrastructure levy
		Total	Mean	Min	Max	[€$_{2020}$/kWh]
Results from the market diffusion modeling:						
2025	120	302	2.5	1	8	0.19
2030	160	1,977	12.4	1	30	0.08
2035	220	4,182	19.0	1	45	0.06
2040	220	5,075	23.1	1	45	0.06
2045	220	4,328	19.7	1	45	0.06
2050	220	3,811	17.3	1	45	0.04
Results from the pure infrastructure modeling:						
Wide2030_Ger_ETIS-U	101	809	8.0	2	15	0.03
Wide2030_Ger_M-TCD	142	741	5.2	2	9	0.03
Dense2045_Ger	190	4,771	25.1	2	57	0.02
Optimization2045_Ger	42					
Optimization2045_Ger_C	124	12,323	99.0	2	334	0.03

Finally, insights can be added to the first research question, initially answered in subchapter 5.1.4. The remaining research questions can be answered:

Q1: Taking into account the locally resolved demand for freight transport, how can a station-based public charging infrastructure for battery electric heavy-duty vehicles in Germany look like and which costs arise due to the infrastructure installation?

As already mentioned, a public charging infrastructure for battery electric heavy-duty vehicles in Germany can consist of fast charging locations that provide vehicles with a peak charging power of at least one megawatt. An infrastructure that is capable to cover the whole German heavy-duty vehicle traffic requires investments in the single-digit billion €$_{2020}$ range. The infrastructure simulation of the market diffusion modeling confirms the calculated infrastructure levy of less than 0.1 €$_{2020}$/kWh of electricity for public fast charging infrastructure in the steady state. However, the market diffusion modeling also shows that an infrastructure for public slow charging with less than 44 kW could be also relevant.

Q1a: Where could a public fast charging infrastructure for battery electric heavy-duty vehicles be spatially located?

The infrastructure simulation of the market diffusion modeling confirms the installation of large public fast charging locations along highly traveled long-distance corridors. However, the simulation also shows that the first step is to build a countrywide infrastructure. In line with the pure infrastructure modeling, the market diffusion modeling calculates approximately 200 fast charging locations as a feasible order of magnitude, considering available parking areas and necessary electricity grid connections.

Q1b: How should the public charging infrastructure be technically dimensioned in terms of charging points and charging power?

The infrastructure simulation of the market diffusion modeling confirms the need for approximately 5,000 public fast charging points with up to 1 MW power, confirming the lower value of the initially given interval from 4,500 to 12,000 charging points. In addition, a demand of up to 44,000 public slow charging points with up to 44 kW average power is identified. The spatial distribution or the substitutability of slow charging points by additional fast charging points is beyond the scope of this thesis and is left for further research.

Q2: What impact does the development of public fast charging infrastructure have on the market diffusion of heavy-duty electric vehicles and which truck technology appears to be economically viable from the user's perspective in Germany up to 2050?

The market diffusion analysis shows both a high technical and high economic potential for BET with a GVW of more than 12 t. Until 2050, a high share of BET in the fleet can be assumed. The assumed public fast charging infrastructure ramp-up in reference to the AFIR proposal (EC, 2021) is sufficient to support the market diffusion of BET. Additionally, the levies required to finance the public fast charging infrastructure are not high enough to slow down the market diffusion of BET. In the presented scenario with repetitive daily driving profiles, public fast charging is required by about 15% of the vehicles in the long-term, accounting for up to 30% of the total mileage.

Q3: What is the impact of battery electric road freight transport in terms of (1) the total amount of electric energy and (2) the load profile in Germany up to 2050?

BET (> 12 t GVW) could generate slightly less than 35 TWh of annual electricity demand after 2030. For comparison, Sensfuß et al. (2022) assumed a total electricity production of clearly more than 600 TWh in Germany after 2030; in highly electrified scenarios, production can rise to as much as 1,200 TWh in 2045. The load profile shows a high load in the evening and night hours and, until around 2040, a clear midday peak. As - with increasing range - intermediate charging becomes increasingly unnecessary, the midday peak weakens clearly in the long-term. At full fleet conversion, peak load exceeds 7 GW. For comparison, Sensfuß et al. (2022) calculated a peak demand of up to 250 GW in Germany in 2045.

6 Summary, conclusions, and further research

This chapter summarizes the most relevant findings of this thesis, presents conclusions, and identifies potential topics for future research. For a more detailed assessment of the implemented model development, the results of individual submodels, and potential uncertainties, please refer to the interim results and discussion sections in the subchapters 4.1.4, 4.2.4, 5.1.1.3, 5.1.2.3, 5.1.4, 5.2.6, and 5.2.7.

6.1 Summary and conclusions

Battery electric trucks are a promising option to reduce greenhouse gas emissions in heavy road freight transport. As shown in the literature review, fast charging for battery electric trucks in less than 45 minutes - the mandatory break of truck drivers - has only been discussed since the beginning of the current decade. Therefore, little is known regarding the need for and the impact of public fast charging infrastructure for battery electric trucks. This thesis aims to investigate the development of a potential public fast charging infrastructure for battery electric vehicles with a gross vehicle weight of more than 12 t from 2025 to 2050 in Germany. In more detail, three research gaps, can be identified: (1) the need for public fast charging infrastructure for trucks and a potential design of a charging network, (2) the interactions between charging infrastructure and the market diffusion of battery electric trucks, and (3) the electricity demand and the load profile of a battery electric truck fleet.

To enable a detailed focus on a public fast charging infrastructure network, the thesis distinguishes two major parts: (1) Modeling a public fast charging infrastructure considering an exogenously given demand, and (2) modeling a public fast charging infrastructure considering a modeled market diffusion of battery electric trucks with integrated techno-economic vehicle assessment and feedback loop for infrastructure needs.

As a data basis for infrastructure modeling, the thesis extensively updates a dataset of European road freight flows. Methodologically, the infrastructure modeling with exogenously given demand is performed with two approaches: (1) Infrastructure deployment at regular intervals, using a simplified node-based approach that allows extensive scenario analysis. (2) Minimization of required infrastructure locations with a path-based, capacity-constrained flow refueling location model, which allows detailed location constraints but is limited in terms of scenario analysis due to the high computational effort. In total, seven scenarios and a sensitivity analysis of the key parameters allow an assessment of the public fast charging demand assuming different market penetration of battery electric trucks.

Using 2,410 daily driving profiles, the market diffusion modeling for battery electric vehicles is based on a newly developed agent-based simulation. Compared to previous approaches in the literature, this thesis extends a detailed technical simulation that allows to evaluate the battery electric feasibility. Additionally, load profiles can be generated. To simulate the public fast charging infrastructure from 2025 to 2050 in 5-year steps, an adapted variant of the capacity-constrained flow refueling location model is developed. The ramp-up of public fast-charging infrastructure meets the demand of the agent-based vehicle simulation and influences the vehicle diffusion via an infrastructure levy.

In the following, the most relevant data-related, methodological, and content-related findings are presented:

Europe-wide origin-destination traffic flows are needed to model local infrastructure needs at high resolution. For some research questions, road traffic count data provide a good proxy. Traffic flow data allow to draw conclusions on specific potential charging locations for individual vehicle trips. Especially with increasing vehicle range, the highly relevant long-distance corridors can be identified. Local traffic count data cannot distinguish between regional traffic and long-distance traffic with charging demand. However, the thesis shows that traffic count data is also suitable to identify particularly relevant relations and to provide an overall assessment of infrastructure needs.

Real driving profiles allow a detailed estimation of the electrification capability, but must be available in sufficient quantity. The modeled vehicle market diffusion in this thesis is based on 2,410 single day driving profiles. The time-resolved analysis allows conclusions on the electrification potential. In particular, it can be determined whether sufficient breaks for recharging are available. Due to the short observation period, it is possible that vehicles have different driving profiles on other days. Given that the overall electrification potential is quite high (94% of all driving profiles in 2030, 97% in 2050), the effect appears to be a minor issue. Additionally, a load curve for the entire fleet can be derived. The load curve is well suited to identify fundamental effects, for example regarding the expected time of peak load or the charging demand with more than 350 kW. However, the load curve shows noticeable spikes, especially for fast charging, which can be attributed to the small sample size. Therefore, the dataset is only partially suitable to forecast load curves with minute accuracy.

Compared to algorithms that distribute charging infrastructure at regular intervals, optimization approaches allow additional insights regarding the minimum charging infrastructure, but are highly computational. In this thesis, a flow refueling location model is applied to 236,000 flows. The optimization approach presented in this thesis enables the calculation of a minimum infrastructure, but requires several days to solve the optimization problem. The effort increases further, if the newly developed capacity restriction is considered, which ensures that charging stations cannot become arbitrarily large. Optimality allows statements to be made about the minimum infrastructure required and exact locations. If an area-covering infrastructure shall be modeled, the algorithm presented in this thesis for modeling infrastructure at regular intervals benefits from low computational effort. Results can be obtained within minutes.

When using a flow refueling location model to model a fast charging infrastructure for electric trucks, the integration of a capacity constraint enables realistic results. The thesis shows that a large-scale conversion of the fleet to battery electric vehicles results in large locations with several dozens of fast charging points. Considering the maximum parking capacity as minimum requirement more than doubles the number of charging locations compared to the uncapacitated flow refueling location model. Considering a maximum power grid connection also increases the number of locations needed.

While vehicle and infrastructure availability may inhibit the market diffusion of battery electric trucks, cost-effectiveness from a user's perspective is typically given. The analysis shows that battery electric trucks achieve high economic advantages compared to diesel trucks for a large share of all applications from the user's perspective, given the framework conditions in this thesis. In the scenario modeled here, economic advantages are initially supported by policy measures, but are available in the long term even without subsidies. From a technical point of view, the electrification of more than 90% of the driving profiles is possible by 2030. The market diffusion is therefore mainly limited by the availability of vehicles and potentially of the infrastructure. Thus, framework conditions, such as CO_2 emission performance standards, should ensure that sales announced by manufacturers (NOW, 2023) are reached.

Fuel cell electric trucks and gas trucks can be relevant, if battery electric trucks are technically infeasible. In the mid- to long term perspective, the total cost of ownership for battery electric trucks are clearly lower than for fuel cell electric trucks, gas trucks, or diesel trucks for almost all driving profiles. Gas trucks and fuel cell electric trucks can be an option for approximately less than 10% of the fleet, where the use of battery electric trucks is not possible due to technical restrictions. It remains uncertain whether a cost-efficient refueling infrastructure can be established for those vehicles and whether the assumed cost reductions for the vehicles can be achieved. In the transition period, diesel trucks may be used for driving profiles with very low daily mileage, where the vehicle investment dominates the cost calculation.

Several thousand public megawatt charging points are needed for an almost full conversion of the truck fleet in Germany to battery electric vehicles. The different approaches in this thesis determine a demand for about 5,000 public fast charging points with 1 MW peak power for an almost complete electrification of truck traffic in and through Germany. Up to one third of them should be installed by 2030. For comparison, approximately 1,500 fast charging points with at least 300 kW were built in Germany in 2022 within one year (BNetzA, 2023b). In the long term, the simulation indicates a reduction to less than 4,000 charging points due to increasing ranges. The calculations show that approximately 120 locations are needed to enable all trips in or through Germany. For a practice-oriented network in terms of feasible electricity grid connections and available parking lots, approximately 200 locations are necessary in the medium to long term. This network also meets, on average, typical policy requirements of less than 60 km for maximum distance between charging locations. A particularly high density of public fast charging infrastructure should be established along long-distance corridors. Given the lead time in building public infrastructure, the construction should be started as soon as possible and, if necessary, the market ramp-up of public fast charging infrastructure should be supported politically.

Public megawatt charging can be offered at reasonable costs. The modeling shows that the required public fast charging infrastructure can be financed by a levy in the single-digit €ct$_{2020}$/kWh range. In particular the high amount of energy charged at the infrastructure allows for low prices. However, if utilization is initially low, the costs are considerably higher. Policy measures for market introduction - either with regard to the charging point operator or with regard to the price to be paid by the customer - may therefore be appropriate. The absolute annual costs for public megawatt charging infrastructure depends on the volume of traffic to be served and can therefore fluctuate remarkably. In the medium term, up to one third of a billion €$_{2020}$/a can be expected. For an initial comparison, annual truck toll in Germany in 2019, before the COVID-19 pandemic, was 7.5 billion €$_{2020}$ (BAG, 2021). Wietschel et al. (2017) calculated 0.7 billion €$_{2015}$/a for 4,000 km of overhead catenary lines in Germany. However, public megawatt charging and overhead lines can only be compared to a limited extent, as they differ in the recharged energy as well as the necessary private infrastructure.

Public megawatt charging is particularly relevant for vehicles with a high daily mileage. However, the majority of charging takes place at private slow-charging infrastructure. In the long term, 30 to 35 TWh of electricity are needed for battery electric trucks (> 12 t GVW). The simulation shows that in the long term, approximately 15% of all vehicles rely on public fast charging, accounting for up to 30% of the total mileage. Changing driving behavior, for example through autonomous driving, could increase the share. However, this is beyond the scope of this thesis. In the long term, fleet conversion generates an electricity demand of 30 to 35 TWh per year. For comparison, a total electricity production of clearly more than 600 TWh in Germany can be expected after 2030. An increase up to 1,200 TWh annually by 2045 seems plausible (Sensfuß et al., 2022). More than half of the energy for trucks is charged at private slow charging infrastructure with up to 44 kW average charging power. This means that almost every truck needs a private slow charging point. In this thesis, it is assumed that private slow charging is always available. Due to the high influence on the electrification of the truck fleet, this assumption should be supported by policy measures and further evaluated scientifically.

The fleet conversion to battery electric trucks causes additional energy demand in the evening and nighttime hours, as well as a midday peak. With almost full fleet conversion, additional load of up to 8 GW in peak can be expected. High loads can be expected throughout the evening and nighttime hours due to slow charging with less than 44 kW average power on mainly private infrastructure. A significant midday peak is also expected until around 2040, due to intermediate charging with high charging power. Due to increasing vehicle ranges, a successive reduction of the midday peak is expected. For comparison, Sensfuß et al. (2022) assumed daily peak power of up to 250 GW in Germany in 2045. The additional load of battery electric trucks should be addressed in grid and power plant planning.

6.2 Discussion and further research

Finally, key aspects of this thesis are discussed in the following with regard to the data used, the methodology applied, and the results obtained. Further research needs are identified.

The modeling of public fast charging infrastructure developed in this thesis is based on a newly created, extensive origin-destination dataset of European road freight transport (Speth, Sauter, Plötz, & Signer, 2022). The dataset corresponds well with road traffic counts in Germany, especially for long-haul routes. However, the dataset does not contain information on individual driving profiles or the combination of individual origin-destination paths to vehicle trips. Therefore, the market diffusion simulation of battery electric trucks as well as the load profiles are based on 2,410 daily driving profiles from a second source (WVI et al., 2012a). Although the modeling considers the harmonization of the dataset in terms of total distance travelled and energy recharged, discrepancies cannot be avoided when using different dataset in different parts of the modeling. In addition, the comparatively small sample of driving profiles leads to fluctuations, especially in the load profiles for fast charging. The analysis shows a high potential for electrification for almost all types of daily driving profiles after 2030. Nevertheless, the short observation period may lead to an overestimation of the electrification potential. Therefore, the collection of comprehensive, spatially and temporally resolved driving profile datasets could strengthen future analyses.

The data selection also implies that driving behavior, represented by driving profiles, remains constant. Future developments, for example autonomous driving, could change driving and parking behavior and thus the need for recharging. Future analyses should therefore examine the influence of potentially changing driving behavior.

As shown in subchapter 2.2.1, there are different approaches to model a public fast charging infrastructure. The suitability of each approach depends on the available data, the objective, and the available computational power. Given the available data, the path-based capacity-constrained flow refueling location model represents the best option for modeling a minimal public fast charging infrastructure. The advantage of modeling local conditions, for example the available total power or the available parking locations, is highly relevant. To the best of the author's knowledge, this thesis is the first attempt to apply a capacity-constrained flow refueling location model to a dataset of approximately 375,000 origin-destination-paths. The resulting mixed-integer optimization problem can be solved with the available computational power (196 GB RAM and 8 cores) only with considerable time effort and high solver tolerances. The approach is therefore not suitable for extensive scenario modeling. Instead, this thesis uses a second approach that places charging locations at regular intervals and scales them based on traffic volumes. Both approaches complement each other and allow an estimation of future public fast charging infrastructure needs. Future studies could improve the efficiency of the capacity-constrained flow refueling location model, for example by aggregating paths.

The integration of the public fast charging infrastructure ramp-up into an agent-based market diffusion model for battery electric trucks represents another methodological development in this thesis. Due to high cost advantages of battery-electric trucks in the medium term, a plausible cost estimate for public fast charging can also result in a similar market ramp-up for battery electric trucks. A limitation of the market ramp-up of the vehicles, taking into account the infrastructure ramp-up assumed to be realistic, could hardly be identified. However, the integration of the vehicle market diffusion allows for time-resolved infrastructure modeling. Future studies could further develop the coupling taking into account extreme scenarios, such as an even more limited infrastructure build-up.

The results show economic advantages of battery electric trucks compared to other alternatives, such as fuel cell electric trucks. Alternatives are mainly used due to technical restrictions of battery electric trucks. Further scenario analyses could substantiate this effect in the future.

As a result, this thesis shows that public fast charging is relevant for full electrification of road freight transport and derives plausible public infrastructure requirements. Corresponding findings of this thesis are already being taken into account today as part of initial projects on public megawatt charging (HoLa, 2021). Yet, the results also show the high relevance of private, and probably also public, slow charging and private fast charging. The spatially resolved modeling of slow charging infrastructure and its interaction with megawatt charging at the same location is beyond the scope of this thesis and left for future research.

Surveys among logistics companies identify a lack of infrastructure as a barrier to purchasing alternative fuel trucks. This thesis shows that public fast charging infrastructure benefits from high utilization in terms of economic operation. This might be a chicken-and-egg problem, as it has been discussed for passenger cars in the past (Gnann, 2015). The results show that in the medium term, 15% of all driving profiles rely on public megawatt charging. As shown in a sensitivity analysis, a delayed expansion of public megawatt charging has only limited impact on the market diffusion of battery electric trucks. Similar to passenger cars, private charging at depots has a high impact on the market diffusion. In contrast to passenger cars, the electrification of depots can require increased effort, especially for larger fleets. Future studies should focus on depot charging to overcome a potential initial chicken-and-egg problem.

The results of this thesis are not an optimum regarding the battery design in relation to the infrastructure. Rather, the modeling is based on plausible estimates regarding technical parameters and the modeling of the charging behavior. Load management, for example, could unlock further potential for cost reductions. Future research could address in more detail the optimal technical design of the battery electric trucks depending on the available infrastructure as well as the impact of different charging strategies on the load curve.

All in all, this thesis provides an estimate for a future public fast charging infrastructure for battery electric trucks. Due to the early market phase, the results are still subject to high uncertainties. Future studies should improve the estimation of public fast charging demands of heavy-duty battery electric vehicles and include private charging infrastructure in more detail.

A Appendices

A.1 Distribution of daily kilometers traveled in the KiD sample

The KiD dataset contains 2,810 vehicle datasets for vehicles with a GVW > 12 t. 1,635 profiles stem from rigid trucks, 1,175 from tractor-trailers. However, incomplete datasets with regard to the individual trip information must be sorted out, leaving 2,410 datasets for further analysis with 1,350 rigids and 1,060 tractor-trailers. Figure A-1 shows the distribution of daily mileage in the sample.

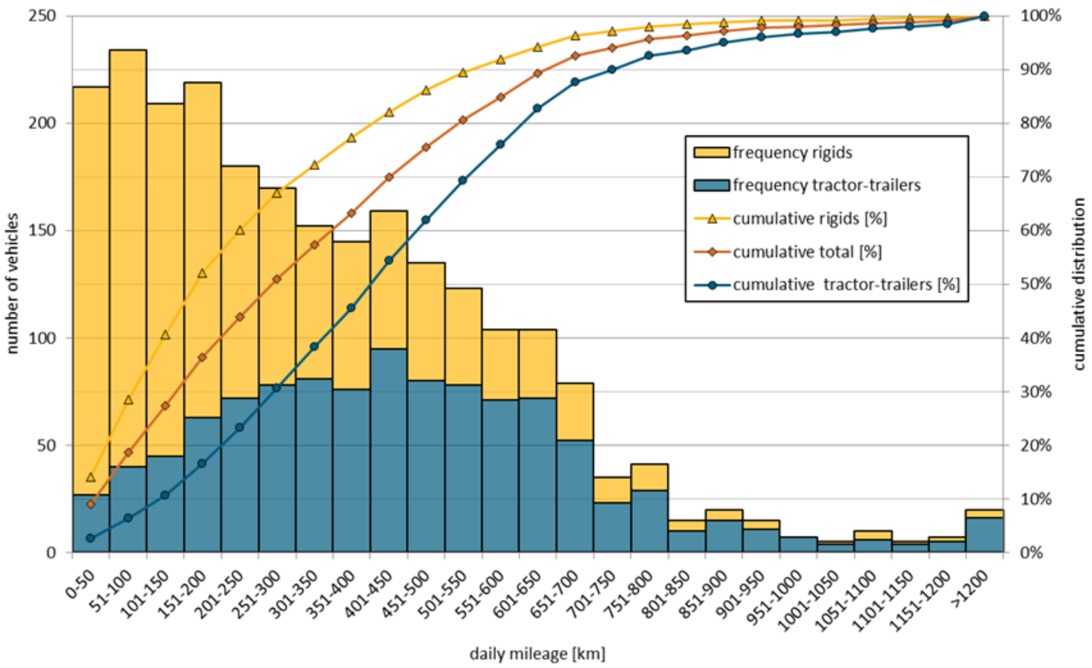

Figure A-1: Distribution of daily km traveled of N = 2,410 HDV in the KiD sample (WVI et al., 2012a).

A.2 Costs for CCS charging infrastructure

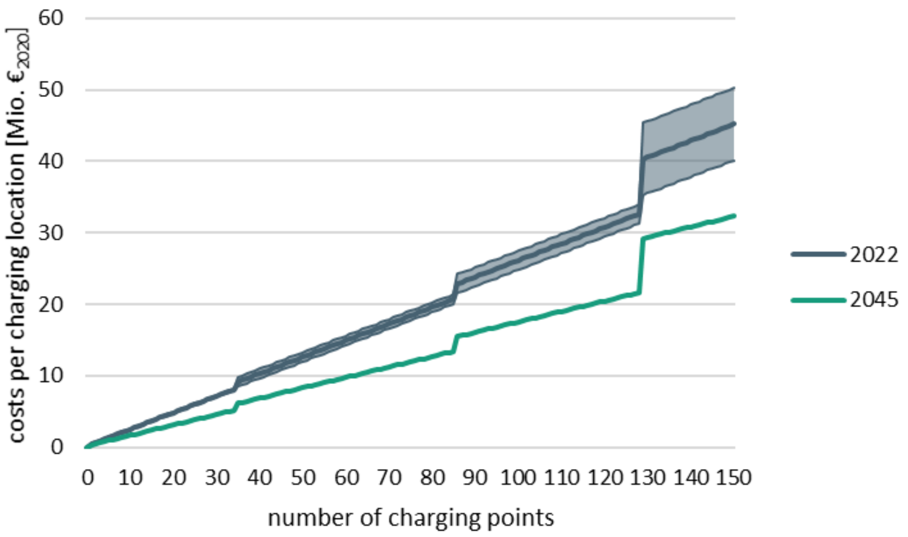

Figure A-2: Costs of charging locations in dependence of the number of CCS charging points. Shaded area for 2022 shows the difference between low and high grid connection costs. Own illustration.

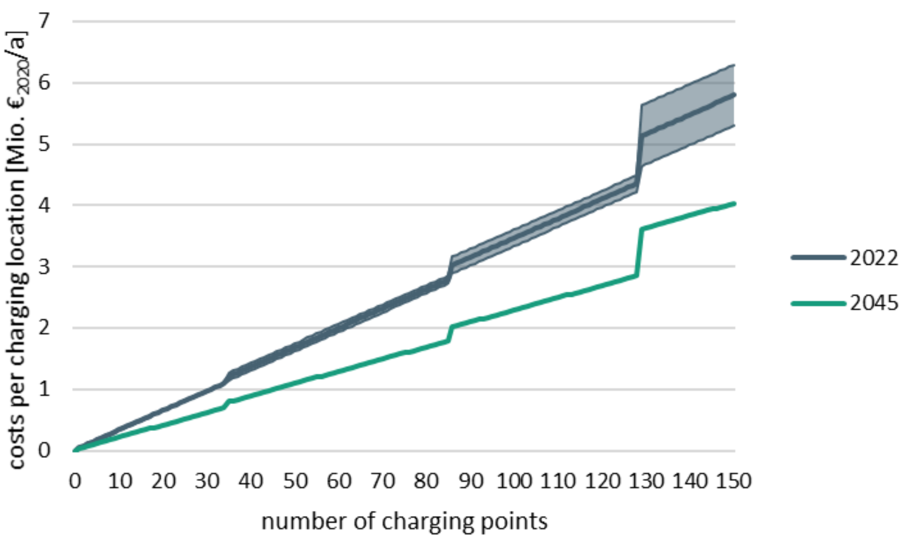

Figure A-3: Annual costs of charging locations in dependence of the number of CCS charging points. Shaded area for 2022 shows the difference between low and high grid connection costs. Own illustration.

A.3 Techno-economic parameters

This appendix presents the parameters, used for the ALADIN - Alternative Automobiles Diffusion and INfrastructure - model for HDV with a GVW of more than 12 t. Unless shown differently in 3.5 or directly in this appendix, this is the most current model state as used in Plötz, Link, et al. (2023) or Gnann et al. (2023). The parameters used in Plötz, Link, et al. (2023) were developed in consultation with the European Automobile Manufacturers' Association (ACEA), based on scientific publications. A brief explanation of the assumed parameters can be found in the footnotes of the tables. Particularly relevant parameters are discussed in chapter 3.5.

Table A-1: Framework parameters for market diffusion modeling for tractor-trailers (TT) and Rigids (R) with a GVW > 12 t.

Parameter	**Abbreviation**	**Unit**	**2020**	**2030**	**2050**
Diesel price[a]	${c_{fuel}}_{DT}^{t}$	€2020/kWh	0.078	0.153	0.281
Gas price[a]	${c_{fuel}}_{GT}^{t}$	€2020/kWh	0.071	0.116	0.200
Electricity price[a]	${c_{fuel}}_{BET}^{t}$	€2020/kWh	0.130	0.118	0.112
Hydrogen price[a]	${c_{fuel}}_{FCET}^{t}$	€2020/kWh	0.240	0.195	0.153
Registrations (TT)[a]	reg_{TT}^{t}	thousands	38.8	40.2	37.5
Registrations (R)[a]	reg_{R}^{t}	thousands	26.2	27.5	27.6
Service life (TT)[a]	$life_{TT}^{t}$	a	6	6	6
Service life (R)[a]	$life_{R}^{t}$	a	6	6	6
Interest rate[b]	$i(t)$	%	9.5	9.5	9.5
Working days[a]	$wd(t)$	d/a	250	250	250
Vehicle availability (TT, R)[c]	${veh_{available}}_{DT,all}^{t}$	%	100	100	100
Vehicle availability (TT, R)[c]	${veh_{available}}_{GT,all}^{t}$	%	16	16	16
Vehicle availability (TT, R)[c]	${veh_{available}}_{BET,all}^{t}$	%	1	60	100
Vehicle availability (TT, R)[c]	${veh_{available}}_{FCET,all}^{t}$	%	0	17	100

[a] Based on Gnann et al. (2023) and BDEW (2022).

[b] EC (2018).

[c] Based on Gnann et al. (2023) and NOW (2023). DT serve as fallback option and are always available. BET and FCET are fitted according to NOW (2023). GT are uncertain, since various manufacturers are currently already offering GT. However, NOW (2023) shows no relevant market share in the future. Therefore, the 2020 availability from Gnann et al. (2023) is assumed to remain constant.

Table A-2: Technical parameters for market diffusion modeling for tractor-trailers (TT) and Rigids (R) with a GVW > 12 t

Parameter	**Abbreviation**	**Unit**	**2020**	**2030**	**2050**
DT consumption (TT)[a]	$cons_{DT,TT}^{t}$	kWh/km	3.14	2.77	2.43
DT consumption (R)[a]	$cons_{DT,R}^{t}$	kWh/km	2.82	2.49	2.18

GT consumption (TT)[b]	$cons^{t}_{GT,TT}$	kWh/km	3.54	2.77	2.74
GT consumption (R)[b]	$cons^{t}_{GT,R}$	kWh/km	3.19	2.49	2.47
BET consumption (TT)[a]	$cons^{t}_{BET,TT}$	kWh/km	1.38	1.10	1.00
BET consumption (R)[a]	$cons^{t}_{BET,R}$	kWh/km	1.24	0.99	0.90
FCET consumption (TT)[a]	$cons^{t}_{FCET,TT}$	kWh/km	2.80	2.27	1.95
FCET consumption (R)[a]	$cons^{t}_{FCET,R}$	kWh/km	2.52	2.04	1.76
Rated power (TT)[c]	$p^{t}_{all,TT}$	kW	350	350	350
Rated power (R)[c]	$p^{t}_{all,R}$	kW	280	280	280
Rated power fuel cell (TT)[d]	${p_{FC}}^{t}_{FCET,TT}$	kW	250	250	250
Rated power fuel cell (R)[d]	${p_{FC}}^{t}_{FCET,R}$	kW	200	200	200
Gas tank capacity (TT)[e]	$tank^{t}_{GT,TT}$	kWh	4,500	4,500	4,500
Gas tank capacity (R)[e]	$tank^{t}_{GT,R}$	kWh	3,000	3,000	3,000
Battery capacity FCET (TT)[d]	$bat^{t}_{FCET,TT}$	kWh	70	70	70
Battery capacity FCET (R)[d]	$bat^{t}_{FCET,R}$	kWh	70	70	70
Hydrogen tank capacity (TT)[f]	$tank^{t}_{FCET,TT}$	kWh	2,666	2,666	2,666
Hydrogen tank capacity (R)[f]	$tank^{t}_{FCET,R}$	kWh	2,000	2,000	2,000
BET minimum range (TT, R)[g]	${bat_{min}}^{t}_{BET,all}$	km	200	200	200
BET maximum range (TT, R)[h]	${bat_{max}}^{t}_{BET,all}$	km	250	450	750
BET charging range (TT, R)[i]	${charge_{range}}^{t}_{BET,all}$	km	188	340	563
BET battery pack size (TT, R)[g]	${bat_{pack}}^{t}_{BET,all}$	kWh	100	100	100
BET usable battery (TT, R)[j]	${bat_{usable}}^{t}_{BET,all}$	%	70	75	85
Average charging power (TT)[k]	${charging_{max}}^{t}_{BET,TT}$	kW	250	998	1,500
Average charging power (R)[k]	${charging_{max}}^{t}_{BET,R}$	kW	250	898	1.350

[a] Based on Speth, Kappler, et al. (2022), Basma and Rodríguez (2022), Ruf et al. (2020), Link et al. (2021), Hülsmann et al. (2014), Dünnebeil et al. (2015), Tschöke and Marohn (2019), and Wietschel et al. (2017). Merged in Plötz, Link, et al. (2023) in consultation with the European Automobile Manufacturers' Association (ACEA). Values for Rigids are 90% of Tractor-Trailers.

[b] According to Mottschall et al. (2020), high pressure direct injection engines for GT are on average 4% less efficient than diesel engines. Spark-ignition engines for GT are 22% less efficient than diesel engines. Therefore 13% less efficiency in total is assumed.

[c] Median Vecto EEA Data for class 4 and class 9 vehicles for Tractor-Trailers and median value for class 5 vehicles for Rigids, according to EEA (2021).

[d] Based on Mayr et al. (2021).

[e] Based on Plötz, Link, et al. (2023).

[f] Based on Basma and Rodríguez (2022).

[g] Own assumptions, based on Volvo (2023a), Volvo (2023b) and Mercedes Benz (2023).

[h] Current values based on Volvo (2023b) and Mercedes Benz (2023); 2030 value allows for 4.5 hours of driving; long-term perspective based on Plötz, Link, et al. (2023).

[i] Own assumption. The ideal relationship between infrastructure and battery size is beyond the research in this thesis. Initial research suggests that larger batteries can support the market-diffusion more than additional infrastructure (Gnann, Speth, Link, & Plötz, 2022). Therefore, it is assumed that the $charge\_range^{t}_{BET,all}$ - thus the range that must be exceeded with the next trip of a tour in order to trigger a charging event - is 75% of the maximum range.

[j] Plötz, Link, et al. (2023), based on Mauler et al. (2022). Conservative scenario, since - in contrast to Plötz, Link, et al. (2023) - no additional battery reserve is considered.

[k] Current values are own assumptions, based on Volvo (2023b) and Mercedes Benz (2023). MCS charging with more than 350 kW is assumed from 2025 onwards. From 2030 onwards, the charging power is defined so that $bat\_max^{t}_{BET,all}$ can be recharged in 30 minutes.

Table A-3: Economic parameters for market diffusion modeling for tractor-trailers (TT) and Rigids (R) with a GVW > 12 t

Parameter	Abbreviation	Unit	2020	2030	2050
Invest diesel engine (TT, R)[a]	${I_{engine}}_{ICET,all}^{t}$	€2020/kW	72	74	77
Invest aftertreatment (TT, R)[b]	${I_{aftert}}_{ICET,all}^{t}$	€2020/kW	19.8	21.8	21.8
Invest gas engine (TT, R)[c]	${I_{engine}}_{GT,all}^{t}$	€2020/kW	67	69	72
Invest aftertreatment (TT, R)[b]	${I_{aftert}}_{GT,all}^{t}$	€2020/kW	14.3	15.7	15.7
Invest electric engine (TT, R)[a]	${I_{engine}}_{BET;FCET,all}^{t}$	€2020/kW	67	50	37
Invest fuel cell (TT, R)[d]	${I_{FC}}_{FCET,all}^{t}$	€2020/kW	200	147	80
Vehicle body (TT)[e]	${I_{body}}_{all,TT}^{t}$	k€2020	90	96	103
Vehicle body (R)[e]	${I_{body}}_{all,R}^{t}$	k€2020	60	66	73
Gas tank (TT, R)[f]	${I_{tank}}_{GT,all}^{t}$	€2020/kWh	5.76	5.76	5.76
Battery costs (TT, R)[g]	${I_{bat}}_{BET;FCET,all}^{t}$	€2020/kWh	156	120	80
Hydrogen tank (TT, R)[h]	${I_{tank}}_{FCET,all}^{t}$	€2020/kWh	9.75	7.58	4.85
Markup components (TT, R)[i]	$markup_{DT,all}^{t}$	%	27	27	27
Markup components (TT, R)[i]	$markup_{GT;FCET;BET,all}^{t}$	%	43	32	27
Invest reduction (TT,R)[j]	${I_{red}}_{FCET;BET,all}^{t}$	%	0	80	0
Insurance[k]	$insurance_{all,all}^{t}$	%	5.8	5.8	5.8
Residual value[l]	${res_{value}}_{all,all}^{t}$	%	25	25	25
Operation & Maintenance[m]	$O\&M_{DT,all}^{t}$	€2020/km	0.19	0.19	0.19
Operation & Maintenance[m]	$O\&M_{GT,all}^{t}$	€2020/km	0.18	0.18	0.18
Operation & Maintenance[m]	$O\&M_{BET,all}^{t}$	€2020/km	0.13	0.13	0.13
Operation & Maintenance[m]	$O\&M_{FCET,all}^{t}$	€2020/km	0.19	0.19	0.16
Vehicle tax[n]	${veh_{tax}}_{all,all}^{t}$	€2020/a	929	929	929
Toll[o]	$toll_{DT,all}^{t}$	€2020/km	0.17	0.17	0.17
Toll[o]	$toll_{GT,all}^{t}$	€2020/km	0	0.17	0.17
Toll[o]	$toll_{BET,all}^{t}$	€2020/km	0	0.04	0.16
Toll[o]	$toll_{FCET,all}^{t}$	€2020/km	0	0.04	0.16

[a] Based on Speth, Kappler, et al. (2022). Electric engine includes power electronic.
[b] Based on Pierre-Louis Ragon and Rodríguez (2021). Scaling for GT based on Link et al. (2021).
[c] Average, based on Noll et al. (2022).
[d] Based on Speth, Kappler, et al. (2022) and Sharpe and Basma (2022).
[e] Based on Speth, Kappler, et al. (2022) and Link et al. (2021), including mark-up.
[f] Based on Noll et al. (2022).
[g] Based on Speth, Kappler, et al. (2022) and Sharpe and Basma (2022).
[h] Based on Ahluwalia et al. (2022). 33% reduction is assumed, since the model assumes liquefied hydrogen instead of compressed hydrogen.
[i] Own assumptions, based on Basma et al. (2021) and in line with Plötz, Link, et al. (2023).
[j] Currently, BET and FCET in Germany receive a purchase price reduction of 80% of the additional investment, compared to DT (BaLM, 2023). It is assumed that this funding is applied from 2022 to 2030.

[k] Annual insurance costs are assumed as share of the investment, according to LastAutoOmnibus (2018).

[l] Plötz, Link, et al. (2023), based on Kleiner and Friedrich (2017). There is a high uncertainty regarding the residual values of BET and FCET, due to the batteries. However, in consultation with representatives from the automotive industry, Plötz, Link, et al. (2023) assumed similar relative residual values as for DT.

[m] Based on Speth, Kappler, et al. (2022), Basma et al. (2021), LastAutoOmnibus (2018), Wietschel et al. (2017), Jöhrens et al. (2018), and Marcinkoski et al. (2019).

[n] Basma et al. (2021) and BMF (2021).

[o] Own assumptions, based on Toll Collect (2023). GT pays full toll from 2024 onwards. BET and FCET are exempted until 2025 and receive a 75% toll reduction until 2030. After 2030, they pay full toll, reduced by the air pollution factor. The introduction of a CO_2-dependent toll, as suggested by Deutsche Bundesregierung (2023), is not implemented. Up to now, the CO_2-dependent toll has been discussed with a corresponding reduction of the CO_2-dependent part of the fuel costs, to avoid double taxation (Umweltbundesamt, 2021). Therefore, the implementation is uncertain.

Table A-4: Infrastructure parameters for market diffusion modeling for Germany.

Parameter	**Abbreviation**	**Unit**	**2020**	**2030**	**2050**
Max. public fast charging locations[a]	$locations_{max}^{t}$		0	160	
Min. public fast charging locations[a]	$locations_{min}^{t}$		0	160	220
Max. plugs per location[b]	$plug_{max}^{t}$		12	30	45
Infrastructure costs slow charging[c]	$c_{infra}{}_{slow}^{t}$	€$_{2020}$/kWh	0.04	0.03	0.03
Infrastructure costs fast charging[c]	$c_{infra}{}_{fast}^{t}$	€$_{2020}$/kWh	0.26	0.05	0.05
Infrastructure costs grid connection[c]	$c_{infra}{}_{fast,grid}^{t}$	€$_{2020}$/kWh	0.05	0.05	0.05
Public charging markup[d]	$c_{infra}{}_{markup}^{t}$	%	10	10	10
Availability private slow charging[e]	$a_{infra}{}_{private,slow}^{t}$	%	100	100	100
Availability public slow charging[e]	$a_{infra}{}_{public,slow}^{t}$	%	100	100	100
Availability private fast charging[e]	$a_{infra}{}_{private,fast}^{t}$	%	100	100	100
Availability public fast charging[e]	$a_{infra}{}_{public,fast}^{t}$	%	100	100	100

[a] The number of public fast charging locations for 2025 and 2030 follows the suggestions in EC (2021). FGSV (2011) foresees a maximum average distance between service areas of 50 to 60 km. This value is ensured in 2035.

[b] The maximum number of fast charging plugs per location is based on Kippelt et al. (2022). Taking into account the assumptions in chapter 3.3, it is assumed that from 2020 to 2025, a maximum of 8 MVA - 12 plugs - can be installed. From 2025 to 2030, the maximum increases to 20 MV - 30 plugs. In the long term, the number of plugs is limited to 30 MVA - 45 plugs - per location, to avoid a completely new high-voltage substation.

[c] Infrastructure costs are based on Basma et al. (2021) and Kippelt et al. (2022). For fast charging infrastructure, the values are endogenously updated in the infrastructure analysis module of ALADIN.

[d] Markup based on Schroeder and Traber (2012).

[e] Initially, infrastructure is assumed to be no restriction. MCS infrastructure, as part of the fast charging infrastructure, is available from 2025 onwards. For public fast charging infrastructure, the values are endogenously updated in the infrastructure analysis module of ALADIN.

A.4 Maximum average arrival rate according to queueing theory

Figure A-4 shows the maximum average arrival rate at a charging location for a given number of charging points, as defined in subchapter 4.1.1.2. An average waiting time w_q of 5 minutes is assumed. The average charging time $charging_q$ is defined as 30 min (green) and 60 min (blue). It can be seen that the maximum average arrival rate converges to the theoretical optimum without considering the queueing theory, as the number of charging points increases.

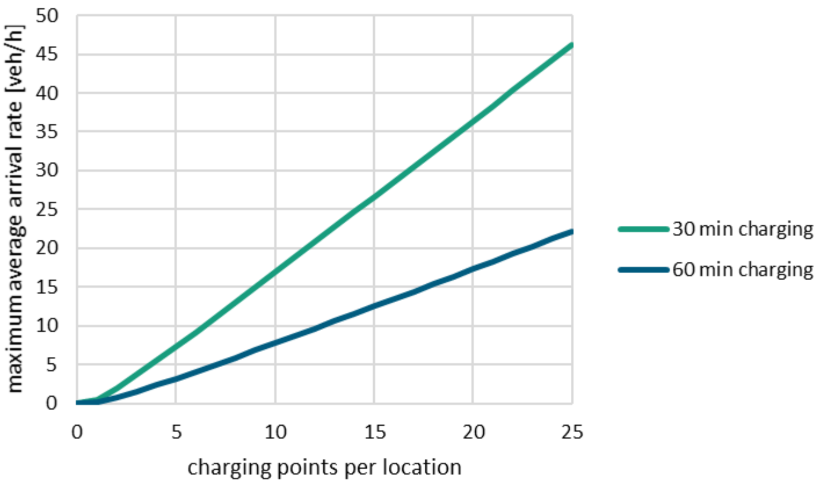

Figure A-4: Maximum average arrival rate at a charging location for a given number of charging points.

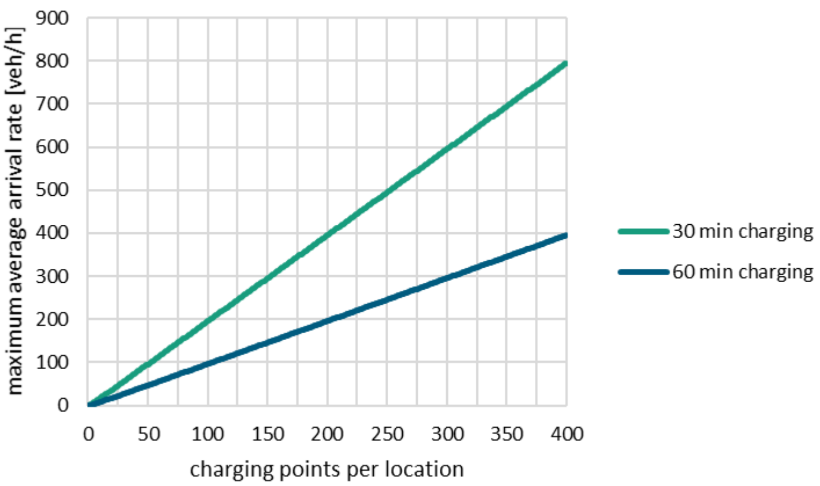

Figure A-5: Maximum average arrival rate at a charging location for a given number of charging points for large locations.

A.5 Modeled number of public fast charging locations in Europe

Table A-5 shows the calculated number of charging location and charging points per country for the scenarios *Startup2025*, *Wide2030*, *Dense2030*, and *Dense2045*. Additionally, the number of charging locations in the optimized network in the scenario *Optimization2045* is given.

Table A-5: Number of charging locations (loc) and charging points (char) per country in the scenarios Startup2025, Wide2030, Dense2030, Dense2045, and Optimization2045.

Country	**Startup2025**		**Wide2030**		**Dense2030**		**Dense2045**		**Optimization2045**
	loc	**char**	**loc**	**char**	**loc**	**char**	**loc**	**char**	**loc**
AT	24	62	24	133	44	161	44	686	8
BE	11	41	11	96	26	132	26	660	4
BG	20	23	20	41	39	63	39	155	10
CH	18	46	18	92	32	101	32	416	5
CZ	22	57	22	123	38	126	38	537	7
DE	101	345	101	809	190	986	190	4,771	42
DK	13	32	13	64	21	73	21	316	5
EE	6	7	6	12	10	14	10	38	3
ES	54	113	54	204	106	281	106	1,065	33
FI	41	43	41	61	78	92	78	176	16
FR	121	334	121	699	218	850	218	3,741	39
GR	40	52	40	76	69	103	69	255	10
HR	19	33	19	53	31	62	31	199	8
HU	20	41	20	73	39	101	39	378	7
IE	8	14	8	21	15	32	15	121	4
IT	82	184	82	378	149	464	149	1,914	29
LT	11	18	11	28	20	40	20	107	3
LU	2	7	2	16	4	17	4	81	1
LV	10	14	10	28	18	31	18	87	3
NL	13	40	13	90	22	95	22	430	4
NO	47	50	47	56	88	99	88	185	17
PL	44	166	44	396	86	451	86	2,192	18
PT	14	18	14	29	29	57	29	126	6
RO	50	62	50	92	92	135	92	325	15
SE	61	103	61	181	124	296	124	955	19
SI	6	16	6	33	10	36	10	138	1
SK	14	34	14	68	25	72	25	295	5
UK	45	135	45	298	78	320	78	1,455	17

A.6 Load profiles for public fast charging

Figure A-6 and Figure A-7 show the daily public fast charging behavior and the corresponding load curves for the simulated market diffusion in this thesis. Please note that the curves are subject to considerable fluctuations due to the sample size. However, general trends, for example the clear midday peak in the first years as well as the shift to the night with increasing vehicle range, as well as the magnitude of the energy demand can be estimated. Charging events with less than 44 kW average charging power are not part of the presented figures.

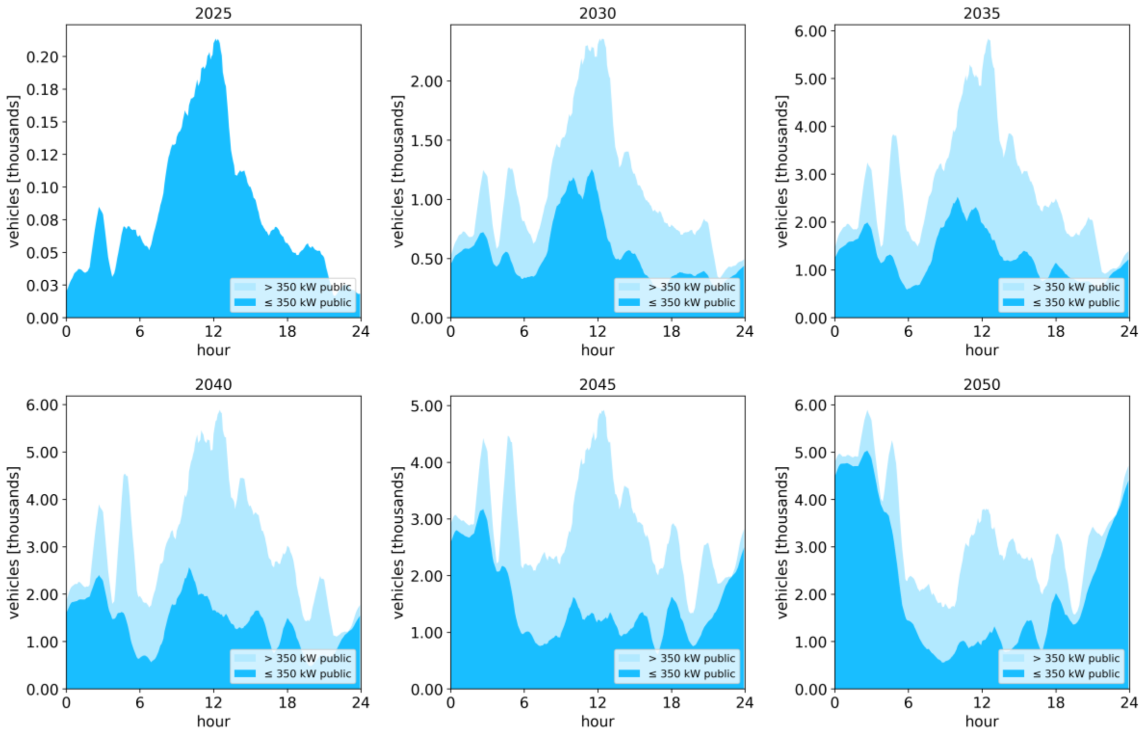

Figure A-6: Public fast charging behavior of the simulated BET fleet from 2025 to 2050. The indicated charging power refers to the average power of the charging processes. All data refers to vehicles with a GVW of more than 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise. Please note the different y-axes.

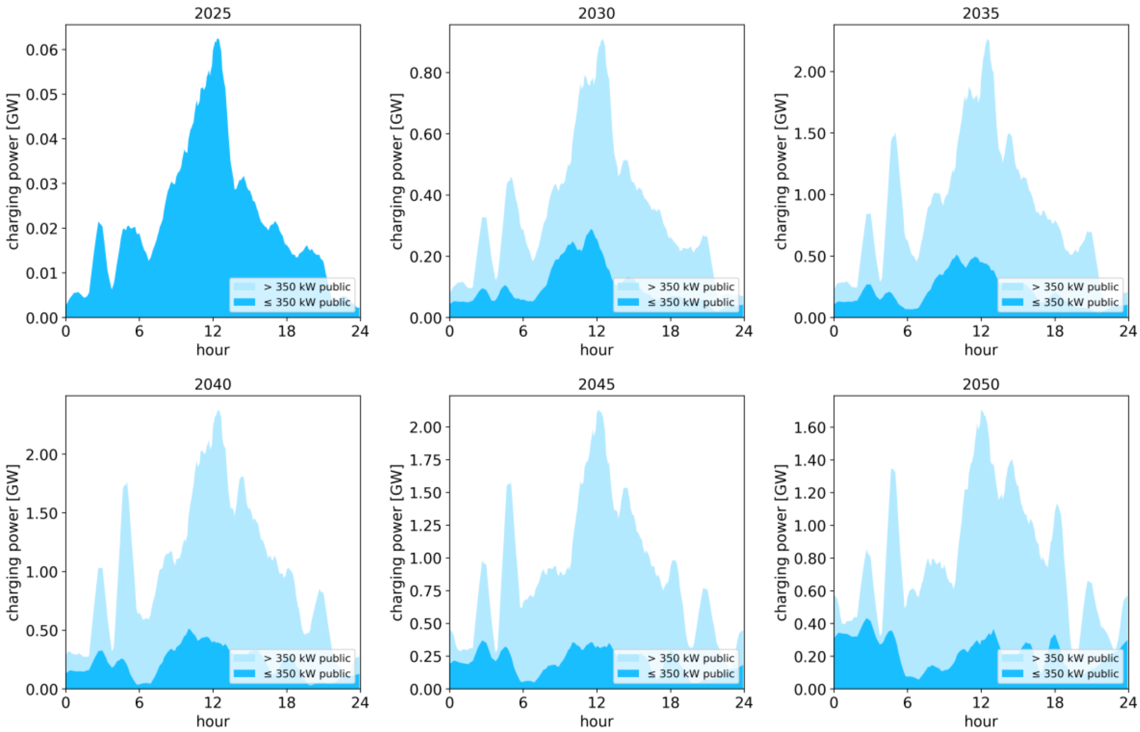

Figure A-7: Daily pubic fast charging load curve of the BET fleet from 2025 to 2050. The indicated charging power refers to the average power of the charging process. All data refers to vehicles with a GVW of more than 12 t. Moving averages with a one hour span have been applied to all lines to reduce finite sample noise. Please note the different y-axes.

A.7 Modeled public fast charging infrastructure for the simulated BET diffusion

The following maps show the required public fast charging infrastructure in Germany for the market diffusion of BET modeled in this thesis. The infrastructure is shown in 5-year-steps from 2025 to 2050. The size and the color of the plotted points in the maps give an overview of the size of the individual charging locations. A distinction is made between the actually installed size and the needed location size. The difference results from charging points that were installed in previous years but are no longer needed due to increasing vehicle ranges. Charging points are assumed to be established for 15 years. Additionally, the installed number of charging points for each location is mentioned on the maps.

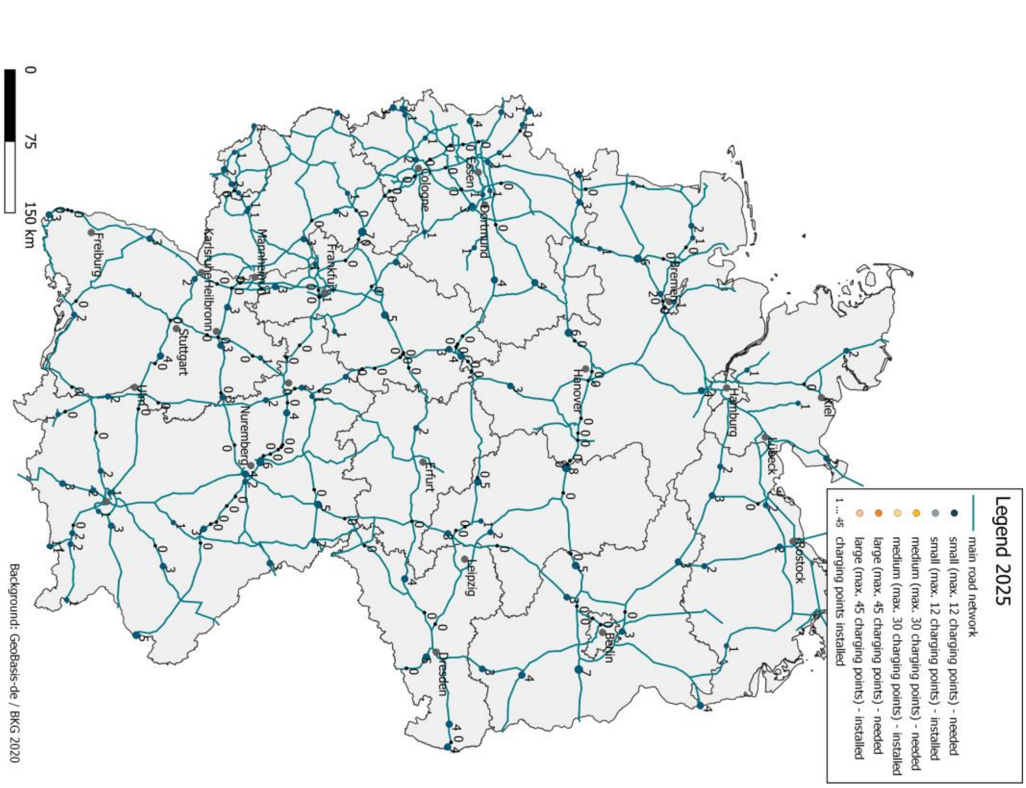

Figure A-8: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2025.

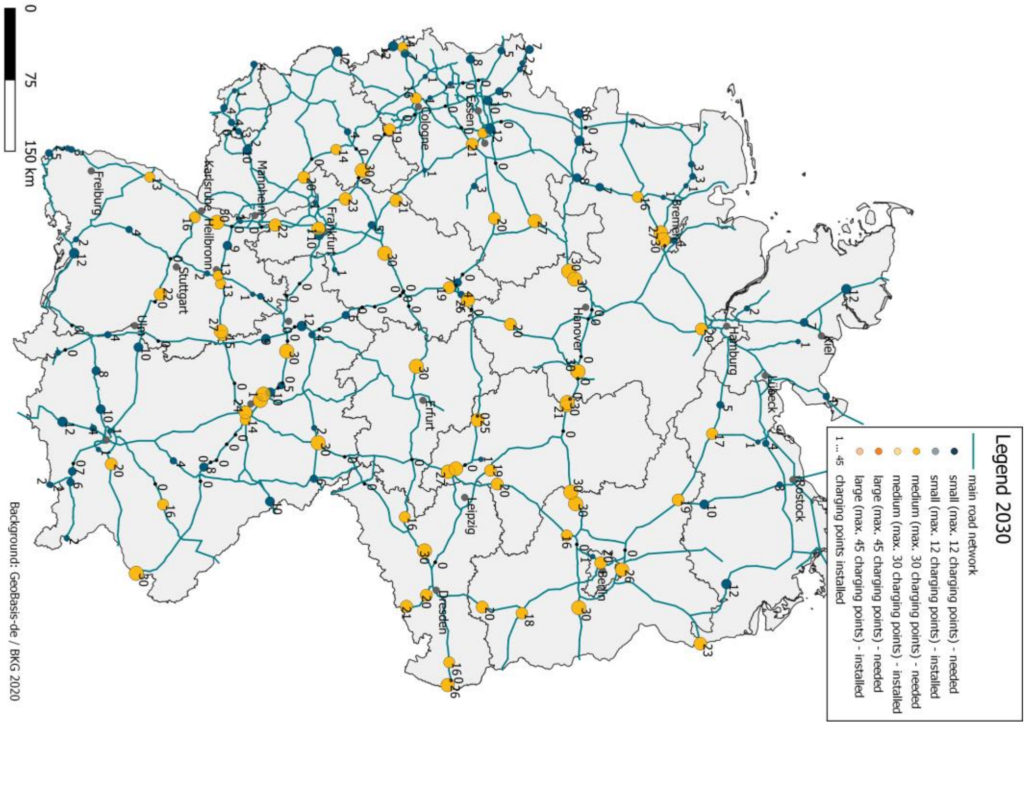

Figure A-9: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2030.

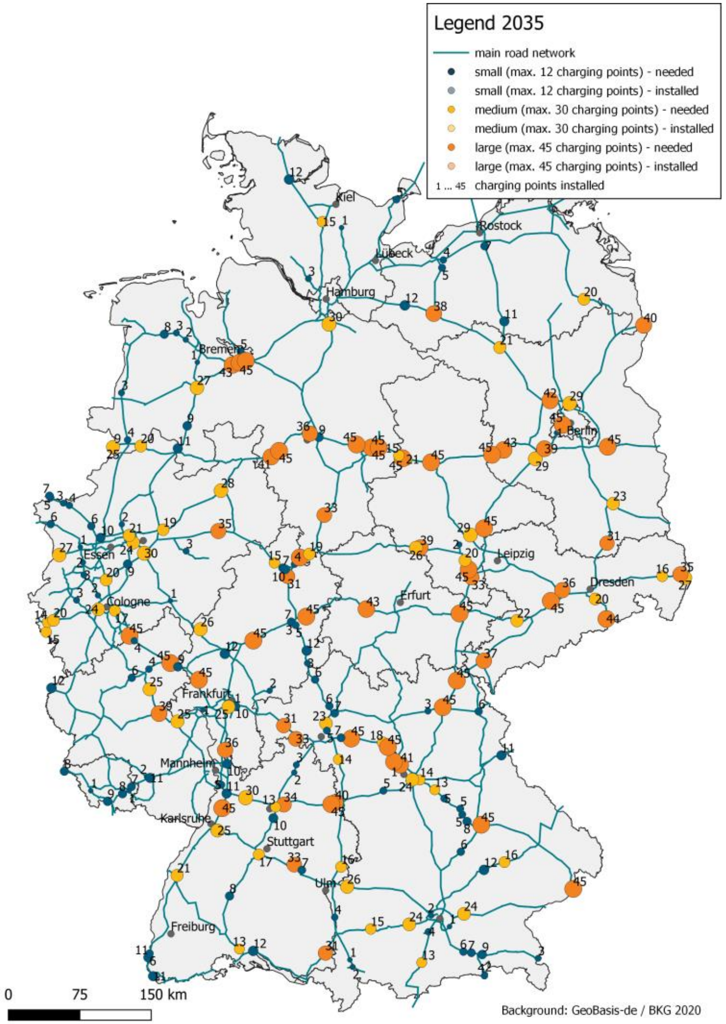

Figure A-10: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2035.

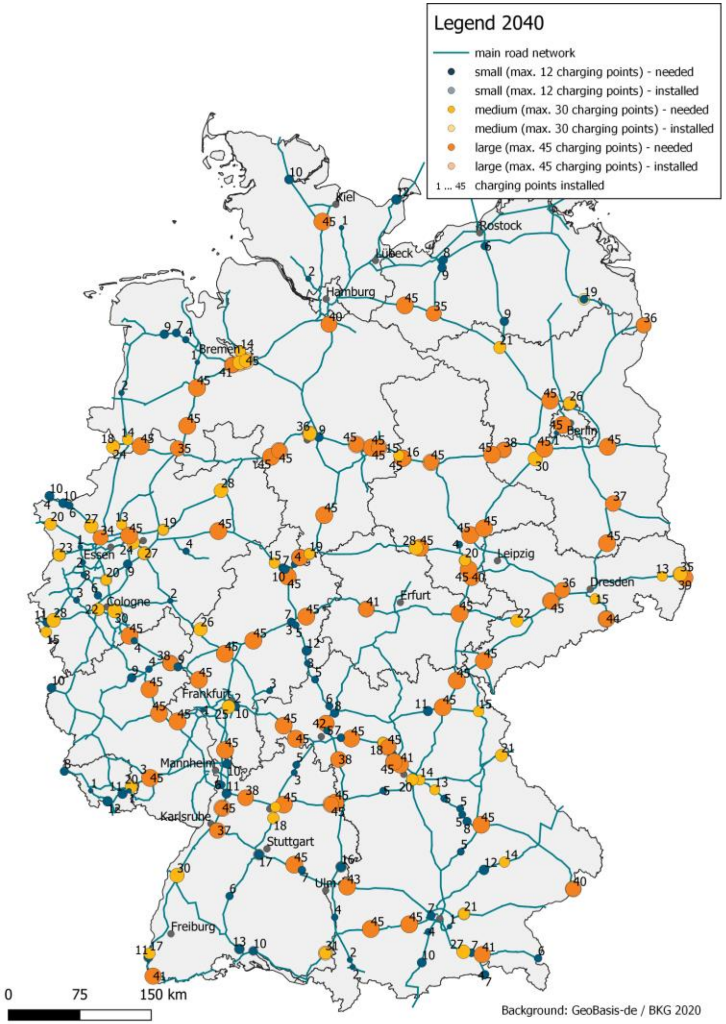

Figure A-11: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2040.

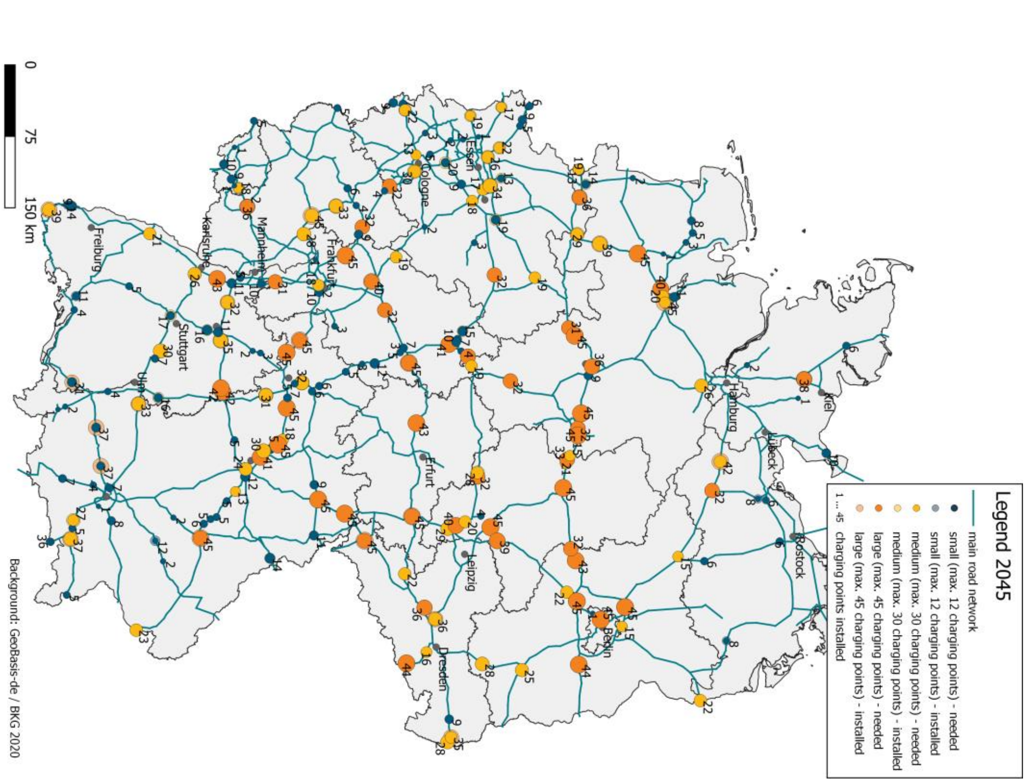

Figure A-12: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2045.

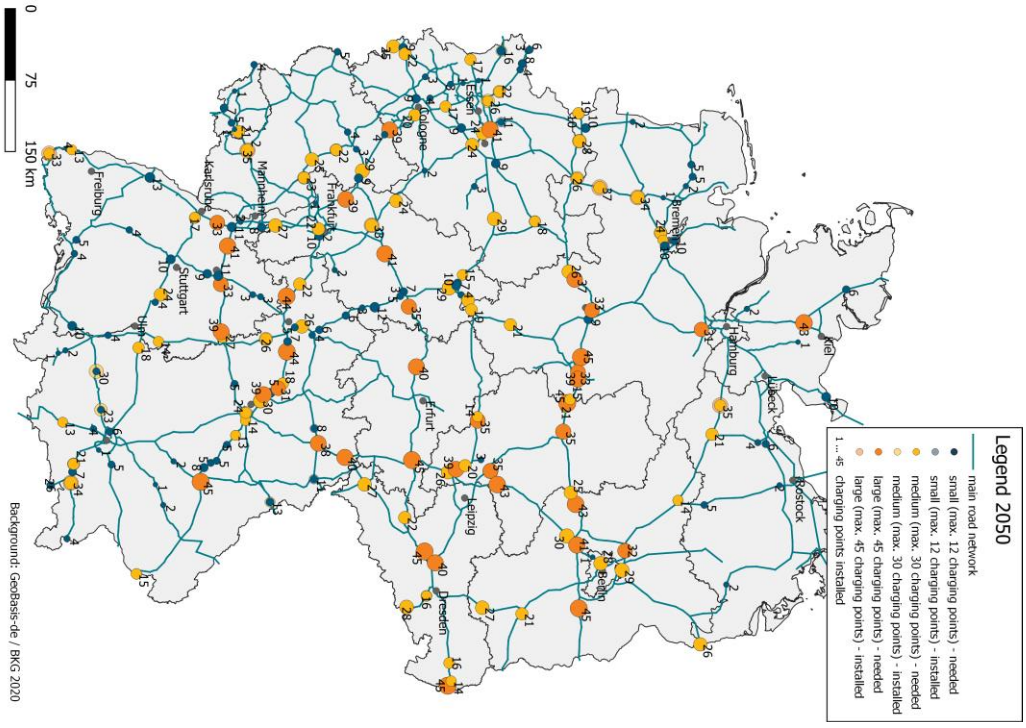

Figure A-13: Public fast charging infrastructure in Germany for the modeled BET diffusion in 2050.

B References

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