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Design of a Public Fast Charging Network for Battery Electric Trucks

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Abstract

The freight transport sector plays a decisive role in meeting national and European emission reduction targets, but it is also one of the most challenging sectors to decarbonize: While electric light commercial vehicles are already ubiquitous in urban applications, electric long-haul transport is especially constrained by the limited availability of fast-charging infrastructure, but also available vehicle range and payload trade-offs. Thus, this dissertation develops a comprehensive planning approach for a public fast-charging network tailored to Battery Electric Trucks (BET) in long-haul operation.

Through the holistic modeling of the interplay between vehicle technologies, charging infrastructure, and operational strategies, the thesis offers a systemic view of the problem. Constraints from the electric grid and regulatory frameworks are incorporated into the methodology to create a comprehensive framework. Germany is selected as a case study due to its central role in the European TEN-T network and its pioneering role in BET technology. Two complementary models are developed and connected: A static optimization model that designs optimized network configurations based on real-world truck mobility data is complemented by a dynamic simulation model that evaluates charging demand, time loss, and necessary station capacities in a time-forward simulation.

The results demonstrate that optimized network design, particularly the alignment of site placement with high-voltage electric grid access, and significantly reduce infrastructure costs, while maintaining a high service quality from the logistics perspective. A total of 1331 MCS charging stations would suffice to serve the long-haul traffic in Germany in a possible 2030 scenario, with up to 1000 charging sessions taking place in parallel. Among future technological advancements, increased charging power emerges as the most promising direction, with higher time loss savings than increased network density or battery capacity. The work not only provides guidance for infrastructure operators but also supports OEMs, fleet operators, policymakers, and electric grid operators in navigating the transition to electric freight transport.

A letter to the future

This thesis is to acknowledge that we know

what is happening and what needs to be done.

Only you know if we did it.

June 2025

430 ppm CO_2

Danksagung

An dieser Stelle möchte ich mir den Raum nehmen, allen zu danken, die mich auf dem Weg zur Dissertation begleitet, unterstützt und ermutigt haben.

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München, im Juli 2025

Georg Balke

Contents

List of Abbreviations

3PL	Third Party Logistics Provider
4PL	Fourth Party Logistics Provider
AADT	Average annual daily traffic
AFIR	Alternative Fuel Infrastructure Regulation
BET	Battery electric truck
BETOS	Battery Electric Truck Operational Strategy
BEV	Battery electric vehicle
CCS	Combined Charging System
CHALET	Charging Locations for Electric Trucks
CMN	Close Meshed Network
CPO	Charging point operator
CT	Catenary truck
ERS	Electric road systems
EU ETS	EU Emissions Trading Scheme
FCET	Fuel cell electric truck
FCLM	Flow-Capturing Location-Allocation Model
FRLM	Flow-Refueling Location Model
HICE	Hydrogen internal combustion engine
HVO100	Hydrotreated Vegetable Oil
ICE	Internal combustion engine
KPI	Key performance indicator
MCS	Megawatt Charging System
MILP	Mixed-Integer Linear Programming
MIQP	Mixed-Integer Quadratic Programming
NREL	National Renewable Energy Laboratory
NUTS	Nomenclature of territorial units for statistics
OEM	Original equipment manufacturer
OSM	OpenStreetMap
RegioStaR	Regionalstatistische Raumtypologie (Regional Statistical Spatial Typology)
SME	Small and medium enterprises
SOC	State of charge

SOH	State of health
TCO	Total costs of ownership
TEN-T	Trans-European Transport Network
VVP	Verkehrsverflechtungsprognose (forecast of transport interconnectivity)
WMN	Wide Meshed Network

1 Introduction

Climate change is an imminent and universal challenge that is caused by human activity and can only be resolved by human intervention [1, 2]. Limiting the climate crisis requires stabilizing the atmospheric CO_2 levels [1]. As one of the primary sources of CO_2 emissions, the transport sector plays a decisive role in meeting national and European reduction targets, but it is also one of the most challenging sectors to decarbonize. Freight transport in particular contributes 40 % of transport-related emissions [3, p. 139]. Consequently, in 2024, the European Union mandated that the emissions of newly registered commercial vehicles must decrease by 45 % by 2030 and by 90 % by 2040 [4], a reduction considered infeasible using conventional diesel technology. As a result, different new technologies have emerged as potential successors of diesel engines as the dominant propulsion technology in road freight transport: The usage of different electric powertrain technologies such as fuel cell electric trucks (FCET), catenary trucks (CT) or electric road systems (ERS) has been researched and tested, as well as retaining the internal combustion engine (ICE) by using synthetic fuels, Hydrotreated Vegetable Oil (HVO100) or hydrogen internal combustion engine (HICE).

Currently, it is becoming increasingly apparent that the most suitable technology to meet this challenge on a broad scale is direct electrification by introducing battery electric trucks (BET), especially in conjunction with the novel Megawatt Charging System (MCS) [5–10][11][*]*. Light electric commercial vehicles, especially in distribution applications, are already ubiquitous: Low daily ranges and low average speeds enable small traction battery sizes and thus good economy. Charging can be carried out overnight in between shifts, using existing AC charging technology.

Diametrically opposed is the long-haul road freight transport: Long daily ranges, high energy demands, and the need for the adaptation of operational patterns make it significantly more challenging to electrify [12]. On top of that, the weight of the large battery packs required competes with the payload of the truck, as the maximum weight of vehicles and their permissible axle loads are constrained [13]. Megawatt charging can resolve this conflict of design objectives, as mid-shift rapid charging enables smaller battery sizes while also reducing investment costs [14][*]. The first BET suitable for long haul transport have been introduced to the market since 2024 [15–17].

However, the availability of these long-haul-capable vehicles alone is not enough. To achieve all-electric long-distance freight transport, the vehicles rely on a widespread fast-charging infrastructure. This charging network requires technological innovation, strategic planning, and significant initial investment. Ideally, vehicles, infrastructure, and operational strategy should be harmonized in order to maximize the synergy potential of the system.

It is in this context that the construction of an initial charging network for BET in Germany was put out for tender in 2024 [18], which is intended to create the basis for the gradual electrification of the long-haul transport sector. However, as the typical first ownership of heavy trucks is around five to ten years [19], it will take decades to fully convert the vehicle stock to BET. The market, therefore, is in a dynamic ramp-up phase in which the coming years and decades will determine the economic viability and practicability of BET in long-haul transport.

[*] Publications marked with an asterisk (*) were authored or co-authored by the author of this thesis.

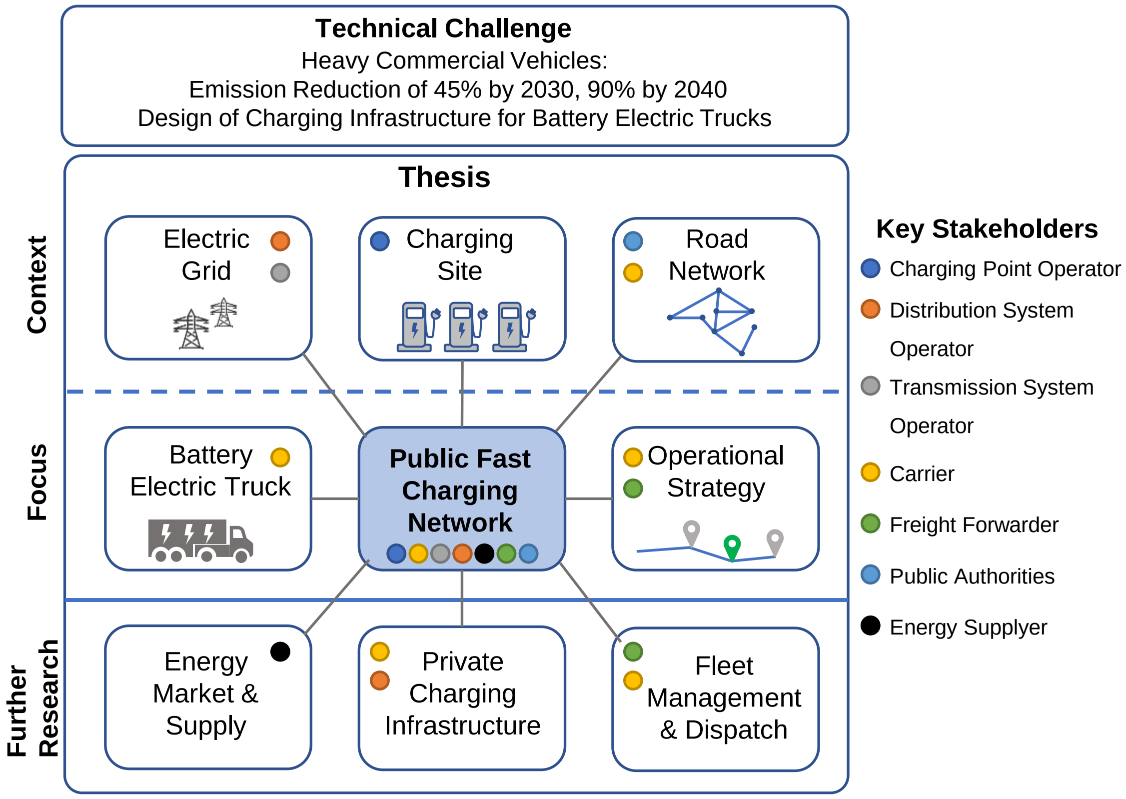

Figure 1.1: Overview of the key system components and stakeholders researched within this thesis, along with contextual areas that are suggested as further research.

The aim of this thesis is to conceive a tool to develop strategies for the design of a public fast-charging network. The functional relations between the charging network and other system components are outlined in Figure 1.1. A key focus is the interconnected system of vehicle, infrastructure, and operational strategy, along with the consideration of the ramp-up phase to determine the target state and milestones of the transformation. Guidelines will be developed for the location of the charging network, including appropriate charging power, for spatial distribution and density, and for vehicle design parameters such as battery capacity and charging power. In addition, compliance with legal requirements and regulations, in particular the EU Alternative Fuel Infrastructure Regulation (AFIR) [20], will be addressed to ensure the feasibility of the strategy. Moreover, the system interface towards the single charging site, the electric grid, and the road network is incorporated into the methodology. The economic and demand-oriented dimensioning of charging sites, the expansion costs of the high-voltage grid, as well as the development of international freight corridors are considered within this thesis. Among the main contributions of this thesis is the holistic modeling approach, connecting stakeholders from distribution grid operators to the carrier operating BET. The focus, however, shall remain on the systemic level instead of the single fleet. The model scope encompasses the study of key system parameters, such as battery capacity, charging power, and charging network topology, in order to quantify their interdependencies. Through the systematic integration of open-source data and benchmarking against state-of-the-art charging network concepts, the approach ensures practical relevance and uncovers optimization potentials within the system.

This thesis will focus on the entire territory of Germany, taking into account European goods flows as well. Therefore, the use of open data is crucial in all development stages. This is the only way to create a consistent methodology that ensures applicability across national borders at a later stage. Due to its comparatively small area and its key position in the Trans-European Transport Network (TEN-T), Germany is suitable as a flagship country for electric heavy goods transport. A solution successfully implemented here can serve as a model for the entire EU and beyond.

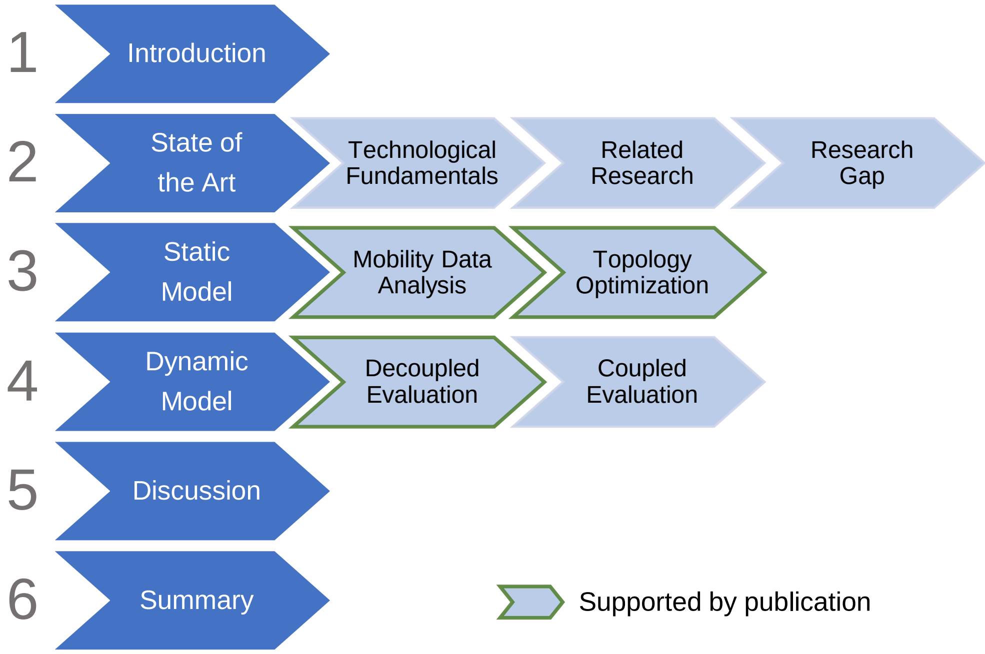

Figure 1.2: Overview of the structure of this thesis.

The structure of this thesis is presented in Figure 1.2: After this introduction, the second chapter (State of the Art) summarizes relevant previous scientific work as well as established methods for the planning of public charging infrastructure that will serve as a basis over the course of this thesis. It also singles out the specific methodological gap that this dissertation aims to fill.

Subsequently, a time-invariant model will be developed in chapter 3 (Static Model) to conceive optimal configurations of charging networks for different optimization targets. These optimized charging networks will subsequently be analyzed within the time-dependent model in chapter 4 (Dynamic Model). It focuses on the complex interplay of vehicles, charging infrastructure, and operational strategy. The aim of this chapter is to research the system performance and scalability, or potential bottlenecks, during the ramp-up phase.

Chapter 5 (Discussion) puts all results from the static and dynamic models into perspective. In this context, uncertainties and strengths related to the model, methodology, and underlying data are examined. Furthermore, an outlook is given on potential further developments and future research priorities that arise from the results and identified uncertainties. Finally, the summary presents the key findings of the dissertation and formulates recommendations for actions that arise from this thesis.

2 State of the Art

This chapter consists of three sections: First, Section 2.1 explains the technological background necessary to understand the dissertation. This is followed by a discussion of the current state of research based on relevant publications and studies (Section 2.2). On this basis, the existing research gap that this dissertation addresses is identified in Section 2.3.

2.1 Technological Fundamentals

BET form a growing market that started out in light distribution vehicles like the Streetscooter [21], where average speeds and daily ranges are low, and batteries can thus be small. But in the past years, medium and heavy electric trucks have increasingly entered the market. With all major European and Asian original equipment manufacturer (OEM) now offering battery electric models, electric heavy trucks are becoming increasingly important [5, p.132].

A brief overview of available models as of 2025 is provided in Figure 2.1. The BET are generally equipped with modular batteries: This means that when configuring the vehicle, more or fewer battery packs may be selected based on the desired use case and the available budget. Typically, around 3 pack configurations

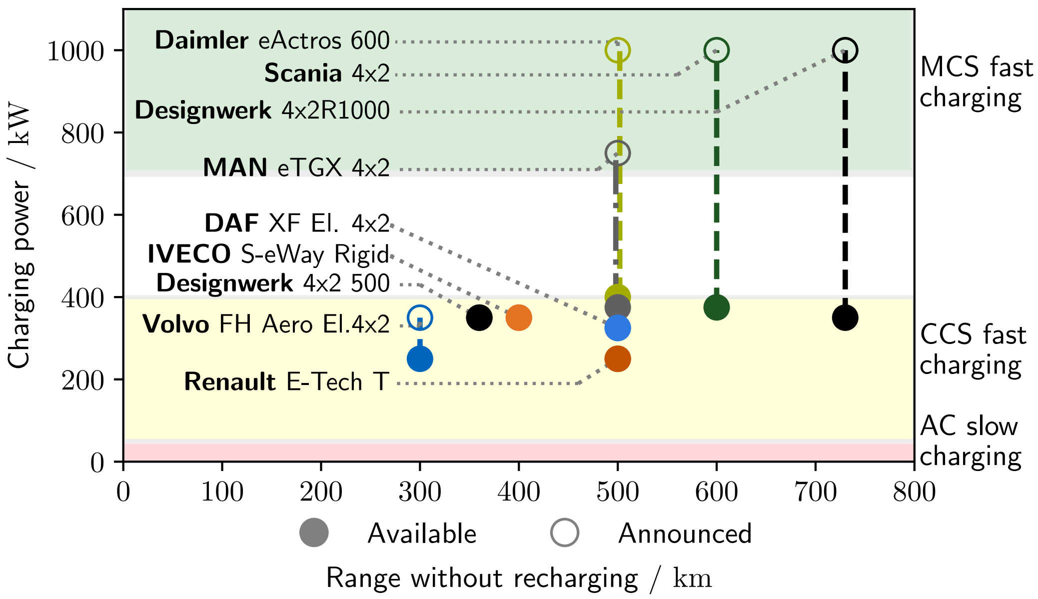

Figure 2.1: Overview of electric ranges and charging powers at fast charging stations for BET models of all major European OEM. Own visualization based on data from [15–17, 22–26]. Each color represents a model, if different trims of the same model exist, the ones most similar to a 4x2 tractor and with maximum battery capacity were selected.

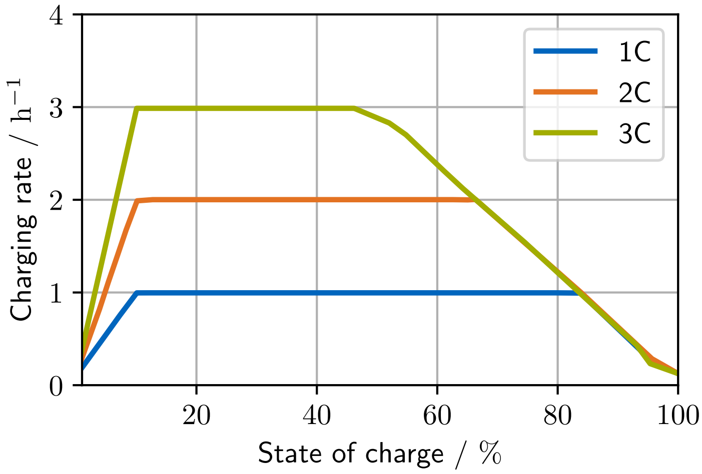

Figure 2.2: Charging rates of Li-Ion cells adapted from [34]*.

are available [15, 17], so the capacity is not freely scalable for a customer. Most OEM can thus offer up to $500\,\mathrm{km}$ of electric range for the vehicle. Net battery capacities of around $600\,\mathrm{kWh}$ are required for such electric range without recharging [16]. The consumption of long-distance BET is thus typically in the range of $1.0\,\mathrm{kWh}$ to $1.2\,\mathrm{kWh}$ per kilometer, but can vary depending on factors such as load, driving speed, and route profile [15, 16].

In terms of charging power, current models can reach from $250\,\mathrm{kW}$ to $400\,\mathrm{kW}$ using the conventional Combined Charging System (CCS) [15–17, 22–26]. But importantly, Daimler Truck, MAN, Designwerk, and Scania have already publicly announced work on the MCS, to increase the charging capability of their vehicles into the range of $750\,\mathrm{kW}$ to $1\,\mathrm{MW}$ [15, 16, 22, 26]. Within the collaborative research project NEFTON [11], megawatt charging using this MCS system could be demonstrated for the first time publicly in 2024.

The most important components of BET are the energy storage and the electric motor(s). Lithium-ion cells with a lithium iron phosphate (e.g., [16]), nickel manganese cobalt (e.g., [15]), or, more rarely, a nickel cobalt aluminum oxide cathode ([24]) are typically used as the energy storage system. To a large extent, the cell properties dictate the system properties of BET: The gravimetric and volumetric energy densities determine the range and payload, while the power density has a great influence on the achievable charging power [27–29][14]*. Cyclic stability and battery system price are key factors for the investment and depreciation, as the battery accounted for around $60\,\%$ of the manufacturing costs of a BET in 2020 [30, p. 11]. While decreasing battery costs of $-57\,\%$ are predicted until 2030 [30, p. 6], the battery will still remain the single most costly component.

Going one step deeper, the Li-Ion cells also influence the so-called *charging curves*, as the charging power is typically not constant during fast charging processes. This behavior serves to protect the battery from accelerated aging and overheating [31]. Factors such as temperature, state of health (SOH), and the selected cell chemistry influence the actual charging behavior [32]. At low state of charge (SOC), the battery can be charged at high current, typically maintaining a plateau of high charging rate before the charging current is reduced during the so-called *derating*, see e.g., Figure 2.2. For these reasons, battery electric vehicle (BEV) as well as BET can minimize the charging time by exploiting the high charging power at low SOC specifically. The choice of a suitable charging strategy proves to be complex: Shorter driving legs with a low SOC upon arrival to minimize the charging time, yet require detours, maneuvering, and handling time [33]*.

As high charging power and high battery capacity are concept-defining parameters, prospective innovations in the BET market aim to increase both. But beyond that, current research projects explore higher voltage levels of the battery pack of over $1\,\mathrm{kV}$ [35], reducing the need for high charging currents and associated costs. The opposite approach is also examined, with charging currents of up to $3000\,\mathrm{A}$ being evaluated by MAN [36]. The synergy potential of autonomous and electric trucks is the main focus of the collaborative research project *eAthlete* [37]*. It explores whether the decoupling of charging and driver breaks enables more cost- and $\mathrm{CO_2}$-efficient long-haul logistics.

The **charging infrastructure** is equally important for the successful market introduction of BET as the vehicles themselves. There are different types of charging infrastructure that are also visualized in Figure 2.1: At lower charging power levels, the energy conversion can be handled by onboard power electronics inside the truck, so providing **AC** power is sufficient. This type of charging typically ranges up to $44\,\mathrm{kW}$ and will only play a role at depots. For higher power demands, the power electronics and their cooling become more expensive and complex, which is why **DC** charging infrastructure was introduced. Here, the power electronics are stationary, and direct current is provided to the vehicle. While the CCS standard, originally developed for passenger cars, supports charging with up to $400\,\mathrm{kW}$ at $800\,\mathrm{V}$, the new MCS standard with redesigned plugs and communication protocol enables charging with up to $2400\,\mathrm{kW}$ at $800\,\mathrm{V}$ [11]*.

Suitable MCS charging stations are required for BET, especially in long-haul applications. ABB, Alpitronic, and Kempower are among the pioneer suppliers in this field: ABB has launched a $1.2\,\mathrm{MW}$ MCS charging station, while Alpitronic has already installed a public $1\,\mathrm{MW}$ charging station, with a modular and scalable architecture to meet the requirements of fast and overnight charging alike [38]. Kempower also already deploys its MCS technology with a charging capacity of up to $1\,\mathrm{MW}$ [39].

To summarize, vehicle and infrastructure technology suitable for heavy, long-haul use cases are entering the market, and the feasibility of electric road freight transport in general is not in question anymore. The ramp-up of public charging infrastructure, along with the steadily improving investment costs and operating costs are the critical enablers for BET. Along with government subsidy strategies, these factors together will determine how fast the market shares of BET will grow.

2.1.1 Electric Grid Integration

To understand the technical difficulties of the grid connection, different technical solutions have to be considered: The "Forum Netztechnik/Netzbetrieb im VDE" (FNN) has issued a guideline on the connection of charging infrastructure to the electric grid and identifies three main ways [40] **:

> If a medium voltage connection already exists, the first charging points can be served by an additional customer substation integrated into a medium-voltage ring. A higher-capacity connection could be established through a direct connection to the distribution substation. At the third stage, to meet the demand predicted for 2030 and beyond, a connection to the high voltage level ($110\,\mathrm{kV}$) may be necessary. In this case, the supplying distribution substation may need to be upgraded with additional transformers, or even a new distribution substation may be required.

Paraphrasing, for early phase of the market introduction of BET, a medium-voltage connection is sufficient [40]. This finding is widely supported, e.g., by Kippelt et al. [41] and Burges et al. [42]. With increasing numbers of electric trucks and parallel charging processes towards 2030, a connection to the high voltage grid, be it through a pre-existing or new distribution substation, becomes necessary [40]. Kippelt et al. [41] estimate that this stage is reached as early as 2030 on highly frequented routes, and 2035 on lower frequency routes, while Burges et al. [42] see it as a 2040-scenario. In real-world scenarios, it is possible that

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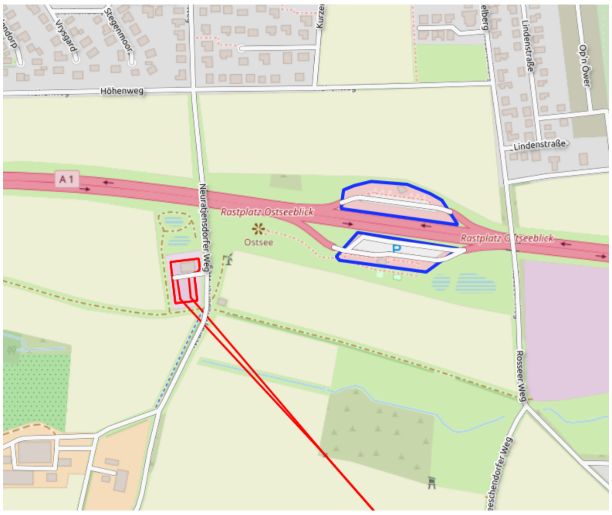


Figure 2.3: Exemplary candidate location: The unserviced rest area "Ostseeblick" (blue) in Schleswig-Holstein is located along the motorway A1. Currently, it provides 20 truck parking spots and 4 $300\,\mathrm{kW}$ fast charging stations for electric cars on its southern part. In approx. $330\,\mathrm{m}$ distance, an electrical substation (red) of "Schleswig-Holstein Netz AG" connected to the $110\,\mathrm{kV}$ grid is located. Data, base map: [48]

the capacity of the medium-voltage grid is already being occupied by other consumers, and high-voltage connections become necessary even for small charging sites [41].

High-voltage grid connections are a challenge for two main reasons: Firstly, the grid is more sparse [43]. As a consequence, longer stub lines drive costs. Secondly, the planning and project phases are significantly longer [44, 45]. Technological solutions to avoid this include load management and stationary battery storage, to cap peak loads [44, 45]. Yet, both could lead to unexpected time losses due to longer charging processes. Alternatively, the distribution of charging points into a more spread-out network instead of hubs could locally relieve bottlenecks [41]. Solar power plants with a direct connection to the charging site are a potential local power source, but fluctuate in their daily yield and seasonally, and are thus not a reliable substitute on their own [46].

Summarizing the literature, the connection of large charging hubs to the high-voltage grid is inevitable, while the connection type for medium-to-small charging hubs can depend on local conditions.

The German federal energy agency (*dena*) estimated costs for all voltage levels of the distribution grid in 2012 [47, p. 146f]. According to *dena* [47, p. 146f], the costs of transmission lines are dependent on the voltage level, with high-voltage infrastructure being more expensive yet more capable, and the technical implementation, with overhead line construction being cheaper than cables per kilometer. It should be noted that only the upgrade of existing overhead lines is considered feasible, as the construction of new overhead lines will likely lack regulatory approval [47, p. 147]. For new transmission routes, cables have to be implemented instead, further driving the per-kilometer costs up [47, p. 147][41].

Applied to public charging infrastructure for BET this means that for each charging site, a decision on the grid connection type has to be made. Figure 2.3 visualizes an exemplary candidate location along the motorway A1 in northern Germany. A distribution substation transforming between the high-voltage and medium-voltage grids is located in the immediate vicinity of the rest area, yet an electrical connection would cross private and public land. So, beyond the material and installation costs for a grid connection, construction costs, as well as engineering, easement, and compensation costs have to be considered when expanding the electrical grid [49]. The Austrian energy corporations' association estimates the costs of grid expansion [49] at approximately $650\,000 € /\mathrm{km}$, while *dena* [47, p. 146], puts the cost of cables even higher at around $800\,000 € /\mathrm{km}$ still excluding necessary upgrades at the substation. Proximity to the high-voltage grid thus constitutes a significant attractiveness factor for charging sites from an energy perspective. More material has to be used, the more complex project requires more project management and engineering, and additionally more landowners have to be compensated for their ground.

As shown in Figure 2.3, publicly available map data can provide solid information not only on the road network, but also on the energy grid. Xiong et al. [50] demonstrate that a complete model of the European high-voltage electric grid (HV grid) can be created based on OpenStreetMap (OSM). OSM is the most comprehensive open-source digital map available and is mainly based on community-sourced data. While Xiong et al. [50] focus mainly on the $380\,\mathrm{kV}$ transmission grid, most relevant grid levels for public MCS charging infrastructure are as previously explained the $110\,\mathrm{kV}$ level and the medium voltage levels below.

Projects like OpenInfraMap [51] and flosm [52] provide an integrated view of energy infrastructure, including information on overhead lines, substations, and voltage levels. Using these projects as reference, Table 2.1 can be extracted, which provides a search pattern to extract the complete high-voltage grid from the OSM database.

Table 2.1: Relevant OSM objects for high-voltage power systems

OSM Object	**OSM Key**	**Value**	**Explanation**
way	power	*	transmission lines, including overhead lines and cables
node/way/relation	power	substation	indicates a substation structure
any	voltage	%110000%	voltage level includes $110\,\mathrm{kV}$, for transforming substations input and output levels are commonly listed
any	operator	!= 'DB Energie'	Deutsche Bahn maintains an own $110\,\mathrm{kV}$ network, excluded for technical compatibility ($16.7\,\mathrm{Hz}$, two-phase) [53]

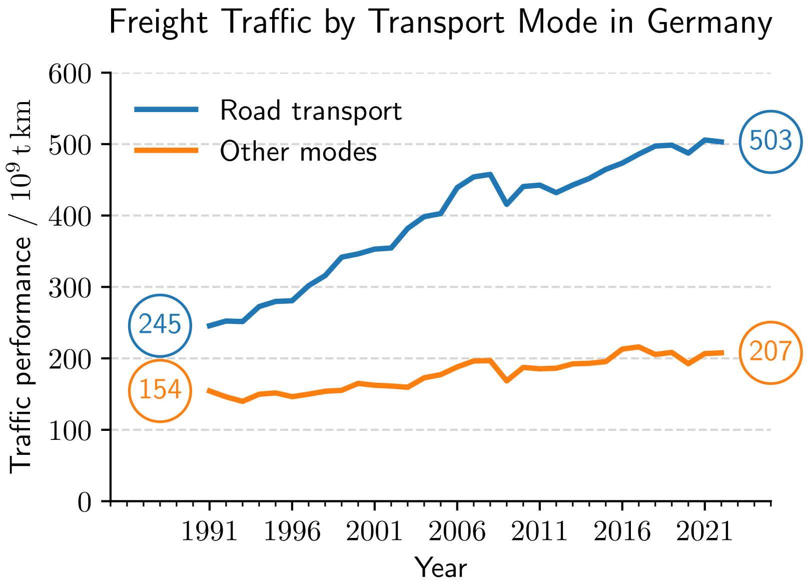


Figure 2.4: Increasing freight traffic performance in recent years can be observed, especially for trucks, which hold a dominant role compared to other means of transport. Own visualization based on data from [56]

2.1.2 Economic Role of the Battery Electric Truck

A total of 689 billion ton-kilometers of goods are transported annually in Germany [54], with the transport volume steadily increasing in recent years. It is expected that the traffic performance will increase by an additional 31.2 % by 2040 [54]. A brief look at the modal split for freight transport in Germany clearly shows that road freight transport plays a dominant role compared to rail, air, and waterways: Figure 2.4 demonstrates that road freight transport is the main driver of increasing traffic performance, doubling since 1990. Other modes of transport increased their combined traffic performance by a mere 34 %, as they could not keep up with the flexibility, speed, and reliability that trucks provide [55]. This highlights the lever BET constitute towards achieving the national climate action goals.

Road freight transport is not only essential for the domestic economy, but Germany also serves as a keystone for logistics within Europe. The TEN-T is the multimodal strategy of the European Union to harmonize transport routes for freight and passenger transport. The network, as displayed in Figure 2.5, is structured into nine corridors, six of which run through Germany [57, 58]. It consists of three layers: the core network, the extended core network, and the comprehensive network. Within the German road network, only *core* and *comprehensive* exist and shall be considered further [57].

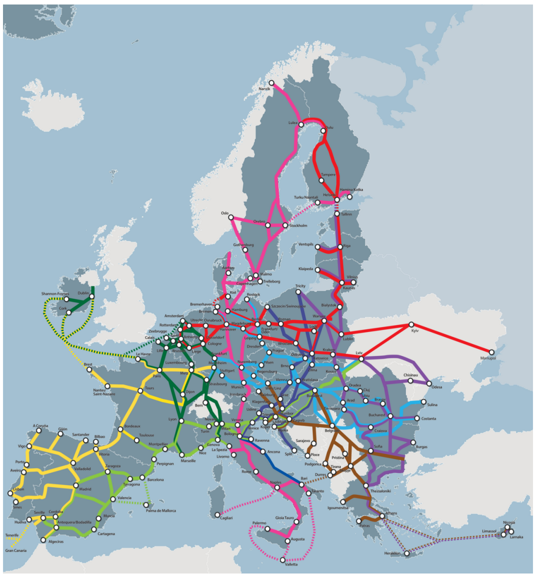


Figure 2.5: TEN-T road network within the European Union and third countries. Image source: European Commission [60]. The core/comprehensive classification of routes for Germany is depicted in Figure 2.6

The EU AFIR [20] complements this TEN-T strategy since it came into force on April 13th 2024 [59]. It regulates the technical and organizational framework conditions for public alternative fuel infrastructure and sets mandatory infrastructure development targets across the EU [20]. Among requirements for e.g., hydrogen refueling stations, it aims to provide a continuous and interoperable charging infrastructure for electric freight transport along the TEN-T corridors [20]. Most notably, it sets constraints for the network density: According to the AFIR, gaps between fast charging stations along the TEN-T *core* network may not exceed $60\,\mathrm{km}$, and $100\,\mathrm{km}$ along the *extended* network [20]. In Germany, $6358\,\mathrm{km}$ of motorway is subject to the AFIR core strategy, while the extended network comprises an additional $4271\,\mathrm{km}$ [58]. The infrastructure coverage targets for the *core* network are to be achieved by 2030 [20].

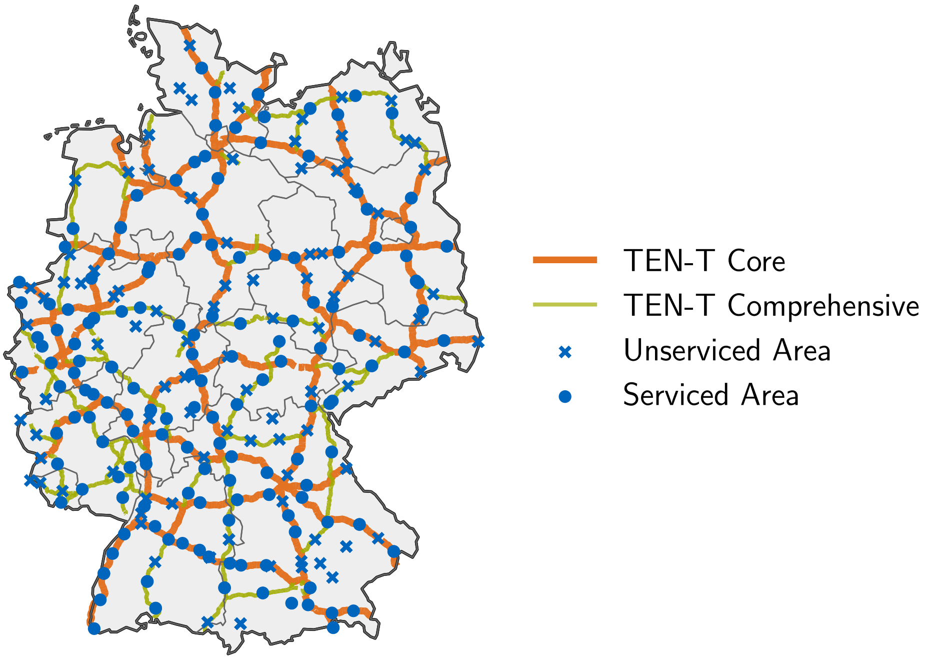


Figure 2.6: Initial charging network (*Initialladenetz*) at serviced and unserviced areas put out for tender since 2024. [61].

Perhaps the most important move in Germany towards fulfilling these targets is the construction of the so-called initial charging network (*Initialladenetz*), that has been put out for tender in summer 2024 [18]. Initially, 125 unserviced rest areas and later all service stations will be considered [61]. At a later stage, serviced areas will be equipped as well, bringing the total to 350 sites [18]. In total, 1800 MCS charging points and 2400 CCS charging points are planned – The power at MCS shall be guaranteed to be at least $800\,\mathrm{kW}$ even in peak demand times [18]. Figure 2.6 visualizes the planned configuration, including the core/comprehensive classification of motorways in Germany.

On top of these public investments, private companies have announced investments in charging infrastructure, too. First and foremost, Milence, the joint venture of European truck OEM plans 25 charging hubs in Germany in 2025 already, while E.ON and MAN jointly plan 125 charging hubs in Germany (80 in 2025) [18].

Estimating the market adoption of BET therefore requires modeling the complex interplay between charging infrastructure deployment, energy cost development, declining production costs, policy changes, and many more. In 2025, Raoofi et al. [62] modeled precisely this system-dynamics model to explore how Sweden's freight transport might shift from diesel to BET during the time until 2060. In the model, the complex interplay between charging infrastructure expansion, technological advancements, cost structures and public investments is reflected, to generate insights into the market adoption of BET. Notably, only diesel trucks and BET are modeled, and market shares are an output of the model instead of a policy instrument [62]. The key findings include that investments in public charging infrastructure yield the greatest effect on the electrification degree, while investments in vehicle technology are the most cost-efficient measure. In the base scenario, they expect that due to shifts in the cost structure of BET and ICE trucks, BET reaches cost parity in 2027 and overtake ICE trucks in their market share in 2039.

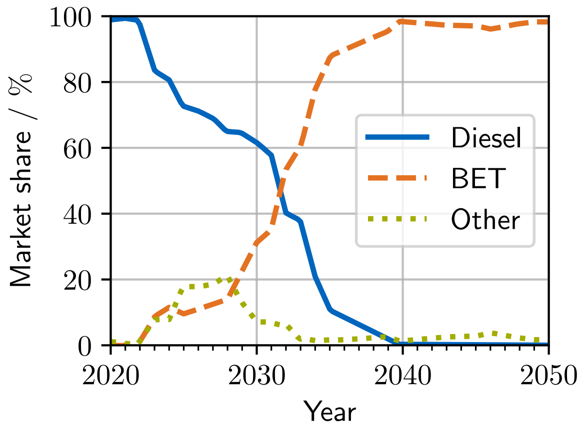


Figure 2.7: Development of market potential of different propulsion technologies for trucks in the DLR VECTOR21 mode. Depicted are new vehicle registrations in the "Business-as-usual" scenario. Own visualization based on [63].

The DLR has presented an equivalent market model and estimated the market ramp-up of BET in 2023 [63]. As illustrated in Figure 2.7, a significant growth in new registrations of BET is anticipated from 2022, 2028 and 2031 on. This indicates, that for a certain use cases even relatively early technology stages of BET provide utility benefits. The highest changes in market share are expected between 2030 and 2035, after which the BET is expected to be the dominant propulsion technology for new trucks, which means that the balance tilts for most applications when technology and cost levels reach maturity. The year of market share equilibrium in new registrations is expected to be 2032 already, and a BET share in the fleet stock of $12\,\%$ in 2030 is expected in the "Business-as-usual" scenario.

Current sales figures indicate that the market ramp-up of BET is delayed by a few years compared to the estimations from VECTOR21 [63, 64]. In Q1/2025, heavy electric trucks made up $1.4\,\%$ of the sales across the EU and $2.1\,\%$ in Germany, which would place the delay at 3 years.

2.2 Related Research

Charging infrastructure for electric vehicles in general [65–68], and for trucks in particular [68–77] has increasingly become the subject of research interest in recent years, as can be seen in Figure 2.8. Interestingly, it seems that the research interest in the electrification of commercial vehicles has been growing faster than the general field of research of "charging infrastructure". Within the research area of charging infrastructure for BET, two main directions can be identified: charging at the depot and public charging [68]. Depot charging (also called off-shift, private, return-to-base, or destination charging) generally has low to medium charging powers, is often carried out overnight, and is mostly based on conventional CCS charging infrastructure in Europe.

The focus of this thesis lies on public charging (also called mid-shift, en-route, during operation, or fast charging), which happens mostly in public areas, and ranges from high power CCS charging ($350\,\mathrm{kW}$ - $400\,\mathrm{kW}$) to actual MCS charging stations ($750\,\mathrm{kW}$ and above). When planning public fast charging infrastructure, the most important field of research is the fundamental trade-off between minimizing investment costs and maximizing utility in terms of coverage and performance [73, 78], a challenge that is further complicated by the need for integration into the existing power grid [73, 79]. Another critical issue concerns station dimensioning, occupancy rates, and waiting times, which are driven by limited on-site capacity [70, 73, 74]. For commercial vehicles in particular, such waiting times can lead to direct economic disadvantages [71][33]*.

Charging Infrastructure Design

The key considerations and design choices to make when planning charging infrastructure include infrastructure costs (both capital and operational), economic integration into the power grid, and the maximization of traffic coverage by the charging network [65, p. 15f]. These costs also account for monetized waiting times

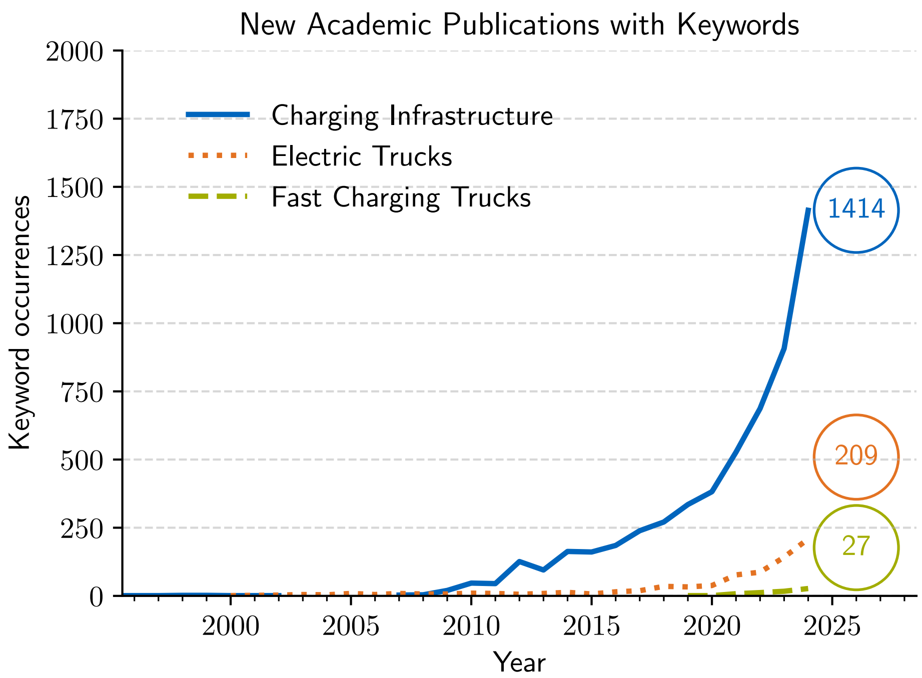


Figure 2.8: Number of scientific articles with related keywords. Own visualization based on data from SCOPUS, obtained according to Narayanan and Antoniou [80]. The query plan is documented in the Section A.1.

due to limited on-site capacity [65, p. 17]. Al-Hanahi et al. [68] highlight the specific challenges associated with charging infrastructure for commercial vehicles, such as medium- and heavy-duty trucks. They point out that the logistics processes of these vehicles, e.g., shift times and delivery windows, can significantly constrain feasible charging operations [68], and that, depending on the processes, a return-to-base approach or an on-route charging strategy carries more benefits [68]. Less frequently considered factors include the spatial coverage that can be achieved through a charging network, as well as its alignment with the present traffic flows and routes – factors that are particularly relevant for long-haul and commercial use [65, p. 18]. For example, Metais et al. [66] review strategic charging infrastructure deployment and identify two main optimization goals: The maximal coverage at given costs or minimal costs at given service level. They discuss the importance of strategic charging station planning, recommending research including the sequential temporal deployment of stations [66].

The design of charging networks not only for private companies, but at the national and European levels is currently a subject of particular research interest [69–72, 74, 75, 79, 81, 82] and is summarized next.

The simulation of potential public charging infrastructures for trucks in Germany has been previously researched [70, 72–76] [83, 84]* from different perspectives: Varying charging infrastructure configurations in combination with non-interacting trucks are, e.g., analyzed in Balke et al. [83]* or Speth et al. [70]. Yet none of the studies so far provide a comprehensive approach to optimize and evaluate the network topology, especially with respect to the coverage targets of the AFIR along the TEN-T corridors.

As the market diffusion of BET is expected to stretch until 2040 [63][76, p. 130], some studies research a strategy for the sequential build-up of the charging infrastructure. This is considered in different degrees in [70, 75, 76] [84]*. Specifically, optimal ramp-up strategies providing maximum coverage at each point during the expansion, or meeting intermediate coverage targets, have only been addressed in recent publications in 2024 [75, 76] [84]*.

The dimensioning of charging sites, especially in terms of charging stations installed, is mostly examined using a time-series simulation of trucks and queues at charging stations to reflect the queuing interaction between trucks [70, 72, 73]. Mathematical optimization methods exist for this purpose and have been applied in the literature to BEV [85, 86] and even to BET [74, 75, 87].

The author of this thesis has previously contributed to the state of the art, too. Through a simulation, it can be shown that the placement of infrastructure and its capabilities have not only a significant impact on resulting time losses compared to ICE trucks, but are closely coupled with the vehicle design and operational strategy and should be considered in conjunction [33, 83]*. Charging stations designed for BET should therefore be strategically planned, sufficiently covering and aligned with the vehicles' capabilities [84]*.

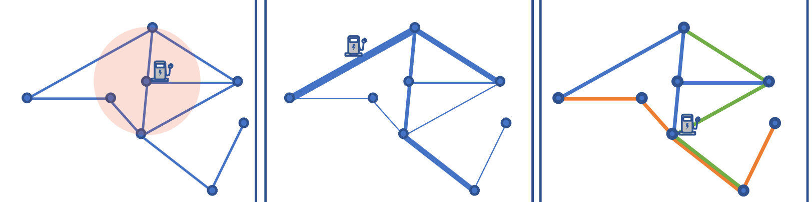
To conclude this brief summary of the existing literature, Table 2.2 provides a comprehensive overview. Where applicable and relevant, literature on BEV and FCET is considered as well. In the following sections, each specific aspect of the existing research shall be examined in detail.

Table 2.2: Overview of related publications. Legend: —: not stated or not applicable, n node-based approach, p path-based approach, t tour-based approach. Harvey balls indicate the modeling depth: empty (○) indicate "Not modeled," full (●) represents the highest modeling depth in the related publications. Intermediate levels (◔, ◑, ◕) represent a qualitative scale in between.

Source	Method	Study Region	Vehicle Type	Optimization of Topology	Optimization of Dimensioning	Varying Vehicle Parameters	Varying Charging Power	Simulated Utilization	Energy System Integration
Balke et al. [83]* 2024	p	Germany	BET	◔	○	●	●	○	○
Balke et al. [84]* 2024	n	Germany	BET	●	○	◑	○	○	○
Borlaug et al. [88] 2021	t	abstract	BET	○	◔	◔	◕	◑	●
Borlaug et al. [69] 2022	t	USA	BET	○	◔	●	◑	○	○
Dimatulac et al. [89] 2023	t	Ontario	BET	●	◑	○	◔	◕	◕
Hecht et al. [67] 2021	p	Germany	BEV	◔	◔	●	◑	○	○
Hurtado-B. et al. [79] 2021	n	USA	BET	●	○	◕	○	○	●
Jochem et al. [86] 2015	p	South Germany	BEV	●	◑	◑	○	○	○
Jochem et al. [85] 2019	p	Europe	BEV	●	◑	◑	○	○	○
Karlsson et al. [90] 2023	p	Sweden, E4	BET	◔	◔	○	◔	●	●
Lange et al. [75] 2024	p, CHALET [91]	Europe	BET	●	◕	●	◕	◕	○
Menter et al. [73] 2023	p, MATSim	Germany	BET	○	●	○	◑	●	○
Mishra et al. [92] 2022	t	California	BET	●	◕	◑	◕	◕	○
Nykvist et al. [93] 2021	—	abstract	BET	○	○	●	◔	○	—
Rose et al. [87] 2020	p	Germany	FCET	●	◕	●	○ —	◕	○
Shoman et al. [72] 2023	p	Europe	BET	○	◑	○	◑	◑	○
Speth et al. [70] 2022	p	Germany	BET	◔	●	○	◔	●	○
Speth et al. [71] 2022	p	Europe	BET	◔	●	○	◔	●	○
Speth et al. [94] 2024	t	Germany	BET	○	○	●	◑	○	◕
Speth [76] 2024	p	Germany	BET	◕	◕	◑	◔	●	◔
Speth et al. [74] 2025	p	Germany	BET	●	◕	○	◔	●	◑
Zähringer et al. [33]* 2022	—	abstract	BET	◔	○	◕	●	○	○
Deb et al. [65] 2018	review - charging infrastructure placement		BEV	●	●	◔	◔	◔	◔
Alhanahi et al. [68] 2021	review - charging infrastructure for HDV		BET, ERS	◕	◔	◔	◔	◑	◕
Metais et al. [66] 2022	review - charging infrastructure planning		BEV	●	◑	○	◑	○	◑
This thesis	n, p	Germany	BET	●	◕	◕	●	◑	◕

Methods

Review papers classify the approaches for charging infrastructure placement into three classes: **node-based**, **path-based**, and **tour-based** methods [66, 68]. A comparative overview is provided in Figure 2.9. Node-based methods mostly assume that charging infrastructure at a network node captures the demand from its surrounding area [66]. The data requirements in this case are often comparatively low [66]. Among the related publications, only Hurtado-Beltran et al. [79] and Balke et al. [84]* have applied node-based approaches to long-haul commercial vehicles. Path-based methods examine traffic flows passing potential charging sites and optimize the capture of these flows. With this approach, site dimensioning is often the center of research. The most widely applied path-based methods are the Flow-Capturing Location-Allocation Model (FCLM) and Flow-Refueling Location Model (FRLM) [66], as applied e.g. in [74, 75, 85–87]. Beyond that, there exist capacitated derivatives of these methods [74, 76, 87]. The exact approaches will be explained later. For path-based methods, OD matrices or at least traffic flow measurements are required [66]. Tour-based methods require the highest amount of data. Here, specific vehicles are traced, mostly via GPS, and a suitable charging network is conceived, e.g., based on dwelling locations of those fleets [66]. Specifically, the tour-based demand of conventional trucks is fed into an agent-based simulation to study the electrification. Such tour-based methods are, e.g., applied in [69, 88, 89, 92, 94]. The advantage of tour-based approaches is, that they provide the best estimation for charging demand and explicitly respect single vehicle's charging need [66]. On the other hand, the limited availability of movement data limits the possible generalization; the applicability to public charging networks where multiple fleets converge is thus limited.



	Node-Based	Path-Based	Tour-Based
Paradigm	A station covers a certain area	A station covers the flow passing by it.	A station covers a place with charging opportunities.
Data Requirements	++	+ e.g. OD Matrices	-- e.g. GPS recordings
Suitability Extra-Urban	-	++	+
Representation of charging needs	- / +	+	++

Figure 2.9: Comparison of charging infrastructure placement approaches. Adapted from [66, Tab.5 , Fig. 3-5], own visualization.

Study Region

Related publications have examined simulation areas of varying sizes and levels of detail. Generally, these reach from abstract models with no particular geographic extent [88, 93, 94] [33]* over small, controlled study areas like a single or a couple of motorways [86, 90] up to large regions and nations [67, 69, 70, 73, 76, 87, 89, 92] [83, 84]*, or even the whole of Europe [71, 72, 75, 85].

Abstract modeling offers the opportunity to highlight the influence of possible design decisions in all components of the system. An example would be the interplay between battery capacities and total costs of ownership (TCO) [93] [14, 33]*. Zähringer et al. [33]* model a long-haul truck trip of $700\,\mathrm{km}$ in a synthetic scenario, varying charging power, the spacing of charging points, battery capacity, and driving strategy. From this, they identify parameter combinations that can reduce time losses due to charging in long-distance transport. Using a comparable level of modeling depth, Nykvist et al. [93] analyze the impact of cell parameters, such as cost, cycle life, and gravimetric energy density, on key vehicle-level key performance indicator (KPI) including payload and TCO, with particular focus on charging powers of up to $1\,\mathrm{MW}$. Schneider et al. [14]* extend this approach by examining the influence of charging powers up to $3.75\,\mathrm{MW}$ on vehicle-level parameters and battery cell characteristics.

A mid-point on this spectrum is represented by studies that process tour-based data. This data is, in most cases, not complete, as it stems from, e.g., a single data source or a single company. Borlaug et al. [88], Dimatulac et al. [89], Mishra et al. [92], and Speth et al. [94] fall into this group. They rely on real-world operational data from conventional commercial vehicles in the United States [88], Ontario [89], California [92], or Germany [94]. A common research target here is the impact of charging on the local electric grid [88, 89, 94].

The largest study area encompasses one or more entire nations: These studies often focus on the dimensioning of charging sites, especially with respect to queuing and time loss [70, 71, 73, 75, 87, 92] as well as integration into the national electric grid [79, 85].

Topology Optimization

A crucial step in the planning process is commonly the selection of locations for charging infrastructure, referred to as topology from now on.

In a first step, suitable candidate locations are determined. These are commonly motorway rest areas or service areas [73, 74, 76, 79, 90][84]*. But also common dwelling locations derived from GPS have been considered [75, 89, 94]. In a few macroscopic cases, no explicit candidate sites are modeled [69, 72], or a simple subset of network nodes may serve as a candidate location [70, 85, 87, 92]

Subsequently in many cases, simple algorithmic placement strategies are used [70–73, 90, 93][33]*, but some publications specifically aim at optimizing the network topology [75, 79, 85–87, 89, 92][83, 84]*.

In the case of publications implementing topology optimization, the optimization targets include e.g., maximizing spatial coverage [79, 89][84]*, maximizing the capturing of freight flows [74, 75, 85–87, 89, 92][83, 84]* or minimizing time loss [83]*. Common constraints include limited budgets of charging stations or capacitated sites [74, 75, 87][84]*, limited vehicle range, and the reliability of service [73]. In the future, the AFIR regulation of the EU mandates that from 2030 onwards, a maximum gap of $60\,\mathrm{km}$ between charging sites along the TEN-T core network and $100\,\mathrm{km}$ along the TEN-T comprehensive network is permissible. As an intermediate goal, $50\,\%$ coverage has to be provided from 2028 on. These legal deployment targets have only been implemented in Balke et al. [84]*.

As an optimization algorithm, the so-called FRLM is commonly used [85–87]. It was developed by Kuby and Lim [78] based on Hodgson's FCLM [95]. The fundamental idea behind the approach is that traffic flows generate a demand for fuel along the route [95]. When planning the refueling stations, this demand for fuel "crystallizes" at the constructed refueling stations, a concept referred to as *flow capturing* [95]. These refueling stations compete to meet the demand, and cannibalization effects may occur.

Kuby and Lim [78] found that the restriction to network nodes may not be suitable for vehicles with alternative drivetrains like BEV. Due to their limited range, it is possible that between two nodes, long edges have to be traveled [78]. To address this limitation, Hodgson's FCLM method was further developed into the FRLM, respecting limited vehicle range and allowing fueling stations to also be set up along network edges. Both methods, FRLM and FCLM, require the OD matrix within the network to be known. OD matrices for the freight transport in Europe are publicly available [96–98], albeit not on a vehicle-class level but only aggregated to tonnes of freight. The FRLM allows for determining either the optimal set of refueling stations for maximum coverage of traffic flows or the minimal set required to reach a certain service level [87].

For the problem of BEV, the FRLM method is applied, e.g., by Jochem et al. [85, 86]. Rose et al. [87] further extend the method to include capacity restrictions for individual H_2 refueling sites and apply it to FCET. The application to BET has been implemented by [74, 76] (unrestricted in Europe, capacitated in Germany).

In contrast to that, Lange et al. [75] utilize the open-source framework Charging Locations for Electric Trucks (CHALET) [91] for topology optimization [75]. This framework is based on an integer programming approach [91]. To limit computational requirements, a randomized subset of OD relationships for long-haul trucks in Europe is drawn from open-source data [96] [75]. The network topology is then calculated to maximize traffic flow coverage [75]. Several constraints are applied during the optimization [75]:

- Detours to charging stations may only amount to $5\,\%$ of the driving time.
- Charging sites have limited capacities and may only serve $100\,000$ vehicles per year at maximum.
- Legal break times can be spent at charging stations, and time loss due to charging is not allowed.
- Edge lengths in the network do not exceed vehicle ranges.

Accordingly, in a scenario of $500\,\mathrm{km}$ electric range and $1000\,\mathrm{kW}$ peak charging power, $97.8\,\%$ of flows in Europe can be covered by 1200 charging sites, notably without time loss compared to a conventional truck. The coverage rate increases with the number of placed charging locations at first, but reaches a saturation at 1200 about charging stations [75, p. 6]. This translates to one charging site per $90.8\,\mathrm{km}$ of TEN-T motorway in Europe, slightly sparser than the $78.7\,\mathrm{km}$ estimated in Balke et al. [84]* for Germany. It should be noted that in Europe, $1.31\,\mathrm{km}$ of TEN-T core motorway exist for every km within the comprehensive network [75]. In Germany, though, $1.47\,\mathrm{km}$ are designated *core* in comparison, which means that Germany requires denser-than-average network coverage.

Mishra et al. [92] aim to maximize the coverage of traffic flows for BET through an optimized network topology. They employ a tour-based approach relying on recorded GPS data. The optimized topology selects charging sites among intersections within the road network. Their mathematical formulation of this is shown in Equation 2.1.

The objective function in Equation 2.1 describes the sum of all vehicle kilometers that could have been driven electrically by the vehicles recorded. The constraints of the optimization ensure that only a specific budget of F_{max} charging stations is selected and that the electric range of the BET is not exceeded [92]. Following the topology optimization, the charging strategy of the vehicles is calculated in a second step [92]. A stochastic approach models the increasing probability of a vehicle requiring a charging stop as the distance traveled increases [92].

In contrast to the Mixed-Integer Linear Programming (MILP) implemented by Mishra et al. [92], Balke et al. [84]* use Mixed-Integer Quadratic Programming (MIQP) to perform a topology optimization. The mathematical formulation can be found in Equation 2.2. The goal is to create a topologically balanced charging network to minimize time losses due to charging. Spatial coverage, on the other hand, is treated as a constraint, not an optimization goal. The coverage constraint is divided into two coverage classes to fulfill the AFIR regulation requirements: The core network of the TEN-T requires charging infrastructure every $60\,\mathrm{km}$, while

Maximize: electrified driving

$$J = \sum_{i \in \mathcal{V}} \delta_i D_i \tag{2.1}$$

Subject to: electric range constraint

$$\sum_{w \in S_{ij}} s_w + \sum_{k \in F_{ij}} f_k - \delta_i > 0 \quad \forall_{i \in \mathcal{V}} \forall_{j \in \mathcal{B}_i}$$

Station Limit

$$\sum_{k \in \mathcal{F}} f_k = F_{\max}$$

Minimize: proximity between sites

$$\min_{\underline{\mathbf{x}}} \underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}} \underline{\mathbf{x}} \tag{2.2}$$

Subject to: coverage, budget constraints

$$\begin{pmatrix} \underline{\underline{\mathbf{A}}}_{\text{core}} \\ \underline{\underline{\mathbf{A}}}_{\text{comp}} \\ -\underline{\mathbf{c}}^T \end{pmatrix} \underline{\mathbf{x}} \geq \begin{pmatrix} \underline{\mathbf{b}}_{\text{core}} \\ \underline{\mathbf{b}}_{\text{comp}} \\ -N_c \end{pmatrix}$$

$$\underline{\mathbf{x}} \in \mathbb{N}^c, x_i \leq 1$$

Figure 2.10: Comparison of optimization problem formulations from Mishra et al. [92] Equation 2.1 and Balke et al. [84]* Equation 2.2. Both optimizations are performed using the Gurobi toolbox [99].

the comprehensive network only requires a charging station every $100\,\mathrm{km}$. The formulation of the budget for charging locations between both optimizations is comparable between both publications [92][84]*. Balke et al. [84]* use a greedy algorithm in a second step to calculate the ramp-up of the charging network, instead of an incremental run of the full optimization problem [92].

The results show strikingly similar behavior in the systems: Both Figure 4 in [92] and Figure 4 in [84]* show the traffic flow coverage in different electrification scenarios. The coverage rises steeply with the first few charging locations installed and saturates early at about a third of the maximum number of charging stations simulated. This means that a sparse charging network can already bring a significant electrification potential, or in other words, that in the early phases of the ramp-up, strong network effects exist, which lead to high marginal benefits of each charging station early on. This hypothesis is further corroborated by Li et al. [100, Fig. 3], also demonstrating this degressive behavior albeit on a smaller scale of locations.

Some publications also investigate strategies for building up a charging network, beyond merely analyzing the target state of the network [75, 79, 92, 100][84]*. Many publications examine varying expansion stages, which, however, cannot be transformed into the next stage [70, 86, 92]. Metais et al. [66] criticize comparable approaches, as they *"do not consider any temporality in deployment: for a given budget, the infrastructure is optimized as if all the stations were placed simultaneously"*. Balke et al. [84]* aim to overcome this limitation by determining optimal build-up steps starting from the initial state [84]*. Other recent publications use optimizations that calculate optimal intermediate states starting from the target state [75, 79] backwards.

To summarize, various levels of modeling depth have been applied to the charging network topology: Depending on the research objective, approaches range from simple placement algorithms to complex optimization algorithms. In more recent publications, the sequential ramp-up of charging infrastructure shifts into focus, too.

Charging Site Dimensioning

Besides topology, the second central design decision of the charging network is the dimensioning of the sites. The key design parameters here are the number of charging points and the grid connection power of the site. The significance is obvious: From a truck's perspective, when either all charging points are occupied or the electric load management restricts the charging power, unexpected delays ensue. Thus, different levels of modeling depth have been proposed.

In the publications [67, 72, 93, 94] [33, 83, 84]*, these charging sites are not explicitly limited in size. Hurtado et al. [79] impose constraints for integration into the power grid by including the maximum permissible distance of a charging site from the high-voltage grid as a constraint in the optimization. However, the number of installed charging points is not determined. Lange et al. [75] constrain the maximum yearly traffic flow served by a charging site, yet do not explicitly model the number or peak power of parallel charging sessions.

The dimensioning of stations is determined by Jochem et al. [85, 86] and Rose et al. [87] based on the "captured flows" of the FRLM. However, the system is not validated in an agent-based simulation. Similarly, Speth et al. [74] propose a capacity-constrained FRLM optimization of charging sites.

Using agent-based simulations, the utilization of charging parks over the course of a day can be determined in high temporal resolution. This type of modeling is employed by several publications [70, 71, 73, 90, 92]. For example, Karlsson and Grauers [90] simulate BET traffic along the E4 motorway in Sweden. The number of charging points is initially manually parameterized, and then the resulting utilization is observed in scenarios, including an increased number of charging points or dynamic pricing strategies. Mishra et al. [92] use agent-based simulations to model the load profile of the determined charging stations but do not impose capacity restrictions.

Speth et al. [70, 71] calculate the required size of charging sites using queuing theory. Based on traffic flows, a vehicle arrival rate at the charging park is calculated, from which the queuing behavior can be determined. The goal is to achieve an average waiting time of no more than $5\,\mathrm{min}$.

Menter et al. [73] choose an approach specifically tailored for the site dimensioning problem: For the initialization, the utilization of stations is simulated in an agent-based MATSim simulation with infinite station capacity. The maximum number of parallel charging sessions yields the initial demand. In every subsequent iteration, the capacity for each station is decreased until the service level drops under a given threshold. Unlike the results of a FRLM optimization, which can only determine aggregated demand over a time period, this approach can also capture the simultaneous usage of assets and emerging queuing behavior.

Operational Strategy

To allocate the trucks' demand for electric energy spatially and temporally to a specific charging station, a model of the operational strategy of the vehicles is required. This means to model the decisions made by a driver regarding where, how long, and how often to charge and take breaks along their routes. In the EU, after each $4.5\,\mathrm{h}$ of driving, a $45\,\mathrm{min}$ break must be completed. It is allowed to split the break into a $15\,\mathrm{min}$ break followed by a $30\,\mathrm{min}$ one, but not the other way around. When respecting certain time budgets, $9\,\mathrm{h}$ or $10\,\mathrm{h}$ of driving time per day is allowed.

The most common modeling approach is the translation of this legal requirement into an operational strategy. It is assumed that the full break of $45\,\mathrm{min}$ is taken statically after $4.5\,\mathrm{h}$ of driving. Examples of this paradigm in the literature can be found in [70–72, 101], as well as [33]* (as the reference case *NGS*). Schneider et al. [14]* explore the possibility of breaking up this rigid constraint and splitting the $45\,\mathrm{min}$ break into three $15\,\mathrm{min}$ breaks or two $22.5\,\mathrm{min}$ breaks. The result is that the truck battery can be designed smaller, but the more frequent recharging leads to higher cyclic stress on the battery cell.

A more complex modeling approach is selected by Mishra et al. [92]: The probability of taking a charging break increases quadratically with the distance traveled until the vehicle's range is surpassed. Thus, each agent follows a stochastic behavior, with a tendency towards charging late. This approach is likely to reflect actual behavior better, as low SOC at the beginning of the fast charging process leads to quicker charging rates and less overall time loss [33]*.

Karlsson and Grauers [90] implement a simple rule-based algorithm for agents, but also foresee dynamic plan adjustments in case the queues at the target station become too long. This reflects an information system in which a driver is aware of the current queuing at the upcoming charging sites and can decide to drive past long queues.

The optimization of operational strategies is the overall focus of research by Zähringer et al. [33, 34, 102]*. Operational strategies are developed using *Dynamic Programming* to achieve a global optimum for time losses due to charging and waiting. To this end, all legal degrees of freedom within the system are explored, including the break time splitting (15/30 min) and exploiting the non-linear charging behavior by charging to a lower target SOC. Balke et al. [83]* integrate these algorithms into a nationwide simulation for Germany. Notably, among the remaining related research, only Hecht et al. [67] also optimizes travel time by selecting an optimal charging strategy through a dedicated algorithm.

Variable Vehicles and Charging Power

The interplay between the charging power and battery capacity of the BET and the charging network is analyzed in a few publications, namely Mishra et al. [92], Hurtado-Beltran et al. [79], Hecht et al. [67], Jochem et al. [86], and, most notably for this thesis, Lange et al. [75]. These studies have analyzed the impact of vehicle range and charging power on network density, coverage, and associated time loss.

Mishra et al. [92] demonstrate that higher vehicle ranges significantly increase the percentage of electrifiable trips. In their study, only BET with a $600\,\mathrm{mi}$ electric range can reach $100\,\%$ traffic flow coverage. At only $90\,\%$ coverage, a $300\,\mathrm{mi}$ range requires a significantly denser charging network with approx. three times as many charging sites. This highlights the trade-off between vehicle range and the density of charging infrastructure. Hurtado et al. [79] conduct a node-based study to estimate spatial coverage. They find that reducing the coverage radius of a single charging site from $100\,\mathrm{km}$ to $25\,\mathrm{km}$ results in an almost $40\,\%$ decrease in coverage, emphasizing the importance of vehicle range, especially in sparse networks. Hecht et al. [67] analyze 4 real-world models of private BEV models, modeled with their respective nonlinear charging curves. Their findings indicate that increasing vehicle range significantly reduces time losses, while higher initial SOC also reduces delays. Jochem et al. [86] conduct an FRLM optimization; thus, the electric vehicle range is a crucial input parameter. They confirm that higher ranges allow for sparser networks, particularly for sub-complete coverage levels (e.g., 80% of flows).

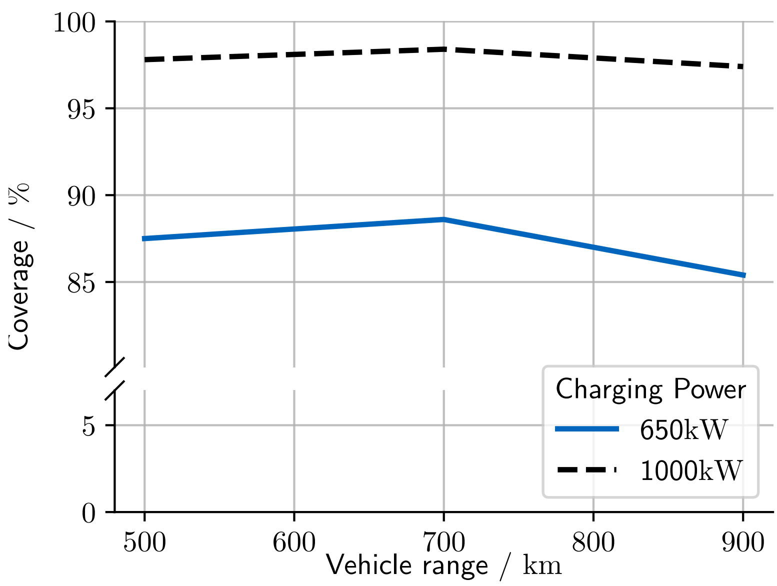


Figure 2.11: Traffic flow coverage as a function of BET battery capacity and charging power. Own visualization based on results from Lange et al. [75]. Note: The slightly declining coverage for higher battery capacities can likely be traced back to the SOC requirements at the destination. [75]

Lange et al. [75] provide one of the most comprehensive analyses for BET, varying both battery capacity and charging power. Their results, visualized in Figure 2.11, show that increasing charging power has a more pronounced effect on traffic flow coverage and the number of required charging sites than increasing battery capacity. For example, a 53 % increase in charging power leads to better coverage than an 80 % increase in electric range. On top of that, the number of charging sites can be reduced by 37 % in the high-power scenario, compared to only 21 % in the high-range scenario. These findings underline that vehicle technology and optimal charging infrastructure are closely coupled.

2.3 Identification of the Research Gap

To summarize, different approaches have been presented to design fast-charging networks on a national scale. The main KPI are traffic flow coverage [75, 85–87] maximized spatial coverage [72, 79], speed of en-route charging [67, 69][14, 33]* and minimal charging queues [70, 71, 73], while costs are also commonly considered in terms of installed infrastructure and electric grid integration.

There are several levers at the system level to design the ecosystem of electric trucks in long-distance transport:

- Suitable models of electric trucks are the central enablers for electric freight transport. In particular, the concept-defining parameters of battery capacity and charging power can be tuned by OEM [27, 28, 69, 75, 93, 94, 103][14]*.
- The public charging network, consisting of charging sites with multiple charging points and an electric grid connection, as well as an overarching network topology, is the second core component. A suitable network *topology* has to strike a balance between spatial coverage, coverage of traffic flows, a limited investment sum, as well as its integration into the public power grid. Furthermore, the *dimensioning* of the charging sites needs to be demand-oriented. This is usually done as part of a mathematical optimization [74, 75, 85–87], or through the investigation of queuing theory or agent-based simulations [70, 71, 73].
- The link between BET and charging infrastructure is established by the operational strategy: Through appropriate planning of charging processes and mandatory breaks, these can be optimally aligned. Additionally, nonlinearities of the system, such as nonlinear charging curves, can be exploited. Overall, the operational strategy and available technology also define the balance between private and public charging [94][33]*.

The current state of the art for determining suitable locations for charging infrastructure (topology optimization) includes approaches ranging from simple placement algorithms to complex optimization methods based on the coverage of OD-pairs. Frequently, flow-capturing methods based on the works of Kuby and Lim (FRLM) [78] are used, while some studies go beyond a simple location optimization to include additional aspects such as successive expansion strategies or local capacity constraints.

Previous publications have mostly focused only on partial aspects of the system. The main modeling levels, the electric grid, the charging network, the single charging site, and the vehicle level are connected by several publications as demonstrated in Figure 2.12. But up until now, no publication connects all levels with a holistic modeling approach. To demonstrate the interdependencies from the electric grid to the vehicle level and to incorporate them into the design of a public charging network remains a significant research gap. The aim of this dissertation is to fill this gap, creating a comprehensive picture of the system and the interplay between its components. A higher modeling depth than in the state-of-the-art makes it possible to also represent nonlinear effects, and to consider the integration into the power grid as well. In brief, this dissertation aims to address several gaps in the current state of the art:

Model Scope

- Guidelines for system design are derived by explicitly modeling and varying key parameters such as battery capacity, charging power, and charging infrastructure topology and density, capturing their interdependencies.
- A systematic comparison of state-of-the-art literature and industry charging networks is conducted with the newly developed holistic modeling approach that integrates vehicle, infrastructure, and grid levels.

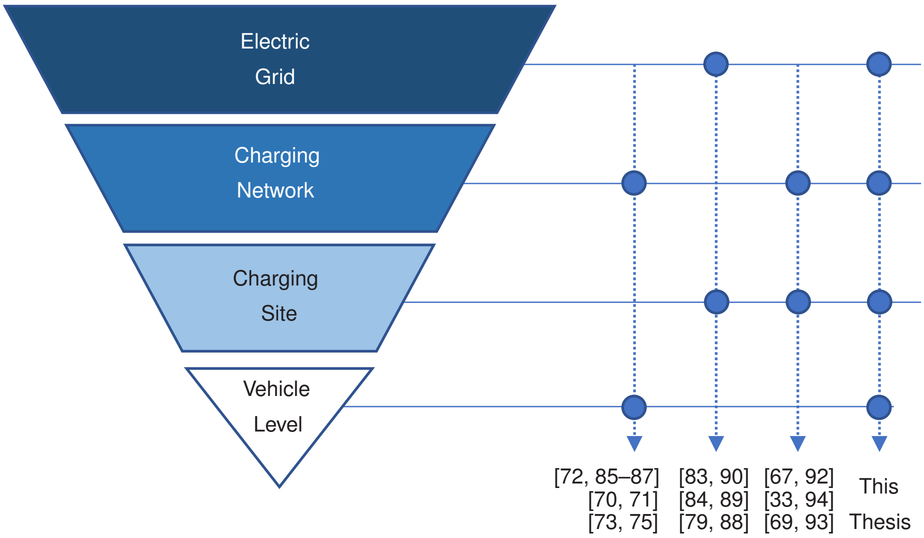


Figure 2.12: Overview of the related research's model scopes and the aim of this thesis.

- The consideration of infrastructure development strategies provides insights into the necessary investments over time.
- The systematic use of open-source data ensures the transferability of the methodology in the future.

Modeling Depth

- Optimization scenarios not only targeting minimization of time loss during charging and maximization of traffic flow coverage, but also addressing the integration with the electric grid, are formulated.
- Infrastructure development strategies aligned with EU AFIR mandates, including network density constraints, are incorporated.
- The data analysis of real-world mobility data of conventional trucks makes it possible to narrow down the specific use cases for public fast charging.
- Integrating an optimal operational strategy into a nationwide simulation reduces uncertainties about the behavioral modeling.
- The usage of suitable real-world locations and their position in relation to the energy infrastructure ensures the feasibility of the proposed solutions.
- The temporal calibration of the traffic model based on traffic count data improves the modeling of charging concurrency and temporal energy demand from fast charging BET.

3 Static Model

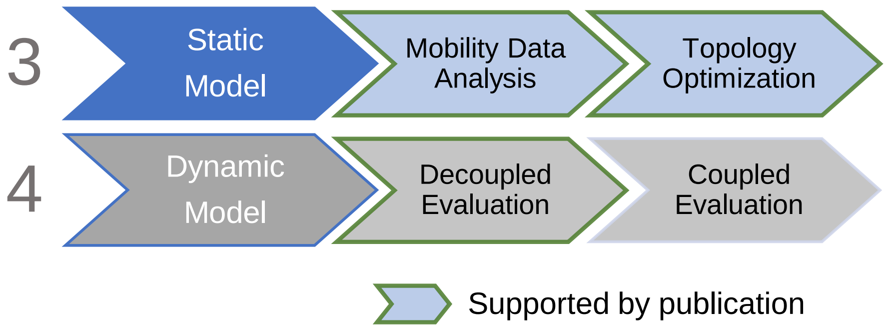


Figure 3.1: Overview of the core methodology and results - consisting of Chapter 3 and Chapter 4.

The target system of this thesis is a public fast charging network for BET. Its core part is structured into the static and dynamic model: The static model encompasses all modeling steps that are invariant in time with respect to the final system, while the dynamic model describes all modeling steps towards a time-forward simulation.

This chapter presents the static model, which designs a charging network top-down while ensuring the fulfillment of all constraints set by technology, users, and public authorities. The static model is presented in two steps, visualized in Figure 3.1. The evaluation of these charging networks is part of the dynamic model presented in Chapter 4.

First, in Section 3.1, the precise use cases for public fast charging infrastructure are identified among the manifold applications for heavy commercial vehicles. The section amends the previous publication, Balke and Adenaw [104][*]. For this purpose, recorded GPS tracks of conventional trucks are evaluated with respect to potential strategies for charging.

In the second step (Section 3.2), an optimal topology for a fast charging network is developed. Here, optimization goals, constraints, and an algorithm are defined, and the two optimization targets of optimal mobility and optimal energy system integration are compared and balanced. This section builds upon the work presented in Balke et al. [84][*].

The following Chapter 4 contains the evaluation of the created charging networks, and a quantitative comparison with the state of the art. For this purpose, a comprehensive evaluation of accessibility and time loss from a mobility perspective is carried out. Foundations of this simulation are published in Balke et al. [83][*]. While [83][*] was published before [84][*], in the context of this thesis, the complete methodology is reapplied and amended through the newly developed Section 4.2. In all sections that amend previous publications, a brief summary of the publication is provided, followed by the original publication and subsequently, the updates and amendments to the original method and results.

3.1 Data Analysis and Use Cases

The previous publication [104]* presents the DT-CARGO dataset [105]*, one of the most comprehensive open-access collections of high-resolution mobility data for heavy commercial vehicles. Over seven months, 54 heavy-duty trucks ($\geq 12\,\mathrm{t}$) from four German fleet operators were equipped with GPS data loggers, capturing $10\,\mathrm{Hz}$ speed and positional data. In total, $1\,260\,000\,\mathrm{km}$ of driving data was gathered. The data collection was performed on fleets based in Germany, yet recorded trips extended into neighboring countries (the Czech Republic, the Netherlands, Belgium, etc.).

The trucks were equipped with OBD-II data loggers previously developed at TUM. Each logger recorded the vehicle location and speed and grouped it into tracks automatically. From these measurements, three primary aggregated datasets were derived and published:

1. The fleet is described in `fleet.csv`, providing technical information for each vehicle, such as gross weight, along with its association with one of the four fleets.
2. The tracking data is summarized in `tracks.csv`. Each trip is listed with start/stop times, distance, average and maximum speeds, and an indication of the type of destination (e.g., service area, industrial zone, or home base). Furthermore, a DBSCAN cluster ID pseudonymously identifies frequently visited locations.
3. `track_id.csv` contains the $10\,\mathrm{Hz}$ speed profiles for every track, enabling detailed analyses of driving dynamics (accelerations, stop-and-go behavior, etc.).

To protect privacy, raw GPS coordinates were removed from the published dataset. Instead, the dataset includes computed attributes (distance, durations) and semantic labels regarding the dwelling locations derived from OSM data. Each stop location is classified into four categories to provide context for the trips:

- Rest areas are unserviced locations with dedicated parking spots.
- Service areas additionally offer amenities like shops, showers, or even refueling facilities.
- Industrial areas are derived from OSM land use data (`land_use = industrial`) and are common locations for pickup and delivery of cargo.
- Finally, the home base is defined manually per fleet. It reflects the premises of the fleet operator, or if not applicable, the dedicated private ground where the trucks are primarily placed when unused.

To summarize the most important findings: Most trips are relatively short ($<100\,\mathrm{km}$), although all fleets operate some long-haul transport in varying degrees. Recorded rest times take place on two magnitudes: short intervals ($<2\,\mathrm{h}$) for loading/unloading or en-route stops and longer overnight stops ranging from $8\,\mathrm{h}$-$18\,\mathrm{h}$. At rest and service areas, notably, breaks often take precisely $45\,\mathrm{min}$, $9\,\mathrm{h}$ or $11\,\mathrm{h}$, reflecting mandated rest breaks and overnight stays. Potential data gaps (e.g., lost GPS signals) are mostly below $10\,\%$ and can be assessed by comparing the line-of-flight gap between recorded tracks with the total recorded distance. The data was further validated by comparison with telemetry data recorded in parallel [106].

Finally, a systematic analysis of all trucks' occupations is presented. The occupation is classified as either dwelling at one of the four labeled location types, dwelling at unknown locations, or "driving". Vehicles spent the largest share of their time at the home base, followed by industrial areas. The peak share of $30\,\%$ of the vehicles are simultaneously driving around 9 a.m., whereas the peak share at service and rest areas is reached shortly after midnight. On a fleet level, fleets that visit rest and service areas can be clearly distinguished from fleets that visit them practically never.

Since the publication, comparable data has also been made available for North America: FleetDNA by the National Renewable Energy Laboratory (NREL) [107] provides data on a slightly more aggregate level than [104][*]. However, the dataset size for heavy-duty vehicles is approximately 10 times larger, with 70 vehicles and 1150 recording days.

Within this thesis, the resulting data acquisition methodology is reapplied to two new fleets, and the collective data is evaluated with respect to the electrification. Especially, the precise use cases for public fast charging are discussed on the basis of the recorded mobility patterns.

3.1.1 Contributions

I initiated and conceptualized the paper, carried out data acquisition and curation, and conducted the data analysis. I led the writing and revision process, while Lennart Adenaw contributed to the data analysis methodology and software, as well as to the writing of the paper and revisions.

3.1.2 Heavy commercial vehicles' mobility: Dataset of trucks' anonymized recorded driving and operation (DT-CARGO)

Georg Balke and Lennart Adenaw

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Publication Notes

The article titled *Heavy commercial vehicles' mobility: Dataset of trucks' anonymized recorded driving and operation (DT-CARGO)* is presented in the following. The article is published in the Journal Data in Brief [104]*. The used code base, along with the anonymized dataset, is published to enable the scientific community to enable future research [105]*.

Data in Brief 48 (2023) 109246

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Data in Brief

journal homepage: www.elsevier.com/locate/dib

Data Article

Heavy commercial vehicles' mobility: Dataset of trucks' anonymized recorded driving and operation (DT-CARGO)

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Road freight transport
Truck
GNSS
Mobility data
Fleet data
Logistics

A B S T R A C T

During a period of 7 months, 54 class N3 trucks from 4 fleets of German fleet operators were equipped with high resolution GPS data loggers. A total of 1.26 million km of driving data has been recorded and constitutes one of the most comprehensive open datasets to date for high-resolution data of heavy commercial vehicles. This dataset provides metadata of recorded tracks as well as high-resolution time series data of the vehicle speed. Its applications include simulation of electrification for heavy commercial vehicles, modeling logistics processes or driving cycle construction.

Specifications Table

Subject	Automotive Engineering
Specific subject area	GNSS Recordings, Truck Electrification, Transport Management
Type of data	Mobility Data Table

(*continued on next page*)

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How the data were acquired	The data were collected using GPS data loggers developed at the Technical University of Munich. The loggers were installed in 54 heavy-duty trucks to record movement data. In order to anonymize the dataset to make it publicly available, GPS coordinates were removed and replaced by track-wise computed information (e.g. track distance) and semantic geographical classification of locations (e.g. service areas) using secondary data from Open Street Maps and proprietary information available from the fleet operators.
Data format	Raw data Analyzed Processed
Description of data collection	54 data loggers were installed in heavy-duty trucks operated by 4 companies between fall 2021 and spring 2022 to continuously measure position and speed with a frequency of 10 Hz. The data were retrieved from the loggers and fed into a PostgreSQL database. Using this database, the recorded GPS traces were pre-processed to create the anonymized and augmented csv-exports published herein.
Data source location	Institution: Technical University of Munich, TUM School of Engineering and Design, Chair of Automotive Technology City/Town/Region: D-85748 Garching Country: Germany Longitude (collected data) between 3.7768° E and 14.9671° E Latitude (collected data) between 45.5992° N and 54.4140° N
Data accessibility	Repository name: Zenodo Data identification number: 10.5281/zenodo.7599687 Direct URL to data: 10.5281/zenodo.7599687 Instructions for accessing these data: The repository contains a set of compressed csv files. A concise description of their contents and the code used for visualization is provided under https://github.com/TUMFTM/dt-cargo.

Value of the Data

- To the best of the authors' knowledge, this is one of the most comprehensive datasets of heavy-duty truck mobility publicly available. It offers a sample of heavy commercial vehicle's movements in the form of a trip logbook comprising both data on trip distance, duration and speed as well as semantic information on trip destinations. Additionally, high-resolution speed profiles and vehicle type information are provided.
- Transportation and automotive engineers, researchers, and public authorities may find the dataset useful especially in the context of electrification for benchmarking heavy-duty truck operation cycles, as it includes detailed information on speed profiles, mileages, operation times, and locations.
- While the sample size may be limited in comparison to the hundreds of thousands of trucks on European roads, the dataset provides valuable and very detailed vehicle-based insights into prototypical operation cycles of heavy-duty trucks that may be used to develop electric vehicle concepts tailored to real usage patterns and for general transportation planning.

1. Objective

An important step in the electrification of commercial vehicles is the understanding of usage pattern and requirements. This dataset was created to provide a detailed view of commercial vehicle utilization and can be employed to develop optimized electric commercial vehicle concepts. The speed-profiles can provide an input for longitudinal dynamics simulations, while spatial context information can be evaluated for possible charging infrastructure.

2. Data Description

This article refers to three published datasets. A characterization of the recorded vehicle fleets (*fleet.csv*), the recorded vehicle tracks (*tracks.csv*), and speed profiles for each track (*{track_id}.csv*). The data is provided online [1]. In order to provide a clearer picture of the contents, short tracks (<=1000 m) are excluded from the following assessments. They make up 82,024 of the 101,826 recordings and mostly contain local shunting and parking operations. Table 1 contains the recorded distances and durations per vehicle fleet.

Table 1
Global information on the recorded fleets, tracks shorter than 1000 m are excluded.

Fleet	Vehicles	Recorded distance / 1000 km	Recorded time / h
1	18	368.43	7494.21
2	5	137.88	3149.70
3	12	170.99	5118.66
4	18	583.61	9227.61

In total, 1260,908,125 km were recorded from four different fleets during the experiment. Fleet four accounts for the largest distance share (46 %). The total recording time of 24,990 h is distributed more evenly, with fleet four providing the largest share at 37 %. The median vehicle recorded 26,780 km.

2.1. {track_id}.csv

For each recorded track, the time series of speed and measurement precision is provided in an individual file named after its corresponding track ({track_id}.csv), placed in the folder named after the corresponding vehicle id. Table 2 shows the structure of these files.

Table 2
Data structure of the {track_id}.csv.

Column	Data Type	Unit	Description
Epoch	float	s	Unix timestamp of measurement in time zone “Europe/Berlin”
Speed	float	m/s	Speed at measurement in m/s
Hdop	float	m	Horizontal degree of precision during recording [2]

The data is provided with a frequency of 10 Hz. Fig. 1 illustrates an example recording of 753 s with an average speed of 48.9 km/h. The track consists of 3 micro trips, separated by a 4 s-stop at 88 s and a 20 s-stop at 250 s. The acceleration ramp at the beginning of the third micro trip is displayed in detail (Fig. 1), indicating the resolution of the data. During the 20 s of acceleration, four clear saddle points, resulting from gear changes, can be observed.

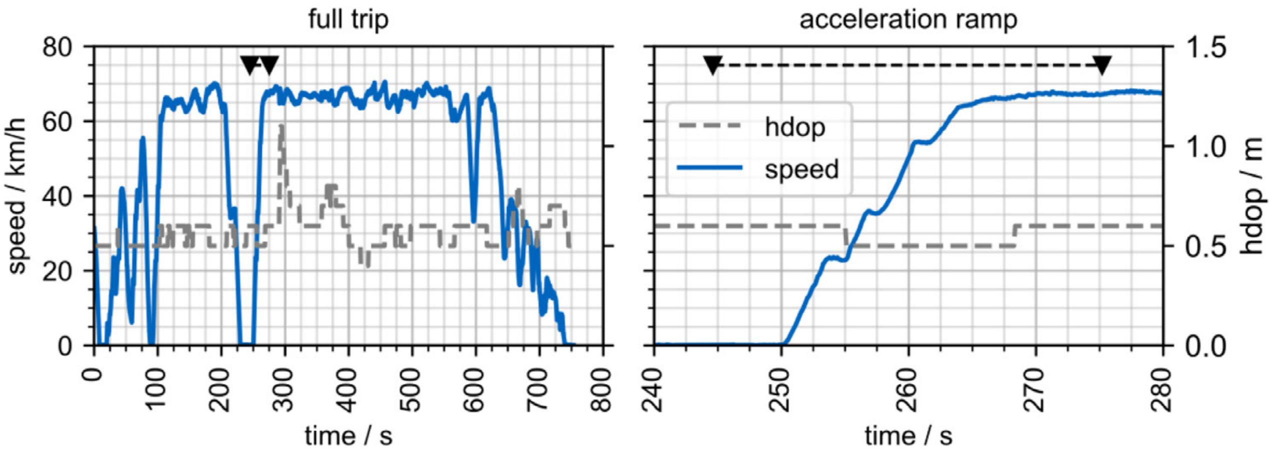

Fig. 1. Exemplary speed profile and horizontal degree of precision. The visualization is based on track 10 of vehicle 1. Left: Overview; Right: Acceleration ramp detail.

2.2. *fleet.csv*

The *fleet.csv* file contains an overview of the vehicles used in the fleet test. Their weight classes and axle configurations are provided. The axle configuration classes of the Federal Highway Research Institute (Bundesamt für Straßenwesen, BaSt) are utilized [3]. Table 3 documents the file structure.

Table 3
Data structure of the fleet.csv.

Column	Data Type	Unit	Description
vehicle_id	Int	–	Unique serial id of each vehicle
fleet_test_id	Int	–	Unique serial id of the fleet the vehicle belongs to
gross_vehicle_weight	Int	kg	Gross Vehicle Weight Rating (without trailer)
total_mass_with_trailer	Int	kg	Gross Combination Weight Rating (with trailer, equals gross_vehicle_weight if no trailer can be attached)
axle_class	Int	–	Vehicle class according to [3]

2.3. *tracks.csv*

The *tracks.csv* provides an overview of the recorded tracks with meta-information and is described in Table 4. A track is a single recording, started and stopped according to the criteria listed in Section 3.1. A tour is a chain of tracks that starts and ends at the home base.

Table 4
Data structure of the tracks.csv.

Column	Data Type	Unit	Description
track_id	Int	–	Unique serial id of each recorded track (ordered by vehicle_id and start_time)
vehicle_id	Int	–	Unique serial id of each vehicle
tour_id	Int	–	Serial id of each tour, assigned to 1..N tracks
start_time	Timestamptz	–	Start time of the recording with time zone at time of recording
stop_time	Timestamptz	–	Stop time of the recording with time zone at time of recording
distance	Float	m	Distance driven during track
track_gap	Float	m	Distance gap to following track
avg_speed	Float	m/s	Average speed
max_speed	float	m/s	Maximum speed within track
n_signal_loss	float	–	Number of signal loss events during recording
d_signal_loss	float	m	Distance covered during signal losses
r_signal_loss	float	–	Ratio of signal loss distance to recorded distance
avg_hdop	float	m	Average horizontal degree of precision during recording
home_base	bool	–	End of recording is at home base of fleet operator
long_haul	bool	–	End of recording is more than 150 km away from home bases
rest_area	bool	–	End of recording is at an unserviced rest area
service_area_fuel	bool	–	End of recording is at a service area
industrial_area	bool	–	End of recording is in an industrial area
cid	int	–	Cluster id of last location in recording, described in Section 2.

2.4. Time of Recording

The recordings took place between September 7 2021, and April 11 2022,. The first fleet to record was fleet one, the other fleets followed in the order of their fleet ids. A ramp-up and phase-out can be observed for all fleets, as data loggers were installed and removed gradually (Fig. 2). Between December 27 and January 10, a decline in recorded kilometers can be observed

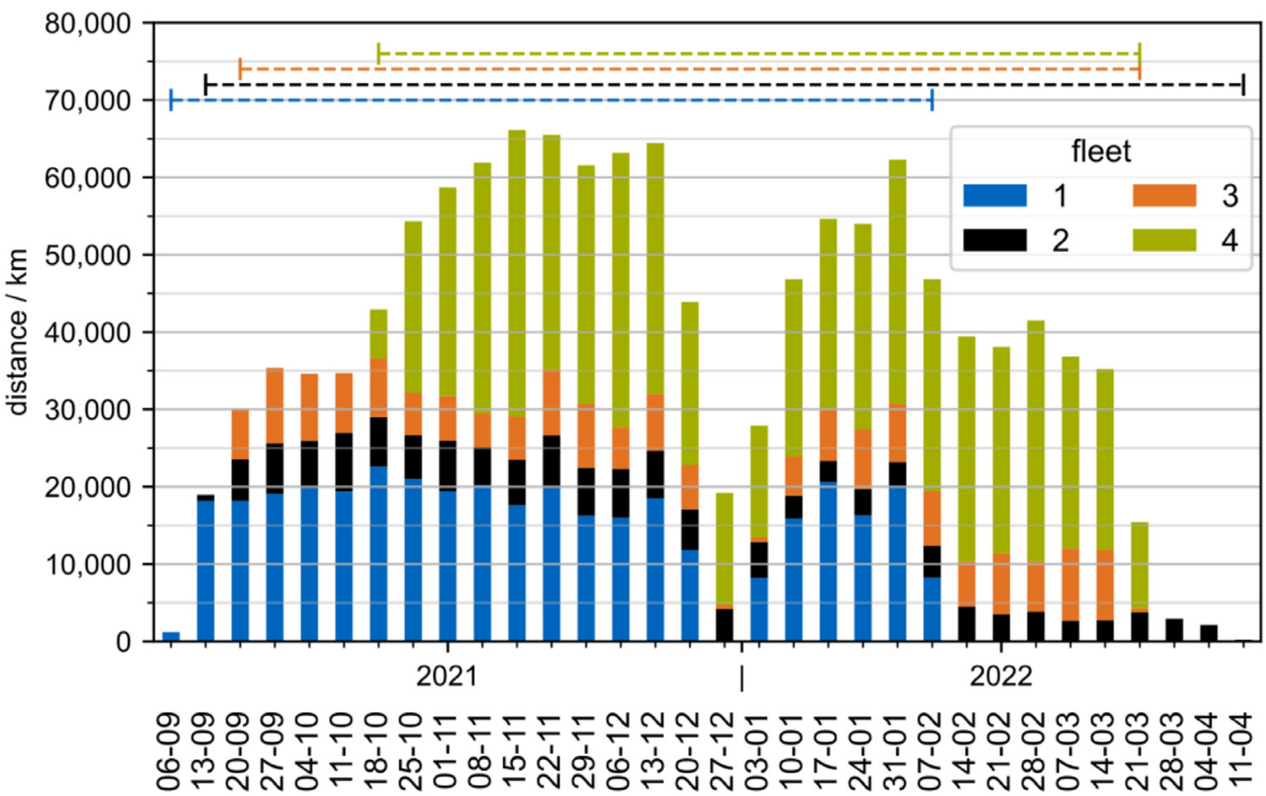

Fig. 2. Recorded distance per calendar week and fleet. Horizontal lines indicate the time between the first and last recording per fleet. The visualization is based on tracks.csv and fleet.csv. Tracks shorter than 1000 m distance are excluded.

for all fleets. In the week following December 27, the total mileage is only 30.2% of a median November week.

2.5. Track Distance and Duration

The most frequent track durations of all fleets are below one hour (Fig. 3). However, fleets two and four feature local peaks at 2.5 h and 3.7 h respectively. The median track duration for fleet two and fleet four ranges from 0.51 h to 1.31 h respectively.

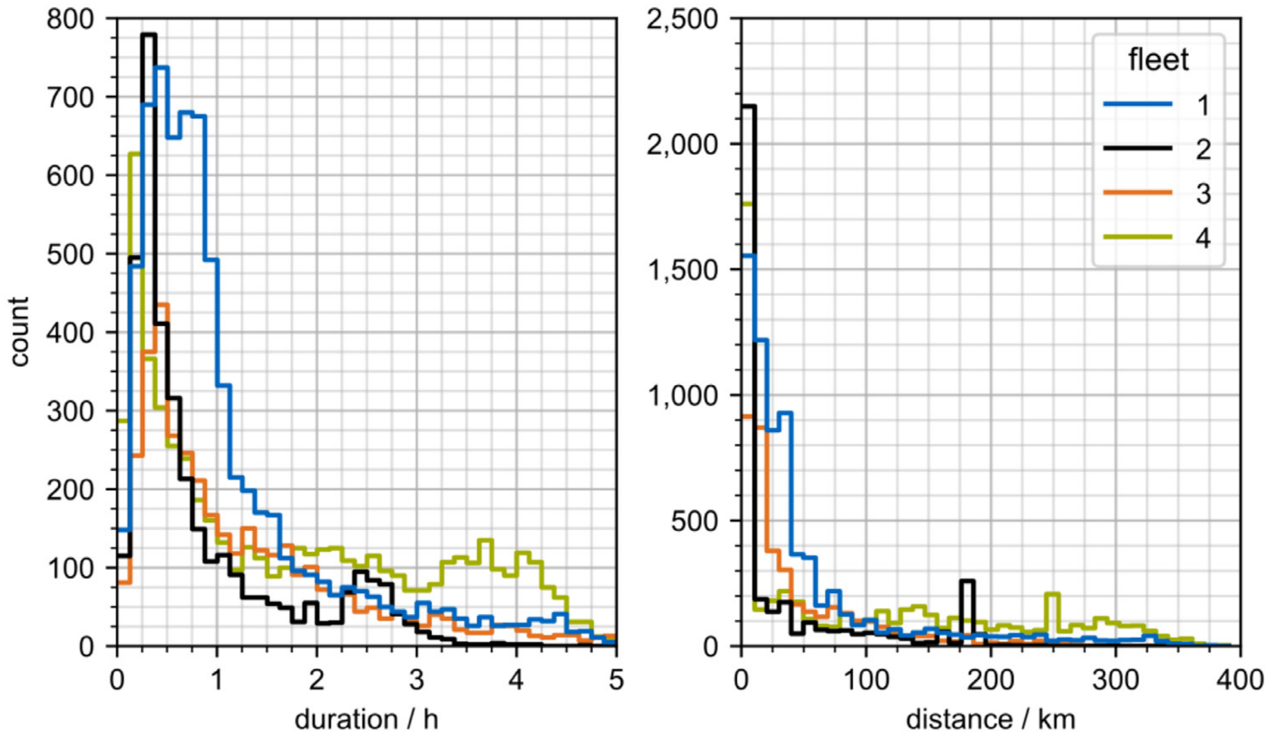

Fig. 3. Histogram of distance and duration of tracks. The figures are limited to a maximum of 5 h and 400 km. Of the recorded tracks over 1000 m, 0.6 % exceed 5 h and none are longer than 400 km. The visualization is based on tracks.csv and fleet.csv. Tracks under 1000 m distance are excluded.

Similarly, the majority of track distances for all fleets falls below 100 km. Long-haul tracks exceeding 150 km are present in all fleets, with fleet four displaying the highest proportion of tracks above 150 km. The median track distance for fleet two and fleet four ranges from 4.4 km to 73.1 km respectively.

The data indicates that while the average speed across all fleets is 38.95 km/h, tractors (axle class 98) exhibit a higher average speed of 48.60 km/h. A national-level survey finds, that tractors have an average speed of 51.90 km/h [4, A22.1] while the average fixed body truck above 3.5 t is slightly slower at 46.51 km/h [4, A21.1]. Considering the average track distance, representative figures show a high variance between fixed body trucks at 15.04 km [4, A21.1] and tractors at 79.11 km [4, A22.1]. The provided dataset's values are between the two values at 63.85 km.

2.6. Rest Time Distribution

Fig. 4 displays the rest times of the vehicles at different locations using a kernel density estimation. Following Scott's rule [5], the kernel density estimation uses a Gaussian kernel with bandwidth 0.2 · n^(−1/5) for the n samples within each location type. Two key intervals can be identified in which rest times frequently occur: The highest density can be observed for durations shorter than two hours. The second interval spans from 6 to 20 h. Both intervals are additionally displayed in detail, to reveal their characteristics.

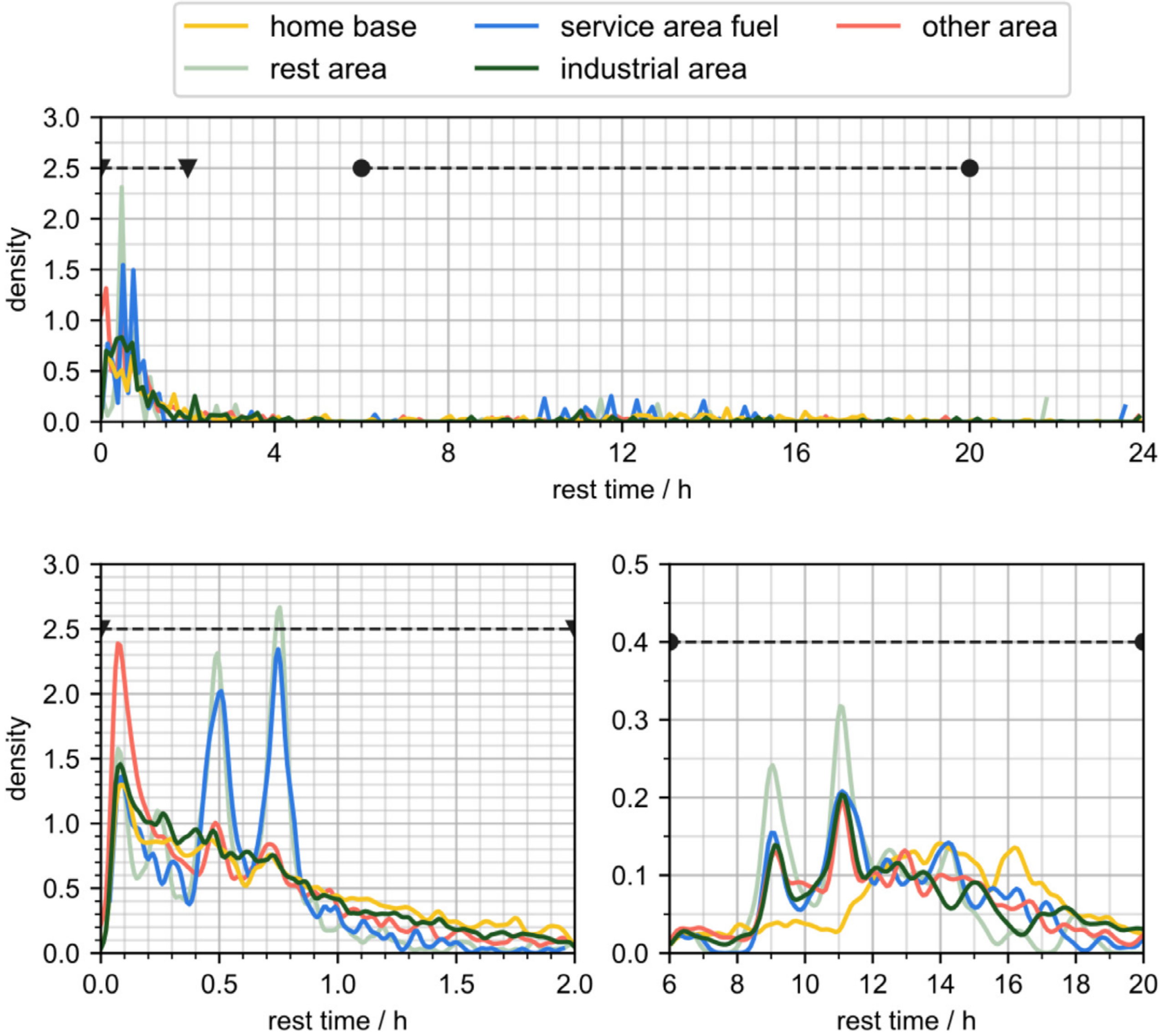

Fig. 4. Kernel density estimation of the recorded rest period. The visualization is based on tracks.csv and fleet.csv and tracks under 1000 m distance are excluded.

In the first interval, containing rest times shorter than two hours, stops at service areas and rest areas are different from other rest locations. Both exhibit density peaks at 30 min and 45 min. In contrast, stops at home bases and foreign industrial areas decline in probability as duration increases. Stops at unidentified areas have a high probability of being shorter than half an hour, peaking at 6 min.

The second interval which contains longer stops, includes peaks at 9 and 11 h observable for the locations rest area, service area, other area, and industrial area. Only stops at the home base do not display this pattern, having the highest relative probability at 14 hours.

2.7. Clusters

Frequent destinations are described in the dataset through clusters. Analyzing the distribution of the stops among the 740 identified clusters, it can be observed, that in more than half of the cases, a small cluster with less than 400 visits was the track destination. The largest cluster, cluster_id 0 was visited 1915 times and can be identified as the home location of fleet 1. A total of 1418 outlier tracks were not assigned to a cluster. Table 5 provides an overview of the visiting vehicles of clusters at different sites. It can be observed, that home locations are the most frequented type of cluster, counting visits and unique vehicles visiting. Among the other

Table 5
Statistics of visits at identified clusters. A track of over 1000 m ending at an identified cluster is counted as a visit.

		home base	industrial area	rest area	service area	other area
visits	**lower quartile**	417.50	3.00	4.00	4.00	2.00
	Median	780.00	7.00	5.00	6.00	5.00
	Mean	988.14	23.81	6.51	9.35	16.45
	upper quartile	1552.50	16.00	8.00	9.00	9.00
unique vehicles	**lower quartile**	10.50	2.00	2.75	3.00	1.00
	Median	12.00	3.00	3.50	4.00	2.00
	Mean	12.29	4.36	3.78	4.81	3.25
	upper quartile	15.00	5.00	5.00	6.00	4.00

identifiable areas, industrial area clusters are the second most visited cluster type with 23.81 visits per cluster on average, while service areas are visited by more distinct vehicles at 4.81 on average.

2.8. Fleet occupation

In Fig. 5, two dependencies considering the occupation of vehicles are displayed: The total time spent resting at different locations or driving is displayed in Fig. 5a. The occupation of all fleets aggregated over the course of 24 hours is provided in Fig. 5b.

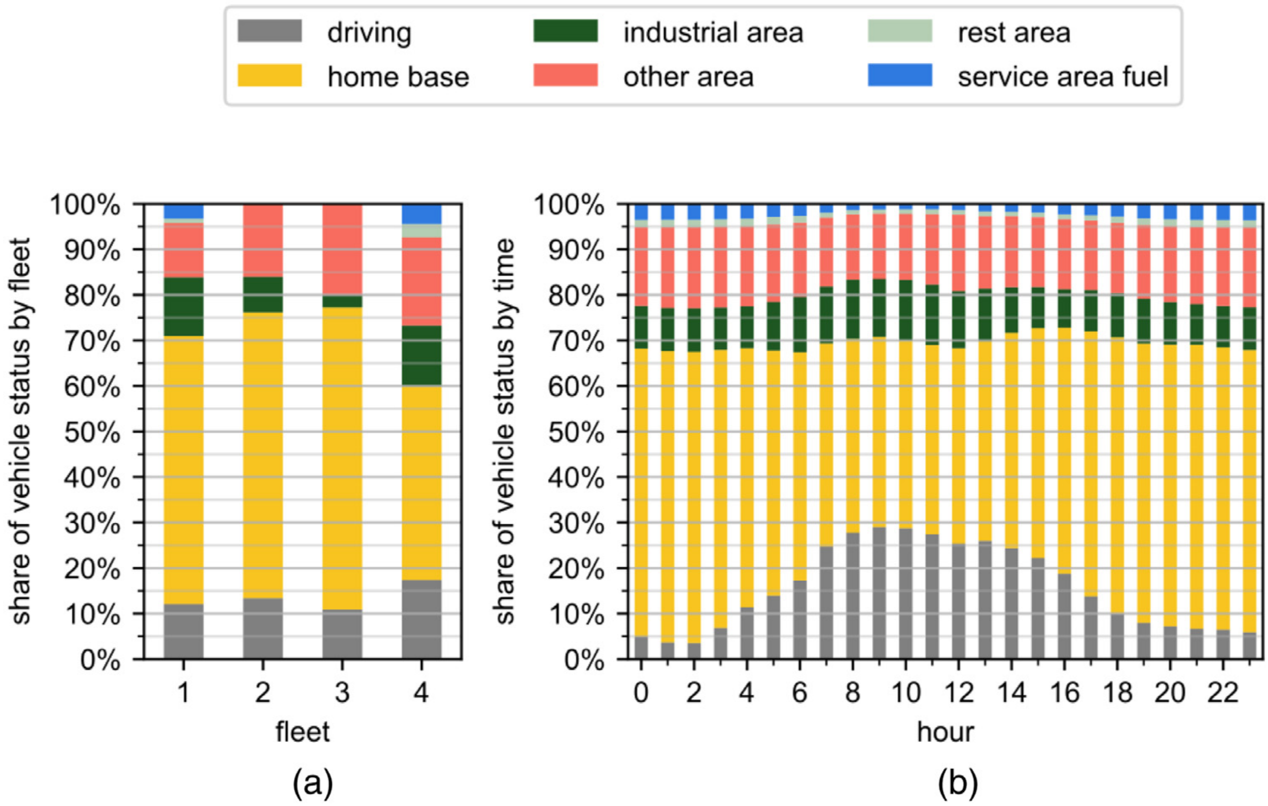

Fig. 5. Occupation of the vehicles during the research period. (a) Vehicle status grouped by fleet, (b) vehicle status by hour of day. The evaluated interval includes working and non-working days. The visualization is based on tracks.csv and fleet.csv and tracks under 1000 m distance are excluded.

For all fleets, dwelling at the home base is the most common occupation. Driving only accounts for 10 % to 17 % of the investigated period, depending on the fleet. Representative figures show, that tractors are driving 21.4% of the week, while fixed body trucks above 3.5t only drive for 10.03% of the week [4, A21.1, A22.1]. While fleets one and four spend 4.2 % to 7.4 % of the time at rest and service areas, fleets two and three only spend 0.22 % and 0.18 % there.

When examining the intra-day variance, driving and dwelling at an industrial area are more prevalent during the day, while dwelling at rest areas, service areas, and the home base are more frequent at night. The highest proportion of vehicles on the road is reached between 9 a.m. and 10 a.m., while the most vehicles begin driving between 6 a.m. and 7 a.m. For unidentified areas, no clear trend can be observed.

2.9. Data quality

In order to assess the completeness of data, unrecorded distances can be evaluated. In some cases, a recording stopped during driving, in other cases whole tracks could not be recorded. Main reasons for missing measurements are technical issues in the software, hardware problems of sensors and suboptimal track recognition. To estimate the data quality of the recordings, an estimation of completeness is carried out. The process is visualized in Fig. 6a.

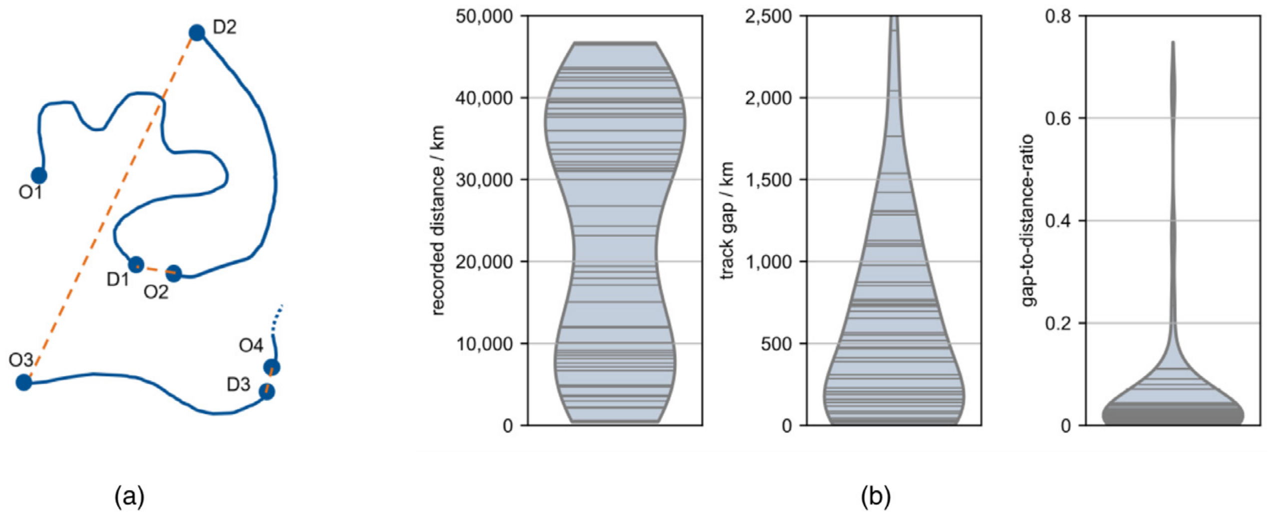

Fig. 6. (a) Schematic depiction of the tracks (solid blue) and track gaps (dashed orange) between origin (O) and destination (D) of tracks 1 - 3. The gap distance is calculated as the aerial distance from the track's destination to the following track origin. (b) Violin plots of the total recorded distance, total track gap, and gap-to-distance ratio. Each line represents one vehicle.

The recorded distance of a vehicle d_{rec} is calculated as the sum of its track lengths (1). The sum of its track gaps d_{gap} is calculated as the line-of-flight distances between the recorded tracks (2). The ratio r of unrecorded gaps to recorded distance is then evaluated per vehicle (3) and visualized in Fig. 6b.

$$d_{rec} = \sum_i l_{track,i} \tag{1}$$

$$d_{gap} = \sum_i d(O_{i+1} D_i) \tag{2}$$

$$r = \frac{d_{gap}}{d_{rec}} \tag{3}$$

The distance gap between the end of the track and the start of the succeeding track is provided as column track_gap in tracks.csv and visualized in Fig. 6b. It can be observed that the gap-to-distance ratio is smaller than 0.2 for all but for two vehicles.

3. Experimental Design, Materials and Methods

During a period of seven months, data loggers were installed in 54 trucks of four fleets. These fleets of heavy commercial vehicles are operated by companies that take part in the “NEFTON” research project (grant 01MV21004A) and were selected in order to represent a wide variety of applications of trucks. Fig. 7 provides a spatial overview of the research area.

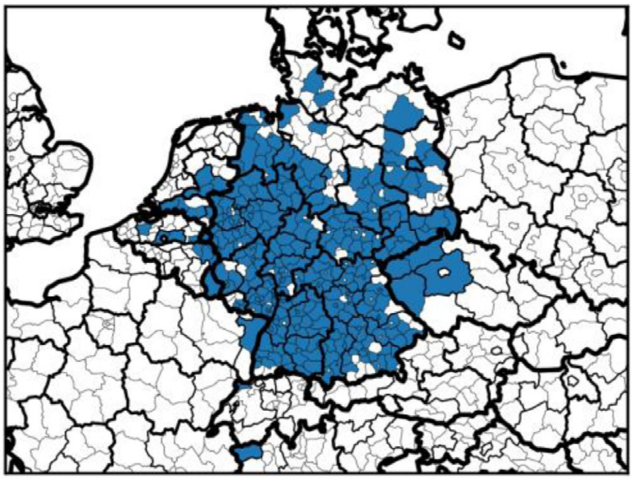

Fig. 7. The NUTS-3 regions that at least one track ended in. Dense coverage can be observed in southern and western Germany. Countries include Austria, Belgium, Czech Republic, France, Germany, Italy, Luxemburg, Netherlands, and Switzerland.

The data loggers (Fig. 8) serve the purpose of providing high-quality data in a reliable manner. They are equipped with a 32GB SD card and able to operate with low energy consumption and no required online connection for several thousand kilometers. The data published was obtained through the IMU and voltage sensors as well as the GPS module of the data logger, while the diagnostic connector was solely used for energy supply.

Fig. 8. The data logger developed at the Institute of Automotive Engineering, featuring an ESP-32 microcrontroller, a MAX-M8W GNSS module by ublox and an external GNSS Antenna.

3.1. Track Recognition

Tracks were detected during operation by the data logger. The information was derived from the recorded GPS data based on parametrized start and stop conditions. These binary stop conditions s_i, evaluated every 100 ms, indicate a possible stop of the vehicle and are described in Table 6. In order to improve track recognition and decrease sensitivity against micro trips, the stop conditions are combined to a unitless composed stop score s_{stop}. The composed stop score exceeding the threshold $s_{stop,thr}$ for a time greater than $t_{stop,1}$ leads to a stop mark being set. The

Table 6
Stop conditions for tracks.

Quantity	Calculation	Explanation
s_{IMU}	$\|\|\alpha\|\| < 1.3\frac{m}{s^2} or \|\|\alpha\|\| < 1.5\frac{rad}{s^2}$	$\boldsymbol{\alpha}$: Translational and rotational acceleration high-pass filtered
s_{VOL}	$U < 27.6\,V$	U: Voltage of vehicle's electrical system
s_{GPS}	Less than 100 m traveled at $v < 1\,m/s$	v : vehicle speed Slow movement at end of tracks with length of at least 800m
s_{SPD}	$v < 6\,m/s$	Stop condition unset if speed rises above 6 m/s again
s_{VCH}	$\Delta\mathrm{U} < -0.5\,\mathrm{V}$	ΔU: Voltage drop due to alternator being shut off

Table 7
Parameters for stop score calculation.

Parameter	Value	Unit
p_{IMU}	15	–
p_{VOL}	25	–
p_{GPS}	15	–
p_{SPD}	15	–
p_{VCH}	10	–
$s_{stop,thr}$	26	–
$t_{stop,1}$	10	s
$t_{stop,2}$	20	s

calculation of s_{stop} is described in (2). If the stop conditions are violated again within $t_{stop,2}$, it is assumed that the stop was brief and the track is continued. The parameters p_i used during data collection are listed in Table 7. The conditions and parameters were tuned during previous research projects in order to avoid missing movements of the vehicle, as false positives can easily be filtered out when post-processing the data. Equation 2 can be summarized as that in most cases a combination of two stop conditions ends a track, while voltage drops only stop a track in combination with a generally low system voltage.

$$s_{stop} = p_{IMU}\, s_{IMU} + p_{VOL}\, s_{VOL} + p_{GPS}\, s_{GPS} + p_{SPD}\, s_{SPD} + p_{VCH}\, s_{VCH} \tag{2'}$$

In contrast, tracks are started when s_{IMU} and s_{VOL} are both violated within $t_{stop,1}$.

3.2. Metadata Calculation

All track-specific metadata is calculated during post-processing. In order to compute this metadata from the location and speed measurements, the data processing pipeline presented in [6] is utilized.

3.3. Track-Specific Metadata

In order to filter outliers, all GPS points that violate the following two quality criteria are excluded from the calculation

- horizontal degree of precision (hdop) smaller than 50 m (Q.1)
- GPS speed between 1.388 m/s and 75 m/s (Q.2)

The distance between two locations is then computed according to the Haversine-Formula and accumulated to calculate track distance (distance). The time difference between the first and last measured point of a track is used as the track duration (duration).

To calculate the average speed (avg_speed) of each track, the track distance is divided by the track duration. It is thus a quantity derived from the location measurements.

Contrary to this, the maximum speed (max_speed) is the maximum instantaneous recorded velocity measured by the GPS module. Internally, it evaluates Doppler measurements of the GNSS signals and thus does not have to rely on differential velocity calculation.

3.4. Spatial Features

To provide spatial context information on the dataset and to retain the participants anonymity, GPS track destinations are matched to and replaced by meaningful area descriptions based on Open Street Maps (OSM) data. Each track end is assigned five boolean labels described in Table 8 based on its last measured location being within a tolerance zone around the respective OSM features. A detailed description of the labeling guidelines within Open Street Maps can be found on [7].

Table 8
OSM-based location labels for track ends.

Column	Source	Description	Tolerance
service_area_fuel	OSM ways and relations with tag highway = service_area	Service areas along the motorway, generally offering a fuel station and other amenities like a restaurant and toilets	200 m
rest_area	OSM ways and relations with tag highway = rest_area	Unserviced areas along motorways and highways.	200 m
industrial_area	OSM ways and relations with tag landuse = industrial	Areas used for industrial purposes.	200 m
home_base	Manually added locations of fleet operators	Sites used for loading, unloading, parking etc.	according to site size
long_haul	Manually added locations of freight forwarders	Aerial distance to closest home base > 150 km	–

For evaluation purposes and visualization in Section 1, the tags home_base, service_area_fuel, rest_area and industrial area are prioritized in that order, e.g. a location that is a home base in an industrial area is classified as a home base. The tag long_haul is based on the fleet operators' company premises.

The trucks re-visit certain destinations. A DBSCAN clustering is applied using an existing implementation within the PostGIS framework [8] to provide information on the cyclicity of movement, using the parameter listed in Table 9. The parameter *minpts* describes the minimal number of tracks that have to end at a similar location to constitute a cluster, while ε is the search radius of the DBSCAN algorithm. In order to calculate the distances between the track destination, a euclidian metric is utilized internally. Thus, the track destinations are reprojected to

Table 9
Parameters of the DBSCAN algorithm used to cluster reoccurring track destinations.

Parameter	Value
ε	1000 m
minpts	5
Projection	EPSG:3857

the Spherical Mercator projection (EPSG:3857) in order to provide a continuous coordinate system throughout the survey area. The resulting cluster id (cluster_id) is assigned to each track, representing the cluster the track destination belongs to, or −1 if no cluster could be assigned (outlier/noise).

In order to construct activity chains from tracks, the tours are reconstructed. A tour, in individual mobility, describes a chain of movements that begins and ends at home. In this context each chain of tracks starting and ending at a home base is considered a tour.

Using this definition, a unique tour_id is generated and assigned to all tracks belonging to a tour. The conditions for the start and end of a tour are as follows:

- consecutive tracks without a stop at a home base constitute a tour
- a tour ends when a home base is reached
- the next tour starts immediately, including all tracks inside the home base
- a track between two home bases with different cluster IDs is considered a tour.

3.5. Quality Measures

A set of quality measures is calculated and provided for each track.

If a location measurement fails the two quality criteria (Q.1) and (Q.2) or if no location is recorded for at least three median recording periods, a signal loss counter is increased by 1. The total number of signal loss events during a track is then provided as n_signal_loss. The line-of-flight distance between the last valid measurement before a signal loss event, and the first valid measurement after the signal loss is calculated and added up per track (d_signal_loss). The ratio of signal loss distance and track distance is provided for each track as r_signal_loss.

The horizontal degree of precision is saved during each location measurement and averaged for each track, yielding avg_hdop. It is an estimate of the standard deviation of the location [2].

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Dataset of Trucks' Anonymized Recorded Driving and Operation (Original data) (Zenodo).

CRediT Author Statement

Georg Balke: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization; **Lennart Adenaw:** Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Supervision.

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References

[1] Georg Balke, & Lennart Adenaw. (2023). Dataset of Trucks' Anonymized Recorded Driving and Operation (1.0) [Data set]. Zenodo. doi:10.5281/zenodo.7599687.

[2] u-blox, "MAX-M8 series u-blox M8 concurrent GNSS modules Data Sheet", UBX-15031506-R05 [Revised May 2019].

[3] Bundesanstalt für Straßenwesen, „Datensatzformat der Achslast-Jahresauswertungen (ALJA)", 2018. Accessed 22 January 2023 [Online]. Available: https://www.bast.de/DE/Statistik/Achslast/Daten/Daten-Beschreibung.pdf.

[4] M. Wermuth et al., "Kraftfahrzeugverkehr in Deutschland 2010 (KiD 2010) Schlussbericht", Brunswick 2012.

[5] D.W. Scott, Multivariate Density Estimation: Theory, Practice, and Visualization, John Wiley & Sons, New York, Chicester, 1992.

[6] M. Wittmann, et al., A holistic framework for acquisition, processing and evaluation of vehicle fleet test data, in: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), Yokohama, Japan, 2017, pp. 1–7, doi:10.1109/ITSC.2017.8317637.

[7] OpenStreetMap Contributors: "OpenStreetMap Wiki", Accessed 22 January 2023 [Online]. Available: https://wiki.openstreetmap.org/.

[8] POSTGIS: "ST_ClusterDBSCAN", Accessed 22 January 2023 [Online]. Available: https://postgis.net/docs/ST_ClusterDBSCAN.html.

3.1.3 Updates to the Published Work

In the original publication, which descriptively describes the dataset, there is no explicit analysis of the potential to electrify the tracked vehicles. Therefore, in this subsection, the dataset is analyzed in depth towards that end. Especially, the question of the actual users who would use public fast charging infrastructure in the future will be answered. Generally, locations for charging infrastructure can be classified into three categories: Public locations are the main focus of this thesis, and are predominantly planned at existing rest and service areas due to the existing space and amenities there.

But besides that, private locations, including the premises of the fleet operator, are viable too, yet require significant investment from the fleet operator. This type of charging strategy is researched in multiple subsequent activities: The electrification of the tracked fleets using private charging infrastructure is analyzed in Paper et al. [108][*] and in a student project by Stuckenberger [109] (supervised). Semi-private infrastructure is located on private grounds, e.g., at large logistics hubs, but is open to usage from third parties. This type of charging infrastructure, and the operational strategies evolving around it, is the focus of the research project SPIRIT-E [110], pursued as a successor to NEFTON.

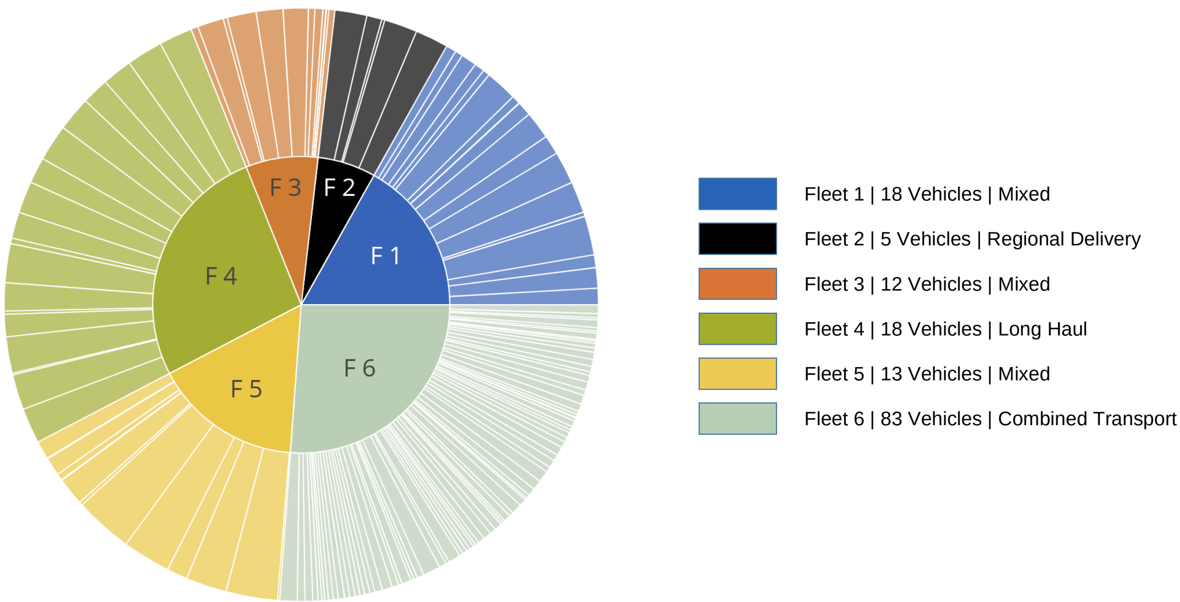

Figure 3.2: Overview of the dataset composition. The dataset is structured into 6 fleets with a total of 149 vehicles with valid recorded driving data. Each sector reflects the absolute driving distance contributed to the dataset, with the outer ring displaying vehicles and the inner ring representing the fleet level.

Before estimating the potential of public fast charging, the dataset [105][*] is expanded to provide a broader view and better context for the original research. Since the original publication, 2 additional fleets have been equipped with data loggers and have been added to the dataset. The updated dataset is published along with publication [108][*]. It contributes an additional recorded driving distance of $+74\,\%$ compared to the original dataset, bringing the grand total to approx. $2\,200\,000\,\mathrm{km}$.

The final composition of the dataset among fleets and vehicles is depicted in Figure 3.2. The hierarchical structure of the chart reflects the fleets and individual vehicles within the fleets. The newly added *fleet 5* (yellow) is a general-purpose shipper with mixed applications of heavy trucks in commerce and industry. *Fleet 6* (mint green) is operating exclusively in combined transport, meaning it shuttles containers from railway cargo terminals to customers in the region. *Fleet 4*, by a narrow margin, still constitutes the largest subset at $586\,000\,\mathrm{km}$. *Fleet 5* consists of only 13 vehicles, which were tracked for 135 days on average. To *fleet 6*, in contrast, 83 vehicles contribute an average of 77 days of recorded time. Generally, freight forwarders operate

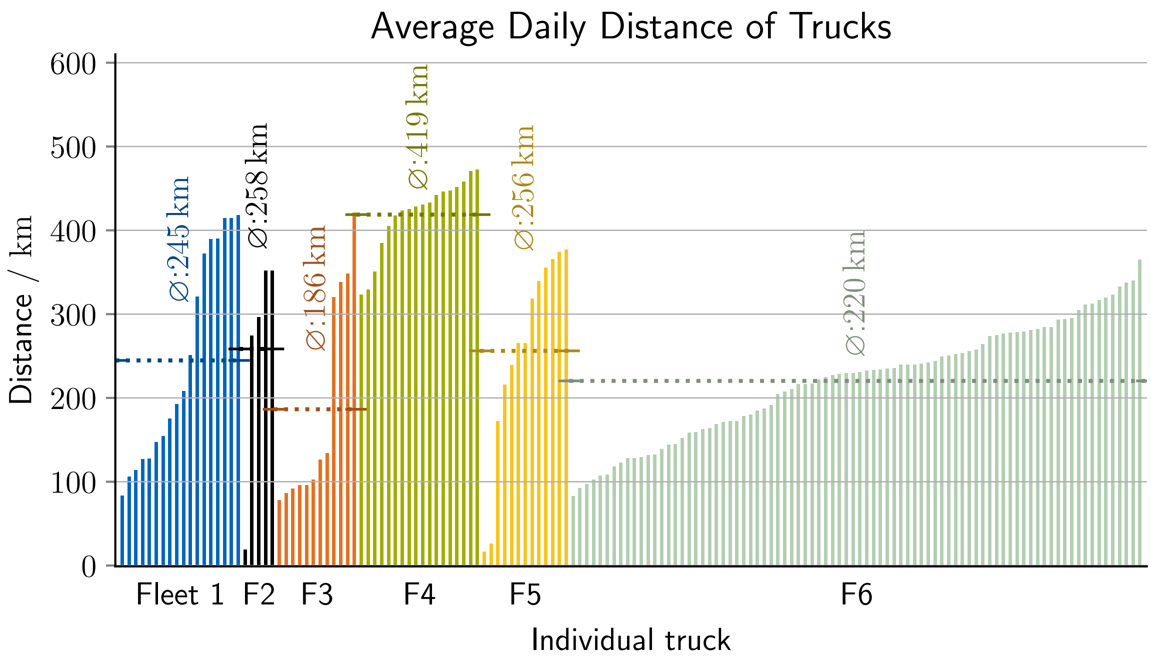

Figure 3.3: Average daily distance of the 149 trucks in the presented dataset. To correct for gaps in recorded data, line-of-flight gaps in the recording were added to the recorded distance with a road curvature correction factor of 1.5.

in a decentralized manner. Freight transport is either a typical domain of small and medium enterprises (SME) [111, 112], or of larger Third Party Logistics Providers (3PL) and Fourth Party Logistics Providers (4PL) that are again organized in a decentralized way or using subcontractors [113]. So the fragmented structure of the dataset reflects the actual fragmented structure of the freight forwarding market.

It can be observed that each truck in fleet 6 contributes a relatively small amount to the recorded distance. The main reason is the rather short recording period in this fleet, but the daily range of the trucks is also below average. This aspect is highlighted in Figure 3.3, where each truck represents a bar in the chart. The average range on days when the truck was in use is displayed on the y-axis. The daily ranges of single vehicles, excluding outliers, vary between approximately. $80\,\mathrm{km}$ and $460\,\mathrm{km}$ with variance observable also within each fleet. Fleet 4 is the only fleet used exclusively in long-haul transport, and its vehicles average $419\,\mathrm{km}$ per day. Fleets 1 and 3 operate in long-haul as well as regional applications, but with dedicated vehicles for each application. This division can also be clearly identified within the daily ranges. Fleet 6 exhibits a broad, continuous spectrum of daily ranges, which could reflect the spectrum of customers for the container transport.

In regard to the dwelling location classification, minor improvements to the method are implemented compared to [[]* Fig. 5]balke2023: Previously, only locations that are labeled as areas or lines in OSM (*way* objects) were included in the spatial analysis [104]*. In rare cases, especially small facilities, locations like rest areas are simply denoted by a point (*node* objects in OSM). This is visualized in Figure 3.4. Their inclusion increases the number of areas of interest (rest area, service area, industrial zone) available to classify parking locations, especially for rest areas. Now, more previously neglected locations of rest areas, service areas, and industrial areas have been added to the spatial search filter. The adaptation was significant for fleet 6 in particular, as the trucks, in most cases, do not return to the home base in the evening and thus park at very diverse locations for a prolonged time.

Figure 3.5 offers a detailed analysis of the trucks' activities across the different fleets and throughout the day. It displays the occupation of the trucks (driving or dwelling at a location class) per fleet and per hour of

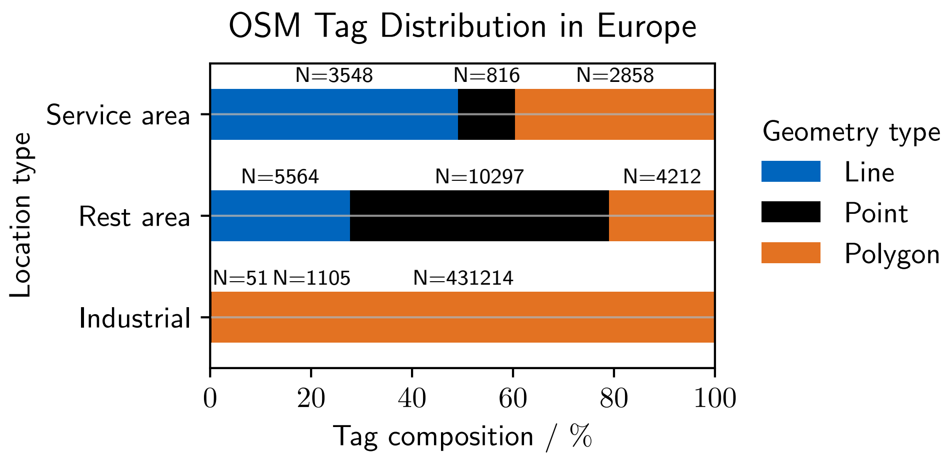

Figure 3.4: Distribution of OSM tags for three regions of interest. Service areas (`highway=services`), rest areas (`highway=rest_area`) and industrial areas (`landuse=industrial`). Point types were not included in [104]* and are now added to the analysis.

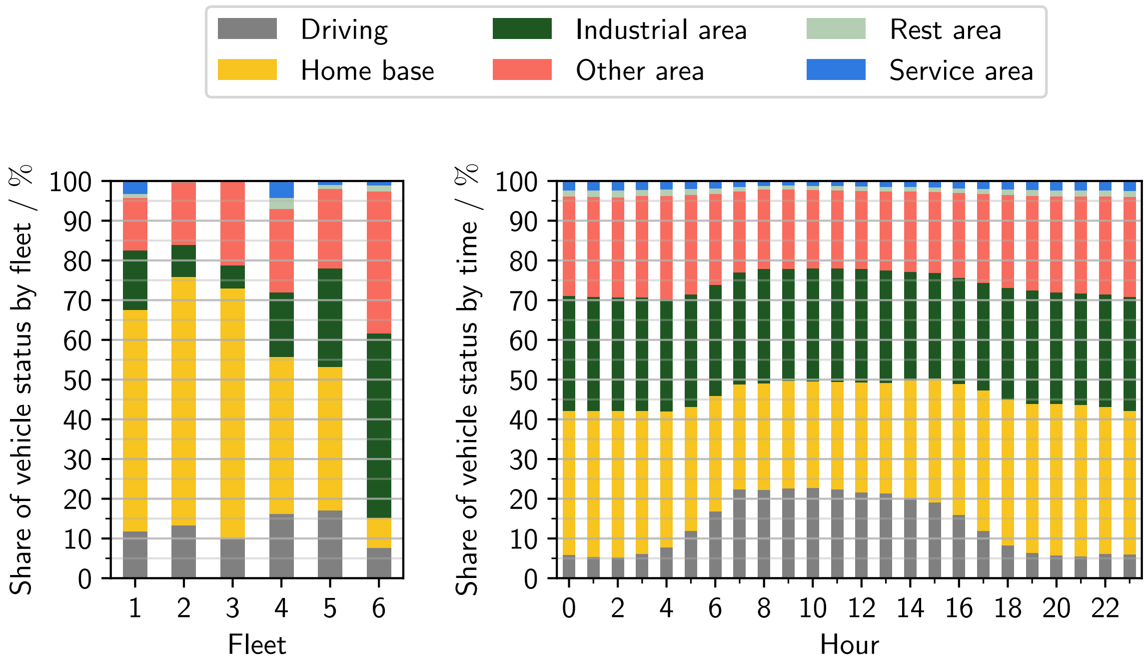

Figure 3.5: Occupation of the vehicles during the research period. (a) Vehicle status grouped by fleet, (b) vehicle status by hour of day. Update of Figure 5 in [104]*, [114]*.

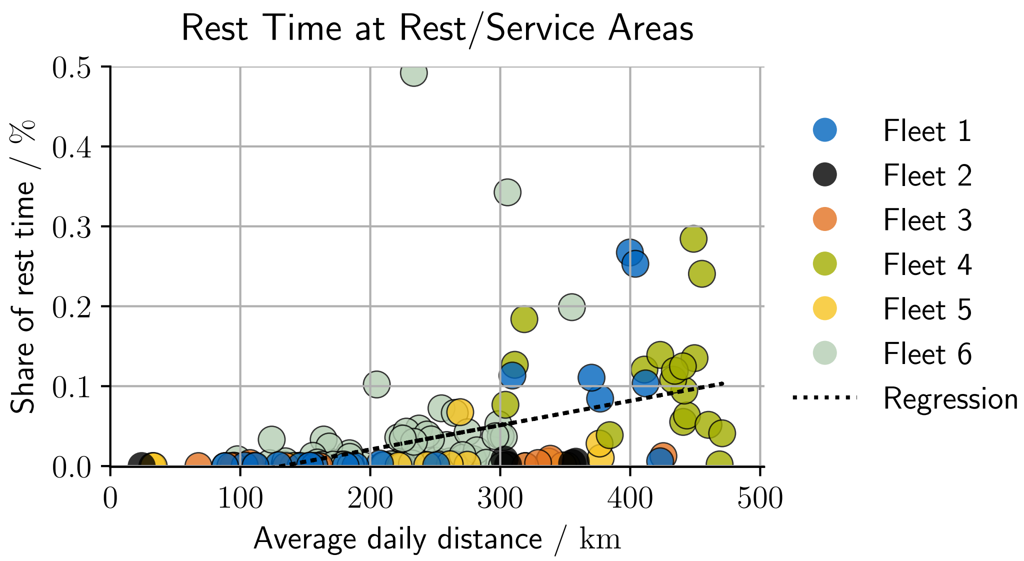

Figure 3.6: Share of rest time spent at rest and service areas over the average daily driven distance of a truck. The colors indicate the fleet to which the respective truck belongs.

day. The left chart clearly shows that the home base is the main location for parking of the vehicles across fleets 1-5. Fleet 6 vehicles, in contrast, are frequently parked in industrial or unclassified locations. This can be explained by the context, as in this fleet, drivers generally take their vehicles home after their shift, and overnight parking constitutes a large time-share in the dataset. Also, it distributes containers from rail terminals, so the core node of its logistics network is not a depot or a warehouse, but the rail terminals it operates from. Fleet 5 opts for the opposite strategy: Trucks are frequently parked on the premises where they operate, and drivers commute to work in the morning. But in comparison to all other activities, the trucks in all fleets rarely stop at rest and service areas. All fleets spend well below $10\,\%$ of their service life at these locations generally well suited for public charging infrastructure.

Hypothesis H.1: Long-haul transport is the main reason for vehicles to visit rest and service areas. The hypothesis was tested from two perspectives: Firstly, by evaluating driving distance patterns on a vehicle-level, and secondly, by evaluating them on a daily basis.

The first supporting argument towards H.1 can be found in Figure 3.5: The trucks of fleet 4 are completely assigned to long-haul transport, and consequently, they exhibit the largest time at public rest areas. Distribution vehicles in fleet 2 and 3, in turn, virtually never visit these areas. A more detailed analysis on a vehicle level is provided in Figure 3.6: It examines the first perspective by calculating the correlation between the average daily distance a truck drives and the percentage of time spent at rest and service areas. The horizontal axis reflects high daily mileage, while the vertical axis represents the time proportion, with each bubble representing one truck. Visual inspection and quantitative analysis both reveal a positive correlation. A Spearman coefficient of 0.6492 and a p-value of 0 indicate a highly significant positive correlation. Yet a strong variance remains in the dataset. Clearly, the analysis supports the hypothesis H.1, but the dwelling patterns cannot be explained sufficiently with the average daily mileage.

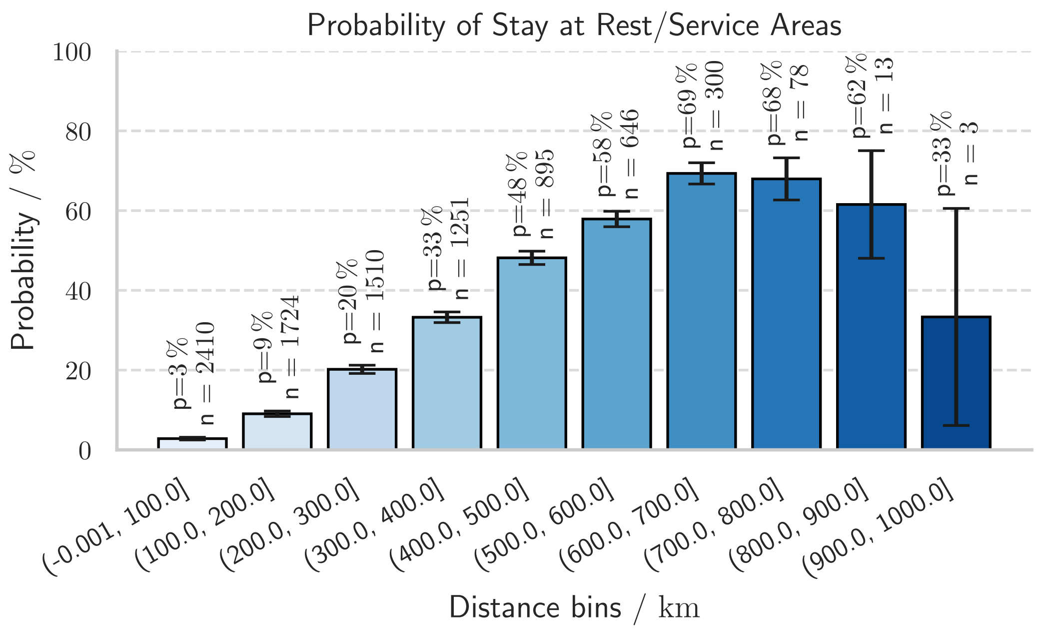

Figure 3.7: Probability of a truck stopping at a rest or service area at all on a daily mission of a given distance. The error bars indicate the variance within a bin.

A modified approach is chosen in the histogram Figure 3.7. Here, single days of operation are evaluated for their traveled distance instead of the *average day* across the recorded period. On the y-axis, the probability that a daily mission includes a stay at rest or service areas at all is displayed. It should be noted that sample sizes decrease at higher daily distances, leading to reduced accuracy and larger error margins. Especially distances over $720\,\mathrm{km}$ are rare in the dataset, as they exceed legal daily driving limits for a single driver and have to be carried out in two-shift operations. Disregarding these rare samples, there is a clear positive relationship between distance and rest area usage: On daily missions of less than $200\,\mathrm{km}$, less than $5\,\%$ of missions include a stop at a rest or service area. In contrast, $61.9\,\%$ of trips above $500\,\mathrm{km}$ stop there. This strongly supports the previously set hypothesis, which can now be refined to *"Long-haul transport missions are a strong predictor for vehicles to visit rest and service areas"*

These findings are further supported by Unold [115], who examined typical usage cycles within the telemetry of fleets 1 and 2 – The representative cycle for freight distribution starts and ends at home, and only visits industrial areas in between. The representative sample for long-haul traffic, on the other hand, visits a rest area as the first intermediate stop for $30\,\mathrm{min}$.

But what does this imply for the prospective charging infrastructure? Figure 3.8 connects the dwelling times at the labeled location types with the immediately following trips. It displays a hypothetical average required charging power to cover the energy demand for the immediately following trip. The plot is adapted from [116]*, with a modified data processing in which multiple legs that are separated by breaks of less than $12\,\mathrm{min}$ are joined together. In a strong simplification, it displays the hypothetical charging power for a BET to cover the immediately following trip electrically, but it assumes that all trips are feasible electrically and that charging can be performed at all dwelling locations. Furthermore, nonlinear charging curves require higher peak power on both the vehicle and infrastructure sides. In reality, the required energy accumulates along multiple trips, as not every location is equipped with charging infrastructure. The real charging powers required are thus significantly higher. Figure 3.8 nevertheless indicates that the combination of long travel distances and short parking times occurs first and foremost at service areas and secondly at rest areas. Very low energy demand is observed in industrial areas. This can be linked to distribution traffic, especially with multiple stops. Clearly,

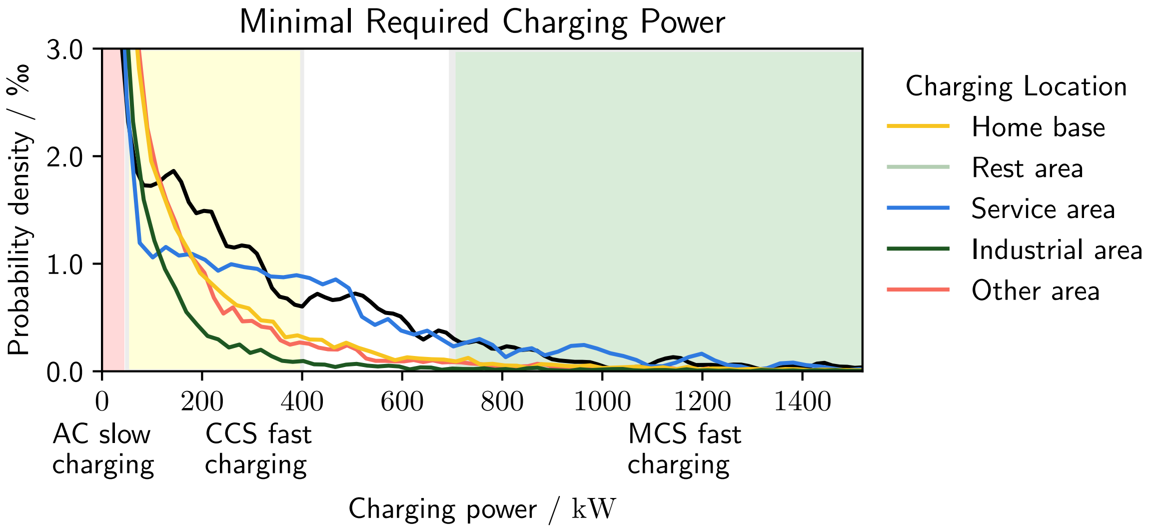

Figure 3.8: Kernel Density Estimation (KDE) of charging power required at certain location types. Energy required for a trip following a break is divided by dwelling time and visualized per location type based on [104]*, method adapted from [116]*. Static consumption of $1.5\,\mathrm{kW\,h\,km^{-1}}$ is assumed, power values above $1500\,\mathrm{kW}$ excluded as noise.

at home and industrial areas, slower charging powers are sufficient than at public locations, as both curves follow a hyperbolic shape, while rest and service areas exhibit a bulge of minimal required charging powers reaching from regions that could be served using the CCS system far into the MCS region.

Conclusion. En-route charging at public locations is relevant primarily for long-haul transportation. Long-haul trucks cannot rely solely on destination charging, as the tour lengths would require prohibitively expensive and heavy batteries [104]*. In regional and distribution transport, in turn, movements are too decentralized, and breaks often take place during loading and unloading. Intermediate charging would result in significant time loss and require substantial re-planning. Private and semi-public charging infrastructure should be the predominant type of charging infrastructure for these users. The focus for public charging infrastructure operators should be to accommodate long-haul transport, as rest periods at rest and service areas are required anyway, and offer the possibility to recharge without time loss, economically optimal.

Based on these findings, the next section Section 3.2, develops a method to conceive a charging network suitable for the needs of BET in long-haul applications.

3.2 Topology Optimization

The previous publication [84][*] addresses the second step towards the static model, as it focuses on the design and analysis of rollout strategies of a national-scale charging network. The core idea is that a strategic approach to designing the fast-charging infrastructure along Germany's motorways can reduce investment costs on the one hand, but also yield a large spatial coverage early on, reducing hurdles for freight forwarders to start operating BET. To comply with future legal requirements, the EU AFIR rules of charging infrastructure every $60\,\mathrm{km}$ along TEN-T *core* routes, and $100\,\mathrm{km}$ along the *comprehensive* network are incorporated into the methodology.

To achieve this, a two-step methodology is conceived. First, an optimization problem is formulated to compute an optimal target state of the network. Then, two strategies for the sequential ramp-up of the network over the next years are evaluated quantitatively.

Firstly, candidate sites are selected. In accordance with the findings of Section 3.1 and the *initial charging network*, rest and service areas are selected as candidate sites. 1264 candidate sites are identified within $5\,\mathrm{km}$ margin from the TEN-T road network. The optimization is constrained by the AFIR's coverage constraints and the budget of charging sites to be electrified. For the mathematical formulation, the distance along the road network from each TEN-T highway segment to each candidate site is computed. This distance matrix $\underline{\underline{\mathbf{A}}}$ enables an algebraic formulation of the inhomogeneous coverage constraints (core network, comprehensive network). The budget for charging sites is kept at the minimal number of sites that could cover all other constraints. The cost function in this case maximizes the distance between charging sites. This ensures that legs between sites are evenly spaced and trucks can synchronize their charging needs and mandatory breaks well. Finally, the optimization algorithm utilized is a MIQP approach to optimally select charging stations among existing candidate sites.

In the German case study, 135 sites (one station per approx. $79\,\mathrm{km}$ of TEN-T road) suffice to fulfill the AFIR coverage targets for 2030. The advantage is that this reduces initial investments by prioritizing fewer but better-placed stations (often at major motorway junctions) while preserving extensive coverage.

In the second major step, an incremental "ramp-up" strategy is proposed to build these stations sequentially. The reference case is multiple runs of random build-up sequences, representing an uncoordinated effort to build the charging network. By implementing a greedy approach, the spatial coverage can be increased by up to $58.7\,\%$ of the total long haul sector in early stages. The greedy approach prioritizes iteratively the single location out of the optimal target configuration set, which enables the most routes to be carried out with BET that were previously not feasible to cover without running out of energy.

The benefits are especially obvious early in the process: $78\,\%$ of domestic long-haul traffic can be served by electrifying only 40 sites if chosen strategically. Notably, this greedy strategy creates a charging network that grows from the central regions outwards. A significant limitation of the study is that only domestic traffic flows were included in the evaluation of ramp-up strategies, whereas approximately a third of the freight transport on German motorways is international and transit traffic.

3.2.1 Contributions

For this publication, I formulated the original idea and developed the concept with the contribution of Maximilian Zähringer and Markus Lienkamp. I then developed the methodology together with Maximilian Zähringer and curated the underlying data myself. The mathematical formulation, implementation, and optimization were my sole work. I led the original writing process as well as the editing, with contributions from both Anna Paper and Maximilian Zähringer. Anna Paper, Maximilian Zähringer, and Markus Lienkamp conducted an internal review before submission.

3.2.2 Navigating the Change: Optimization and Ramp-Up Strategy of a Charging Network for Battery Electric Heavy Trucks

Georg Balke, Maximilian Zähringer, Anna Paper and Markus Lienkamp

2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC), 24-27 September 2024, Edmonton, AB, Canada

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Navigating the Change: Optimization and Ramp-Up Strategy of a Charging Network for Battery Electric Heavy Trucks

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Abstract— **This study presents a strategic approach to designing a nationwide public fast-charging infrastructure for battery electric trucks in Germany. First, it optimizes the placement of charging stations at existing rest areas using a Mixed-Integer Quadratic approach, ensuring coverage required by the new EU Alternative Fuels Infrastructure Regulation (AFIR) while optimizing spatial distribution. Second, an optimal ramp-up strategy is calculated to meet intermediate targets and enhance accessibility early on for electric long-haul traffic. The proposed approach integrates Open Street Maps data with traffic flows to identify strategic locations for charging stations, minimizing the total number while maximizing coverage and utility for long-haul freight transport. The results show that the strategic placement of charging stations could reduce initially developed sites by $36\,\%$ compared to previous work while still ensuring $93.8\,\%$ coverage of domestic long-haul traffic in Germany. The proposed ramp-up strategy improves coverage during the phase-in of electric long-haul transport by up to $58.7\,\%$, thereby contributing to the EU's emission reduction targets. This approach facilitates a cost-effective transition to electric freight transport and establishes a scalable model for EU-wide implementation.**

INTRODUCTION

The European Union (EU) CO_2 emission reduction targets require truck manufacturers to reduce vehicle emissions by $45\,\%$ by 2030 and $90\,\%$ by 2040 [1]. As the Diesel technology only improved by $9.5\,\%$ over the past 3 decades [2], the necessary improvements in local emissions can only be achieved through electrification. The most promising technology economically and ecologically are Battery Electric Trucks (BET) [3]. Heavy trucks, despite making up only $7\,\%$ of commercial vehicles, contribute $48\,\%$ to the emissions of road freight transport. Thus the electrification of heavy trucks is the biggest lever in the effort to decarbonize the transport sector. To enable transport that extends beyond the battery range from private charging infrastructure, a public charging network is required. Initially, the build-up of this network is tied to high investment costs and low revenue due to the gradual market introduction of BET. To assure a basic level of service, from 2030 onwards the EU Alternative Fuel Infrastructure Regulation (AFIR) mandates a maximum gap of $60\,\mathrm{km}$ between charging sites along the core Trans-European Transport Network (TEN-T) network and $100\,\mathrm{km}$ along the comprehensive TEN-T network [4]. As an intermediate goal, $50\,\%$ coverage has to be provided from 2028 on.

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This publication sets out to merge these requirements into a holistic build-up strategy: The main goal is to implement an algorithm, that yields an economically viable solution for the electrification of existing rest areas, such that the AFIR requirements are met with a minimal effort and maximal utility. Following this, an optimal ramp-up strategy is crafted to electrify as much traffic flow as possible early on, enabling early implementation of long-haul electric goods transport. Finally, the results of the algorithmic approaches will be interpreted to derive general guidelines for the creation of a charging network for BET.

While this study primarily concentrates on Germany, the methodologies and data sources employed are designed with scalability in mind to be applicable throughout Europe. The main reasons are, that the limited area makes in-depth analysis of the results feasible, and that Germany serves as a hub for European road freight transport. Besides 5 TEN-T corridors transiting the country [5], Germany itself is heavily reliant on road freight transport for domestic traffic. The successful electrification of the German motorways is thus a precondition to electric road freight transport on a European level.

Within this paper we will address the problem of designing an efficient charging network and a ramp-up strategy for it, addressing the complex needs of transitioning towards electric freight transport in a structured manner.

RELATED WORK

Charging networks for electric vehicles in general [6, 7, 8] and trucks in particular [9, 10, 11, 12, 13, 14] are the subject of intense research efforts. In the terms of charging network design, the trade-off between low investment budgets and maximum utility in terms of coverage with charging infrastructure or occupancy is a significant conflict of objectives [14, 15], highlighted by the necessary integration into the existing electricity grid [14, 16]. A further crucial aspect are waiting times at charging stations due to limited site capacities, which are economical disadvantages in commercial vehicles [12, 17]. Each site to be electrified requires an electric grid connection, project management and construction works. The concentration of plugs at sites thus reduces investment costs, yet previous publications plan low numbers of charging points per site [11], even down to a single charging point [14].

Simulations of possible public charging infrastructure for trucks in Germany have been carried out previously [11, 13, 14, 18]. In [11, 13, 14], the problem is approached through time-forward simulation of trucks and queues at charging infrastructure. Systems of non-interacting agents on varying charging networks are analyzed in [18]. Yet no study to date provides a comprehensive approach to fulfill the coverage targets set by AFIR on the TEN-T corridors optimally. Especially, start-up and expansion networks are computed independently [11], meaning expansion networks are not augmentations of the startup networks presented. When there is a continuity, only the target states are given [12, 14]. Furthermore, a ramp-up strategy that achieves the required coverage goals, while providing maximal coverage at any stage of expansion is a significant research gap.

Hurtado-Beltran et al. [16] investigate the feasibility of a network of fast-charging stations for electric trucks on the U.S. Interstate Highway System. The main goal is the estimation of road network coverage if fast-charging stations were located at existing truck stop facilities along this system. Utilizing GIS network analysis, the study identifies the coverage of potential infrastructure could provide for long-haul routes. In following scenarios, the proximity of sites to high-voltage electric transmission lines is constrained to assure that a charging site can be supplied with electricity. The study found that truck stop facilities could potentially provide $60\,\%$ to $99.5\,\%$ road network coverage for electric trucks on the Interstate Highway System, depending on the assumed range of vehicles and allowed distance of charging sites to high-voltage transmission lines. In the most restrictive scenario, $40\,\text{km}$ of coverage radius is assumed for each charging site and $1.6\,\text{km}$ of distance to high voltage transmission lines is permitted. To achieve optimal coverage in the restrictive scenario, the electrification of 348 truck stop sites is required. By iterative pruning of the network, the number of sites is reduced to 162, equalling to one station per $594\,\text{km}$ of motorways. In the case of long vehicle ranges, one charging site per $2189\,\text{km}$ of Interstate network suffices.

This article aims to build up on the state of the art and amend it in key points. Firstly, the layout of the charging network is being optimized under multiple constraints: A budget of charging sites ensures an economically viable concentration of charging points per site. Simultaneously, the spatial coverage has to comply with the new EU AFIR regulation criteria. In this context, the inhomogenous coverage requirements on core and comprehensive network are addressed. The candidate locations are constrained to existing service and rest areas. Finally, an incremental strategy for the ramp-up of the charging network is conceived and evaluated. Throughout the publication, we adhere to the principle of open data that is available throughout Europe, to ensure the scalability of the developed method.

METHODOLOGY

The approach is structured into two steps: First, an optimized target network configuration is computed, then ramp-up strategies to incrementally build this target state are evaluated. An overview of the approach and the data sources is provided within the graphical abstract Figure 1.

Network optimization. In order to plan the charging network, an optimization problem is formulated. The objective is, that the full TEN-T core network is covered with maximum permissible gaps, and that charging sites are spaced as uniformly as possible. Furthermore, it is desirable to develop as few sites as possible initially in order to reduce investment costs. In the following paragraph, the problem modeling will be discussed in detail.

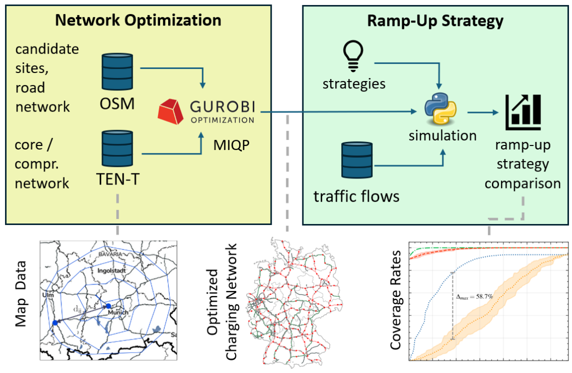

Fig. 1. Graphical abstract of the work presented. This publication relies on open data and a two-step approach: Firstly, the optimal charging network layout fulfilling the given constraints is computed, secondly, the ramp-up strategy is analyzed.

The objective of the optimization is to find a configuration, in which charging sites are distributed evenly throughout the network, to offer regular charging opportunities to passing long-haul transport. This objective is reformulated as a penalty for closely located sites. Let $\underline{\underline{\mathbf{D}}}$ be the $c \times c$ distance matrix among all candidate sites. The Objective Function Matrix $\underline{\underline{\mathbf{Q}}}$ is then computed, by replacing each entry d_{ij} with $q_{ij} = \frac{1}{d_{ij}^2}$, or zero if $i = j$. Binary-valued vector $\underline{\mathbf{x}}$ describes the portfolio of candidate sites to be equipped with charging infrastructure. Then, the term $\underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}} \underline{\mathbf{x}}$ sums up all entries q_{ij} where x_i and x_j are both equal to 1. Followingly, the objective function is the sum of distance penalties among candidate sites selected into the portfolio (Equation 2).

$$\underline{\underline{\mathbf{D}}} = \begin{pmatrix} d_{11} & \dots & d_{1c} \\ \vdots & \ddots & \vdots \\ d_{c1} & \dots & d_{cc} \end{pmatrix} \tag{1}$$

$$\begin{aligned} \underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}} \underline{\mathbf{x}} &= x_1 x_1 q_{11} + x_1 x_2 q_{12} + x_1 x_3 q_{13} + \dots \qquad (2) \\ &= 0 \cdot x_1 x_1 + \frac{x_1 x_2}{d_{12}^2} + \frac{x_1 x_2}{d_{13}^2} + \dots \end{aligned}$$

To formulate the coverage constraints mandated by the AFIR, the distances between individual road segments and candidate sites are considered. The AFIR mandates maximum permissible gaps d_{max} between charging sites. This is remodeled, such that no road segment of the TEN-T core network shall be further than $\frac{d_{max}}{2}$ from the closest charging site. With $\underline{\underline{\mathbf{A}}}$ as the distance matrix of size $s \times c$ between and s road segments and c candidate sites, a coverage constraint of the road network can be derived from $\underline{\underline{\mathbf{A}}}$. The entries of $\underline{\underline{\mathbf{A}}}$ are replaced by zeros, if the distance to the respective charging site is greater than d_{max}, elsewise by ones, to obtain coverage matrix $\underline{\underline{\mathbf{A}}}_c$. All road segments lie within $d_{max}/2$ of a charging site, if product $\underline{\underline{\mathbf{A}}}_c \underline{\mathbf{x}}$ is at least 1 in all rows (Equation 3).

$$\underline{\underline{\mathbf{A}}}_c = \begin{pmatrix} f(a_{11}) & \dots & f(a_{1c}) \\ \vdots & \ddots & \vdots \\ f(a_{s1}) & \dots & f(a_{sc}) \end{pmatrix}, f(x) = \begin{cases} 0, & x > \frac{d_{max}}{2} \\ 1, & x \leq \frac{d_{max}}{2} \end{cases}$$
$$\underline{\underline{\mathbf{A}}}_c \underline{\mathbf{x}} \geq \begin{pmatrix} 1 & 1 & \dots \end{pmatrix}^T = \underline{\mathbf{b}}_c \tag{3}$$

To account for inhomogenous coverage constraints on the TEN-T core and comprehensive networks, the matrix is computed twice as $\underline{\underline{\mathbf{A}}}_{core}$ and $\underline{\underline{\mathbf{A}}}_{comp}$ with $d_{max,core}/2$ and $d_{max,comp}/2$ respectively.

Finally, the budget of charging sites to be electrified is also expressed as a vector operation (Equation 4). This budget is initialized with a reasonably high value (1 station per 30 km) and parametrized by iteratively reducing the budget until infeasibility of the problem is reached.

$$\begin{pmatrix} 1 & 1 & \dots \end{pmatrix} \underline{\mathbf{x}} = \underline{\mathbf{c}}^T \underline{\mathbf{x}} \leq Nc \tag{4}$$

To improve convergence, entries in $\underline{\underline{\mathbf{Q}}}$ corresponding to distances greater than 65 km are set to zero before solving the problem, as these candidate sites lie outside of the permissible gaps in any case and a discontinuity of the objective function at 60 km is to be avoided.

By concatenating the matrices $\underline{\underline{\mathbf{A}}}_{core}$ and $\underline{\underline{\mathbf{A}}}_{comp}$ and the vector $\underline{\mathbf{c}}^T$ final optimization problem formulation is obtained (Equation 5). It takes the form of a mixed-integer quadratic problem and can be solved using Gurobi Optimizer version 11.0.0 [19] in 49 s on an Intel® Core™ i7-10850H CPU (Ubuntu 22.04).

$$\begin{aligned} \min_{\underline{\mathbf{x}}} \quad & \underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}} \underline{\mathbf{x}} \\ \text{subject to} \quad & \begin{pmatrix} \underline{\underline{\mathbf{A}}}_{core} \\ \underline{\underline{\mathbf{A}}}_{comp} \\ -\underline{\mathbf{c}}^T \end{pmatrix} \underline{\mathbf{x}} \geq \begin{pmatrix} \underline{\mathbf{b}}_{core} \\ \underline{\mathbf{b}}_{comp} \\ -N_c \end{pmatrix} \\ & \underline{\mathbf{x}} \in \mathbb{N}^c, x_i \leq 1 \end{aligned} \tag{5}$$

Ramp-up strategy. In order to meet the intermediate coverage targets of 50 % in 2028, and to generally provide a good coverage early on, the next paragraph examines strategies to incrementally select candidate sites for the build-up of charging infrastructure. For this purpose, all routes of domestic long-haul traffic in Germany are evaluated. The possible charging stations are projected onto the route, and combined with the simulated energy consumption. With this information, the minimal State of Charge (SOC) during such a journey is determined. The resulting feasibility or infeasibility is then multiplied with the actual annual traffic flow on the respective route. The underlying process of consumption prediction has been previously published [20] and the application to real world road networks was researched in [18]. The traffic flow data is obtained from [21]. For this publication, the traffic flows from the year 2019 are employed, but data for the year 2030 is also available.

In the following, two approaches for a ramp-up are compared: *Greedy* and *random*. The random approach forms the baseline and aims to represent an uncoordinated effort to build the charging network. Incrementally, a random site among the selected optimized sited is picked and added to the network. This process is repeated $n = 10$ times to provide insights on the variance among the performance of these random strategies.

The greedy strategy represents an informed approach aiming for maximum return on investment for charging point operators. The operator has perfect knowledge and decides unilaterally optimally. At each decision point, the electrification of all single candidate sites is simulated and the one site enabling the greatest traffic flow to be electrified is picked. Subsequently, all remaining charging stations are iteratively evaluated again and the best station is added to the list.

DATA

The basis of the analysis is a dump of the European Open Street Maps data, retrieved from the Geofabrik server [22].

The candidate sites selected are rest areas along the German motorways. By applying the filter `highway = services` and `highway = rest_area`, 1732 rest areas within Germany were identified. Of those, 1264 were located within a reasonable 5 km margin from the TEN-T-network.

In order to compute the road network coverage, the road network is first extracted from the Open Street Maps (OSM) data as a routable graph using the open-source software osm2po [23]. For the sake of simplicity and performance, minor roads such as residential roads were neglected. The cost of each edge is equivalent to the time needed to complete it at the maximum allowable speed, the parameters are selected according to [18, Table A1]. As only spatial coverage is of interest, and minor links can be built relatively easy, reverse travel on links is allowed. This removed the influence of directionality when assessing the spatial coverage of a specific candidate site. To avoid optimization infeasibility, 353 of 48 329 road segments (0.7 %) were removed from the analysis, as they are further than 25 km away from the next rest area.

The distance matrix $\underline{\underline{\mathbf{A}}}$ is obtained by computing the shortest driving distance from each individual candidate site to all motorway road segments using `pgr_drivingDistance` function of the pgRouting library [24]. This is visualized in Figure 2: As the driving distance to a specific road segment is dependent on the road shape and routing, the iso-distance lines are not necessarily convex. Especially in short distances as relevant to the AFIR, the shape differs strongly from a circle.

The distance matrix $\underline{\underline{\mathbf{D}}}$ among candidate sites consists of the airline distances among all candidate sites. $\underline{\underline{\mathbf{Q}}}$ is thus diagonal and the main diagonal entries are zero. Figure 2 visualizes the process.

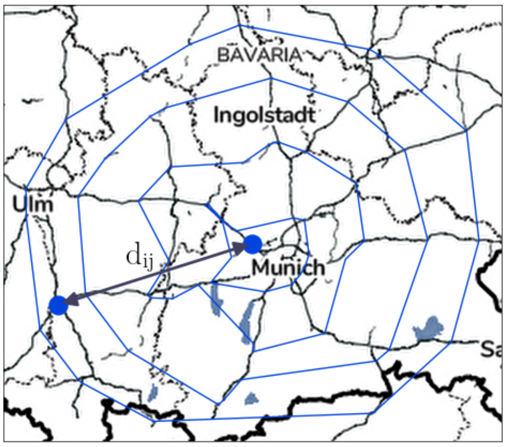

Fig. 2. The iso-distance lines around an exemplary candidate site (service area "Autohof Bergkirchen") extend along the major highways. Distances of 30, 60, 90 and 120 km are displayed as concave hulls. To comply with the AFIR regulation along TEN-T core routes, the next charging site has to be located within the 60 km ring around this site. For the objective function matrix $\underline{\underline{\mathbf{Q}}}$, the airline distances d_{ij} are used. Credit map: OSM Contributors

The TEN-T initiative is an EU strategy designed to enhance the free movement of individuals and goods by creating a coherent, efficient and multimodal transport infrastructure network throughout the EU. The TEN-T road network is structured into two levels: the core network, targeted for completion by 2030, and the comprehensive network, by 2050. The TEN-T freeway network examined in this study reflects the status of the TEN-T regulation as of 2024 and is obtained from the TENtec Interactive Map Viewer [5]. The TENT-T core highway network used in this study covers a length of $6358\,\mathrm{km}$ in Germany and the comprehensive network covers a length of $4271\,\mathrm{km}$.

To evaluate the utility of charging networks, truck traffic flows of the year 2019 as published in [21] are used to compute the optimal ramp-up strategies.

Simulation assumptions. The simulated vehicles have a usable battery capacity of $500\,\mathrm{kWh}$ and the minimum permissible SOC is at $15\,\%$. The simulated payload (influencing the consumption) is $19.3\,\mathrm{t}$ and the permissible detour to a charging site is $10\,\mathrm{km}$.

RESULTS

Tis methodology aims to design a minimal charging network for Germany based on the processed data, compliant with the EU AFIR Regulation [4] along the TEN-T road network. Figure 3 shows the result of the optimization Equation 5. The target requirements for 2030 can be achieved with 135 electrified service areas, equaling to 1 charging site per $78.7\,\mathrm{km}$ of TEN-T road, or $100.7\,\mathrm{km}$ of motorway in total. Junctions appear to be preferable locations, congruent with the intuitive assumption. These sites can provide coverage for multiple motorways simultaneously. Especially the junctions between core and comprehensive network are frequently electrified, as this often suffices to meet the lower coverage requirements. This leads to relatively large portions of the comprehensive network not being equipped

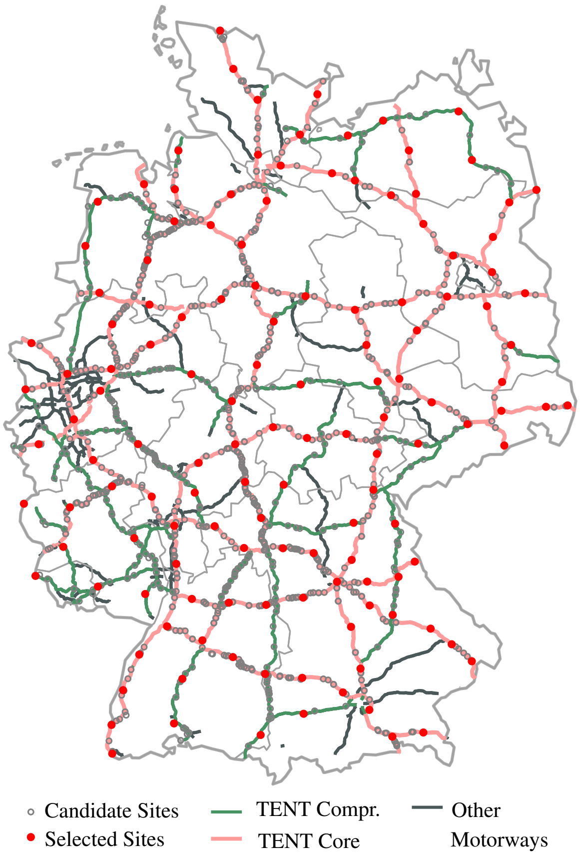

Fig. 3. Optimized AFIR-compliant charging network consisting of 135 out of 1732 candidate sites. Approx. $80\,\%$ of German motorways are associated with either the core network (red) or the comprehensive network (green), as Germany sits on the junction of 5 of the 9 TEN-T corridors [5].

with dedicated charging infrastructure apart from the sites shared with the core network, e.g. the A7 in southern central part of Germany. Along longer linear stretches of highway, additional charging sites are installed.

To compare this approach to previous research, the coverage constraint for the core network was tightened to $50\,\mathrm{km}$ instead of $60\,\mathrm{km}$, equivalent to the close-meshed network approach in [11, p. 9]. We found a minimal set of 171 charging sites, $36\,\%$ lower than the benchmark. The electrification of each site requires costly processes, such as an electrical grid connection, and negotiations with land owners. Compared to small sites of 3 to 4 charging points (median, [11, p. 10]) this aggregation can bring economical benefits.

The charging network in Figure 3 represents a possible expansion stage for 2030 in Germany but does not provide a strategy for the successive installation of charging points. For this purpose, this paper analyzes two ramp-up strategies: Figure 4 compares the greedy strategy to 10 sampled random strategies. The key performance indicator is the share of the traffic flow that can successfully reach its destination. For that purpose, only long-haul traffic flow from [21] with distances of over $320\,\mathrm{km}$ was analyzed, in accordance with the filtering employed in [18]. The feasibility is dependent on the initial SOC of the vehicles, which corresponds to

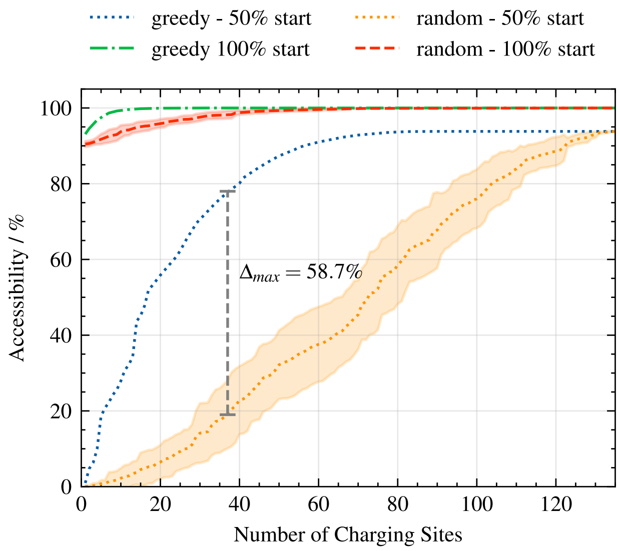

Fig. 4. Comparison of different ramp-up strategies for the optimized charging network from Figure 3. The initial SOC of the vehicle is either 50 % or 100 %. For each scenario, 10 runs of random selection are carried out. Mean and standard deviation of the results are visualized as lines and bands. The greedy approach iteratively picks the single candidate site, that provides the greatest increase in coverage of traffic flows.

available private charging infrastructure. To model different scenarios, the initial SOC was varied, too (50 % vs. 100 %).

Obviously, all strategies offer better coverage with a higher number of electrified sites. Yet the intermediate results vary strongly: Compared to an average random strategy at 50 % initial SOC, the greedy strategy can provide spatial coverage for up to 78 % of traffic flow, while the random approach only covers 19 % at 37 electrified sites, the greatest absolute difference found. Both strategies converge at 93.8 % coverage. This corresponds to the widely-known Pareto principle: 83 % of the final result can be achieved at only 27 % of the final network completed. The convergence is reached at 89 charging sites already. It should be noted, that further densification of the network beyond this point is not futile, as it would still improve spatial coverage, if the initial SOC is below 50 %. Furthermore, the time loss can still be significantly reduced for long-haul travel, as drivers can synchronize their mandatory breaks better with the charging processes of the vehicle [18].

At 100 % initial SOC, coverage is distinctly higher even without any public charging infrastructure, and the final spatial coverage is at 100 %. This can be explained, as many routes can be covered with the approx. 425 km range without recharging at all. Yet also here, the greedy strategy is dominant compared to random approaches in terms of spatial coverage.

In both scenarios, the greedy strategy performs better, than the range of the standard deviation of random approaches, even 2σ. It is thus extremely unlikely, that in an uncoordinated ramp-up such high coverages can be reached early on. Thus, we will finally explore the underlying approach of the greedy strategy to derive practical guidelines, by focusing on Figure 5.

The Figure 5 compares the different phases within the greedy strategy approach: The first sites electrified are geographically central and an already form a small but dense network. In the subsequent phase, the network is expanded radially. At 50 sites, almost full coverage is reached. The next 30 charging sites lead up to the convergence by enabling peripheral traffic flows to be realized with BET, and densifying the existing network in places. The final stage includes border crossings and unattractive sites. As only domestic traffic is modeled, border regions are naturally less attractive sites. Yet we do expect truly transeuropean long-haul BET traffic to pick up after domestic electric traffic, as it requires a coherent charging network throughout the EU. The greedy approach thus enables early applications for battery-electric transport, while also paving the way to an AFIR compliant comprehensive charging network throughout Europe.

Considering the optimality of the solution, it has to be noted that the greedy approach only increments the network by one station in each iteration. This could lead to attractive routes requiring more than one station to be covered only late in the process. The approach is thus not mathematically optimal, but the margin for optimization from an engineering

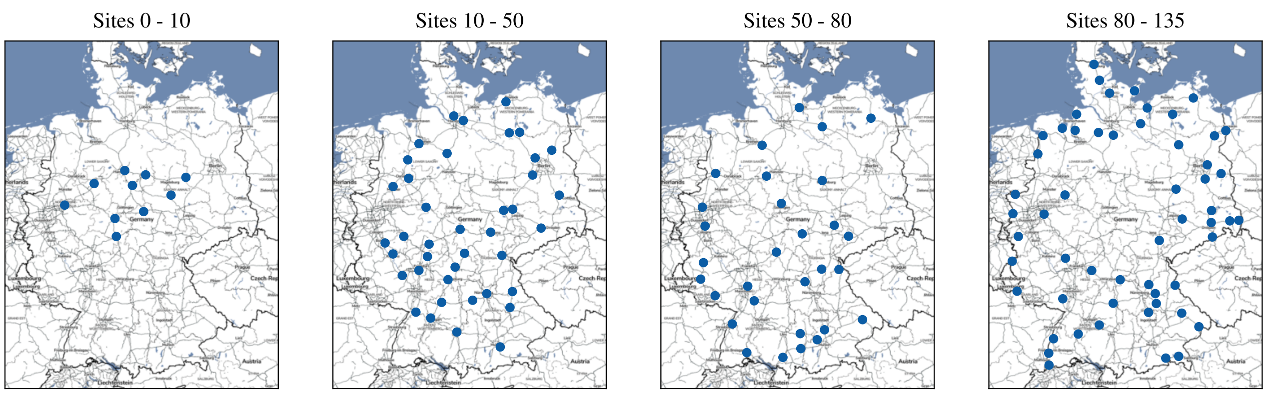

Fig. 5. Visualization of the greedy ramp up strategy at 50 % initial SOC. The first 10 charging sites are located centrally and relatively close to each other. A radial expansion follows. In the third stage, the density of the intermediate network is further increased. Finally, border regions are equipped with charging infrastructure. As only domestic traffic is evaluated, these contribute only marginal benefits to the system.

perspective seems marginal, at the cost of strongly increased computation time. The current greedy approach model took 8 h of computation time on an Intel® Core™ i9-14900K CPU (Ubuntu 22.04 LTS).

CONCLUSION

This study presented a methodology for, first, the optimal spatial positioning of charging sites, to cover a real road network, and second an optimized ramp-up strategy for the strategic installation order of those sites. The aim is to provide early coverage of the freight flows for early adopters, while aiming for a fully covering and legally compliant target state.

Based on the traffic flow data and road network of Germany, the methodology yields 135 charging sites, which together ensure a maximum distance of 60 km between two sites along the TEN-T core network of Germany, as well as 100 km on the comprehensive network. Well suited locations often include core network junctions and core/comprehensive network junctions. Yet the current approach neglects the suitability of a site regarding the grid connection. This should be taken into account in future work, e.g. by incorporating distance of candidate site to the transmission lines into the optimization.

In comparing the random ramp-up processes with the greedy strategy, it could be found that the greedy strategy performs up to 58.7 % better. A spatial coverage of 80 % can be achieved by the strategic installation of just 40 charging sites in Germany. The strategy can generally be interpreted as an center-to-edge approach, which grows an initial charging network radially outwards. This raises the question, whether this pattern can be reproduced on a European level, which should be addressed in future research.

ABBREVIATIONS

The following notations are used in this manuscript: **AFIR** - Alternative Fuel Infrastructure Regulation, **BET** - Battery Electric Trucks , **NUTS** - Nomenclature of territorial units for statistics, **OSM** - Open Street Maps , **SOC** - State of Charge , **TEN-T** - Trans-European Transport Network,
$\underline{\mathbf{x}}$ - vector, $\underline{\underline{\mathbf{X}}}$ - matrix

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REFERENCES

[1] Council of the EU. (2024) Heavy-duty vehicles: Council and parliament reach a deal to lower co2 emissions from trucks, buses and trailers. [Online]. Available: https://europa.eu/!cjCKdb

[2] Umweltbundesamt. (2023) Emissionen des verkehrs. [Online]. Available: https://www.umweltbundesamt.de/daten/verkehr/emissionen-des-verkehrs#strassenguterverkehr-

[3] S. P. Wolff, "Eco-efficiency assessment of zero-emission heavy-duty vehicle concepts," Ph.D. dissertation, Technische Universität München, 2023.

[4] Council of the EU and the European Council. (2023) Fit for 55: towards more sustainable transport - consilium. [Online]. Available: https://www.consilium.europa.eu/en/infographics/fit-for-55-afir-alternative-fuels-infrastructure-regulation/

[5] European Commission, "Tentec interactive map viewer," 2024, accessed: 2024-04-03. [Online]. Available: https://ec.europa.eu/transport/infrastructure/tentec/tentec-portal/map/maps.html

[6] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Review of recent trends in charging infrastructure planning for electric vehicles," *WIREs Energy and Environment*, vol. 7, no. 6, p. e306, 2018.

[7] M. Metais, O. Jouini, Y. Perez, J. Berrada, and E. Suomalainen, "Too much or not enough? planning electric vehicle charging infrastructure: A review of modeling options," *Renewable and Sustainable Energy Reviews*, vol. 153, p. 111719, 2022.

[8] C. Hecht, K. Victor, S. Zurmühlen, and D. U. Sauer, "Electric vehicle route planning using real-world charging infrastructure in germany," *eTransportation*, vol. 10, p. 100143, 2021.

[9] B. Al-Hanahi, I. Ahmad, D. Habibi, and M. A. S. Masoum, "Charging infrastructure for commercial electric vehicles: Challenges and future works," *IEEE Access*, vol. 9, pp. 121 476–121 492, 2021.

[10] B. Borlaug, M. Moniot, A. Birky, M. Alexander, and M. Muratori, "Charging needs for electric semi-trailer trucks," *Renewable and Sustainable Energy Transition*, vol. 2, p. 100038, 2022.

[11] D. Speth, P. Plötz, S. Funke, and E. Vallarella, "Public fast charging infrastructure for battery electric trucks—a model-based network for germany," *Environmental Research: Infrastructure and Sustainability*, vol. 2, no. 2, p. 025004, 2022.

[12] D. Speth, V. Sauter, and P. Plötz, "Where to charge electric trucks in europe - modelling a charging infrastructure network," *World Electric Vehicle Journal*, vol. 13, no. 9, 2022.

[13] W. Shoman, S. Yeh, F. Sprei, P. Plötz, and D. Speth, "Battery electric long-haul trucks in europe: Public charging, energy, and power requirements," *Transportation Research Part D: Transport and Environment*, vol. 121, p. 103825, 2023.

[14] J. Menter, T.-A. Fay, A. Grahle, and D. Göhlich, "Long-distance electric truck traffic: Analysis, modeling and designing a demand-oriented charging network for germany," *World Electric Vehicle Journal*, vol. 14, no. 8, 2023.

[15] M. Kuby and S. Lim, "The flow-refueling location problem for alternative-fuel vehicles," *Socio-Economic Planning Sciences*, vol. 39, no. 2, pp. 125–145, 2005.

[16] A. Hurtado-Beltran, L. R. Rilett, and Y. Nam, "Driving coverage of charging stations for battery electric trucks located at truck stop facilities," *Transportation Research Record*, vol. 2675, no. 12, pp. 850–866, 2021.

[17] M. Zähringer, S. Wolff, J. Schneider, G. Balke, and M. Lienkamp, "Time vs. capacity - the potential of optimal charging stop strategies for battery electric trucks," *Energies*, vol. 15, no. 19, 2022.

[18] G. Balke, M. Zähringer, J. Schneider, and M. Lienkamp, "Connecting the dots: A comprehensive modeling and evaluation approach to assess the performance and robustness of charging networks for battery electric trucks and its application to germany," *World Electric Vehicle Journal*, vol. 15, no. 1, 2024.

[19] Gurobi Optimization, LLC, "Gurobi Optimizer Reference Manual," 2023. [Online]. Available: https://www.gurobi.com

[20] M. Zähringer, O. Teichert, G. Balke, J. Schneider, and M. Lienkamp, "Optimizing the journey: Dynamic charging strategies for battery electric trucks in long-haul transport," *Energies*, vol. 17, no. 4, 2024.

[21] D. Speth, V. Sauter, P. Plötz, and T. Signer, "Synthetic european road freight transport flow data," *Data in Brief*, vol. 40, p. 107786, 2022.

[22] OpenStreetMap contributors. (2023) Europe.osm.pbf dump retrieved from https://download.geofabrik.de/. [Online]. Available: https://download.geofabrik.de/

[23] C. Moeller. (2023) Osm2po-OpenStreetMap Converter and Routing Engine for Java. Software Version 5.5.6. [Online]. Available: https://osm2po.de/

[24] pgRouting Project - Open Source Routing Library. Software Version 3.5.0. [Online]. Available: https://pgrouting.org/

3.2.3 Updates to the Published Work

In the original publication [84][*], the problem is formulated to optimize the positioning of charging infrastructure. The optimization happens solely from a mobility perspective: Spacing between charging stations is optimized, so truck drivers can synchronize their rest time schedules with the required charging stops.

For this thesis, another objective shall be introduced and compared: The integration of large charging sites into the electric grid constitutes a major challenge [44]. As the grid load of multiple megawatt chargers can easily exceed $10\,\mathrm{MW}$, the capacity of medium voltage distribution grids can be exceeded, and direct connections of the charging sites to the high-voltage distribution grid become relevant.

In order to incorporate this into the optimization, three investigation steps are conducted: First, a score is developed that determines how easy or difficult the connection of a candidate site to the high-voltage grid is. Second, this optimization problem is reformulated to include the score. And third, the results using both optimization goals are compared, and charging networks are derived. These networks form the basis of the following Chapter 4, where they are evaluated from a mobility perspective. To compare the different connection types listed in the state of the art (Subsection 2.1.1, [40]), Figure 3.9 is presented. It displays the distance the 1732 candidate sites ([84][*]) have from the closest high-voltage transmission line (orange) or substation (blue). Many sites are located in proximity to transmission lines: at the lower quartile, a transmission line is located only $1.73\,\mathrm{km}$ away. This is plausible, as electric transmission routes along motorways are less intrusive towards the landscape, and are preferred. On the other hand, substations (blue) are rarer; the lower quartile of candidate sites is already located within $4.83\,\mathrm{km}$ of an existing substation.

In the former case, only an upgrade to existing substations has to be built. The latter case requires erecting a new substation. A decision for one way or the other is not trivial: Depending on local conditions, either solution may not be feasible or uneconomical considering local circumstances. For example, in practice, pre-existing consumers on the same existing medium-voltage rings could make a simple connection infeasible and require

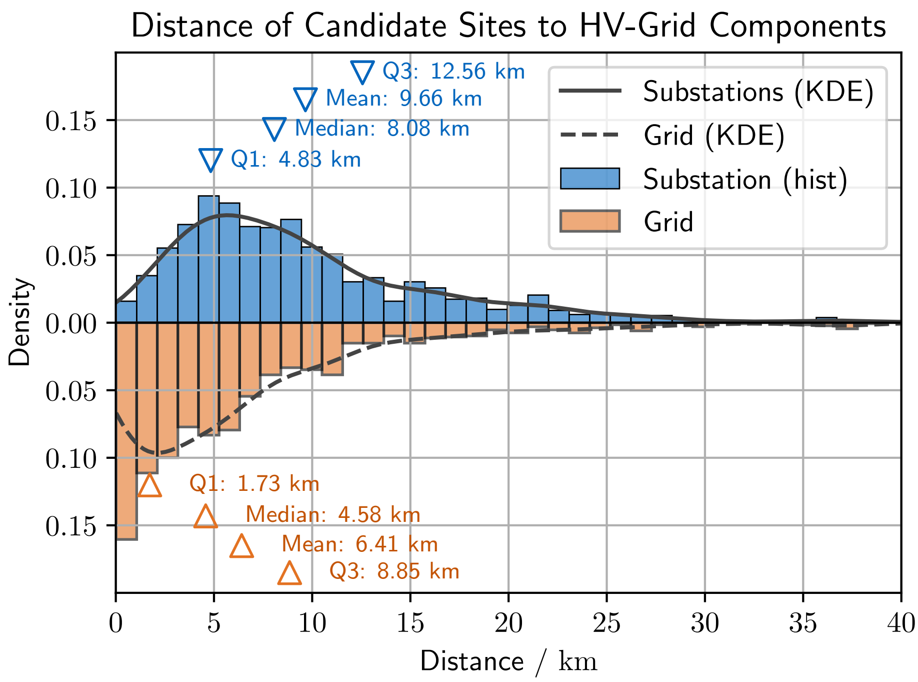

Figure 3.9: Distribution of distances from candidate sites to the closest $110\,\mathrm{kV}$ substation (blue) or transmission line (orange). Generally, transmission lines are closer, but in order to provide a grid connection, a new substation would have to be constructed. Data: [48]

new transmission lines towards a substation anyway. On the other hand, unused capacities, e.g., due to deindustrialization in an area, can locally shift the business case. In this thesis, the attractiveness trade-off between the variants is managed via a penalty weight α_{sub}, which is determined later on.

Multi-Objective Optimization

The optimization goals and constraints in [84]* are set purely from an accessibility perspective. The full mathematical formulation is provided in Equation 3.1: The optimization goal is to provide equal spacing among charging stations throughout the network to enable trucks to synchronize their rest schedules with their charging needs more efficiently. The constraints guarantee that all segments of TEN-T motorway are covered according to the legal AFIR requirements. Furthermore, only a certain budget of N_c stations is given.

$$\begin{aligned} \min_{\underline{\mathbf{x}}} \quad & \underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}} \underline{\mathbf{x}} \\ \text{subject to} \quad & \begin{pmatrix} \underline{\underline{\mathbf{A}}}_{\text{core}} \\ \underline{\underline{\mathbf{A}}}_{\text{comp}} \\ -\underline{\mathbf{c}}^T \end{pmatrix} \underline{\mathbf{x}} \geq \begin{pmatrix} \underline{\mathbf{b}}_{\text{core}} \\ \underline{\mathbf{b}}_{\text{comp}} \\ -N_c \end{pmatrix} \\ & \underline{\mathbf{x}} \in \mathbb{N}^c, x_i \leq 1 \end{aligned} \tag{3.1}$$

where:

$\underline{\mathbf{x}}$: binary decision vector indicating selected sites

$\underline{\underline{\mathbf{Q}}}$: matrix representing the spacing cost between sites

$\underline{\underline{\mathbf{A}}}_{\text{core}}, \underline{\mathbf{b}}_{\text{core}}$: coverage constraint for core network

$\underline{\underline{\mathbf{A}}}_{\text{comp}}, \underline{\mathbf{b}}_{\text{comp}}$: coverage constraint for comprehensive network

$\underline{\mathbf{c}}$: vector of ones used to count selected sites

N_c : total budget of charging sites

Now, in Equation 3.2, a second optimization term $\underline{\mathbf{f}}^T \underline{\mathbf{x}}$ is introduced, which reflects the attractiveness of a certain site with respect to the electric grid. Weight β balances the two optimization goals and shall be varied in the following results. A low beta prioritizes the optimization towards mobility, while a high beta optimizes grid compatibility. Vector $\underline{\mathbf{f}}^T$ represents the minimum distance of a charging site to the high voltage grid as presented in Subsection 2.1.1. α_{sub} expresses that a connection to an existing substation is competitive, even when the distance to the substation is α_{sub} greater than the distance to the next continuous transmission line. The value is chosen as $\alpha_{\text{sub}} = 5$ for the reference case, which has been discussed and the general range confirmed as plausible by energy grid experts. But additionally, the sensitivity of the results towards α_{sub} will be investigated by varying the parameter to $0\,\text{km}$ and $10\,\text{km}$ in the following. Finally, the number of charging sites is now expressed by an equality constraint $\underline{\mathbf{c}}^T \underline{\mathbf{x}} = N_c$, ensuring comparability among all calculated variants of the optimization problem.

$$
\begin{aligned}
\min_{\underline{\mathbf{x}}} \quad & (1-\beta)\underline{\mathbf{x}}^T \underline{\underline{\mathbf{Q}}}\underline{\mathbf{x}} + \beta \underline{\mathbf{f}}^T \underline{\mathbf{x}} \\
\text{subject to} \quad & \begin{pmatrix} \underline{\underline{\mathbf{A}}}_{\text{core}} \\ \underline{\underline{\mathbf{A}}}_{\text{comp}} \end{pmatrix} \underline{\mathbf{x}} \geq \begin{pmatrix} \underline{\mathbf{b}}_{\text{core}} \\ \underline{\mathbf{b}}_{\text{comp}} \end{pmatrix} \\
& \underline{\mathbf{c}}^T \underline{\mathbf{x}} = N_c \\
& \underline{\mathbf{x}} \in \mathbb{N}^c, x_i \leq 1 \\
\text{with} \quad & \underline{\mathbf{f}} = \begin{pmatrix} \min(d_{\text{sub,i}}, \alpha_{\text{sub}} + d_{\text{line,i}}) \\ \vdots \end{pmatrix}
\end{aligned}
\tag{3.2}
$$

where:

$\underline{\mathbf{f}}$: vector of grid connection attractiveness scores,

β : weight balancing mobility and energy optimization,

$d_{\text{sub,i}}, d_{\text{line,i}}$: distance to the closest substation / transmission line

α_{sub} : penalty weight for substation connections.

With this reformulated optimization problem, new charging networks are computed in the following section.

Results

For this optimization, as in [84]*, $N_c = 135$ charging sites have been selected as the target configuration, again fulfilling the legal AFIR [20] requirements. The weight β has been varied between 0 and 1 to demonstrate the extreme states of optimization towards mobility or energy. The quantitative results of this optimization function for varying β are displayed in Figure 3.10. Generally, for a beta of zero, the spacing between the charging sites is prioritized absolutely. The total distance of selected candidate sites towards the next substation amounts to almost $1100\,\text{km}$, while the total distance to the next transmission line is at approx. $700\,\text{km}$.

Between $\beta = 10^{-11}$ and $\beta = 10^{-6}$, the energetic attractiveness of charging sites gains weight and becomes the dominant contributor to the optimization goal. The total distance to substations can be reduced by $33\,\%$ to $916\,\text{km}$, and the distance towards transmission lines drops by $38\,\%$ to $556\,\text{km}$ in total. The overlap of selected charging sites between the initial $\beta = 0$ configuration and the final $\beta = 1$ result remains at only $34.8\,\%$. Generally, the changes to the results for β values greater than 10^{-6} remain marginal.

This means that a significant potential for optimization exists from the perspective of the electric grid connection: According to estimations from the Austrian electricity industry's association, $1\,\text{km}$ of high-voltage transmission line costs approximately $650\,000€$. In 2012, the dena [47, p. 146] estimated these costs at approx. $800\,000€$ The total savings potential across the system could thus reach up to $354\,000\,000€$.

The two charging network configurations at $\beta = 0$ and $\beta = 10^{-6}$ are displayed in full in Figure 3.11. The more grid-connection efficient selection of charging sites is clearly visible: Smaller rings indicate smaller connection distances, so these sites are selected significantly more often. To give a practical example, the rest area "Ostseeblick" from Figure 2.3 is among the selected sites for $\beta = 10^{-6}$, yet not for $\beta = 0$. It could be assumed that the inclusion of grid proximity into the optimization biases the result towards urban and infrastructure-dense areas. Yet this bias can not be confirmed under a thorough investigation: Firstly, the share of sites located along the TEN-T core network (in contrast to the comprehensive network) remains almost constant at $80\,\%$ with varying values of β. Secondly, an analysis of the Regionalstatistische Raumtypologie (Regional Statistical Spatial Typology) (RegioStaR) regions the chargers are located in yielded no significant

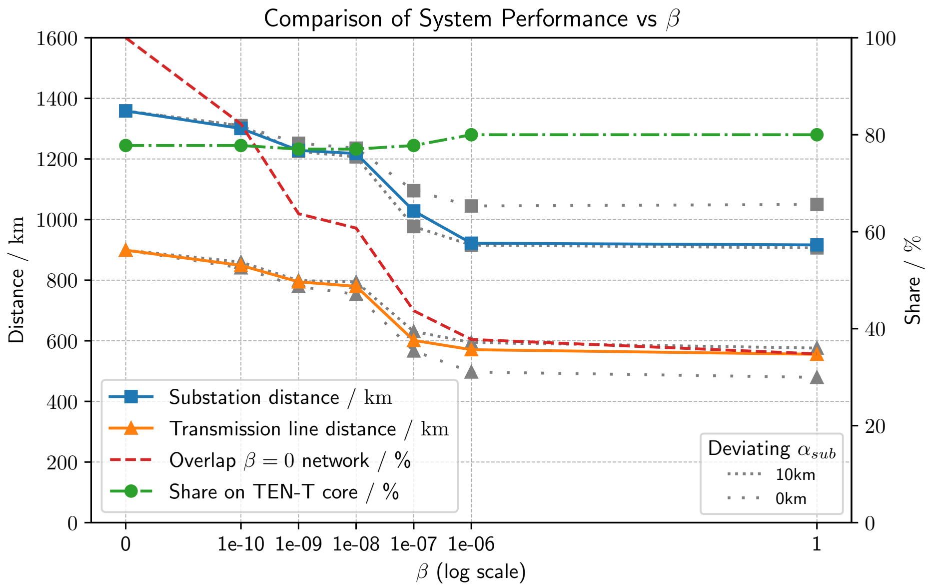

Figure 3.10: Results of charging network optimization. The result for $\beta = 0$ is added to the logarithmic x-axis at the indicated position. The spatial distances towards the next high-voltage grid connection point decrease with increasing β by up to 50 %. In the final configuration, only 25 % of the charging sites from the mobility-optimal case are selected for the energy-optimal configuration.

shift between urban and rural areas, including subtypes. This stability is likely a direct cause of the AFIR coverage requirements, which constrain the location of charging sites in relation to each other. Both networks, at 135 charging sites, are generally comparatively dense. As could be shown in [83]* and confirmed in [84]*, a network consisting of approximately 100 sites could sufficiently serve the long-haul traffic in Germany. Moreover, Fig. 4 of [84]* shows that both networks are within the area of saturation, where no improvement in spatial coverage can be achieved by adding more charging stations.

To summarize, two main goals for optimization have been implemented: The optimization towards mobility and towards electric grid compatibility yields results that overlap only by 21.3 %. The electric optimization offers significant cost savings potential through shorter grid connections and reduced material, project management, and legal costs associated. The former method prioritizes a layout that enables efficient scheduling of charging stops for trucks. This gives rise to the following hypothesis:

Hypothesis H.2: In terms of spatial coverage, both charging networks are expected to show excellent results, as they have a high density. Considering the time loss, the optimization of charging sites from a mobility perspective provides better service to main transport routes, especially in terms of time loss.

If the hypothesis holds true, it means that the optimization towards electric grid compatibility is not purely a cost-saving measure, but comes with a trade-off. The optimization goals would have to be carefully balanced against each other to ensure that the charging network is not only cost-efficient but also demand-oriented. On the other hand, if the hypothesis can be falsified, the optimization towards electric grid compatibility would be the dominant strategy to reduce costs across the system, and existing incentive systems would have to be reevaluated accordingly. This hypothesis shall thus be tested using the dynamic model in the following Chapter 4, where both charging networks are thoroughly evaluated from a mobility perspective.

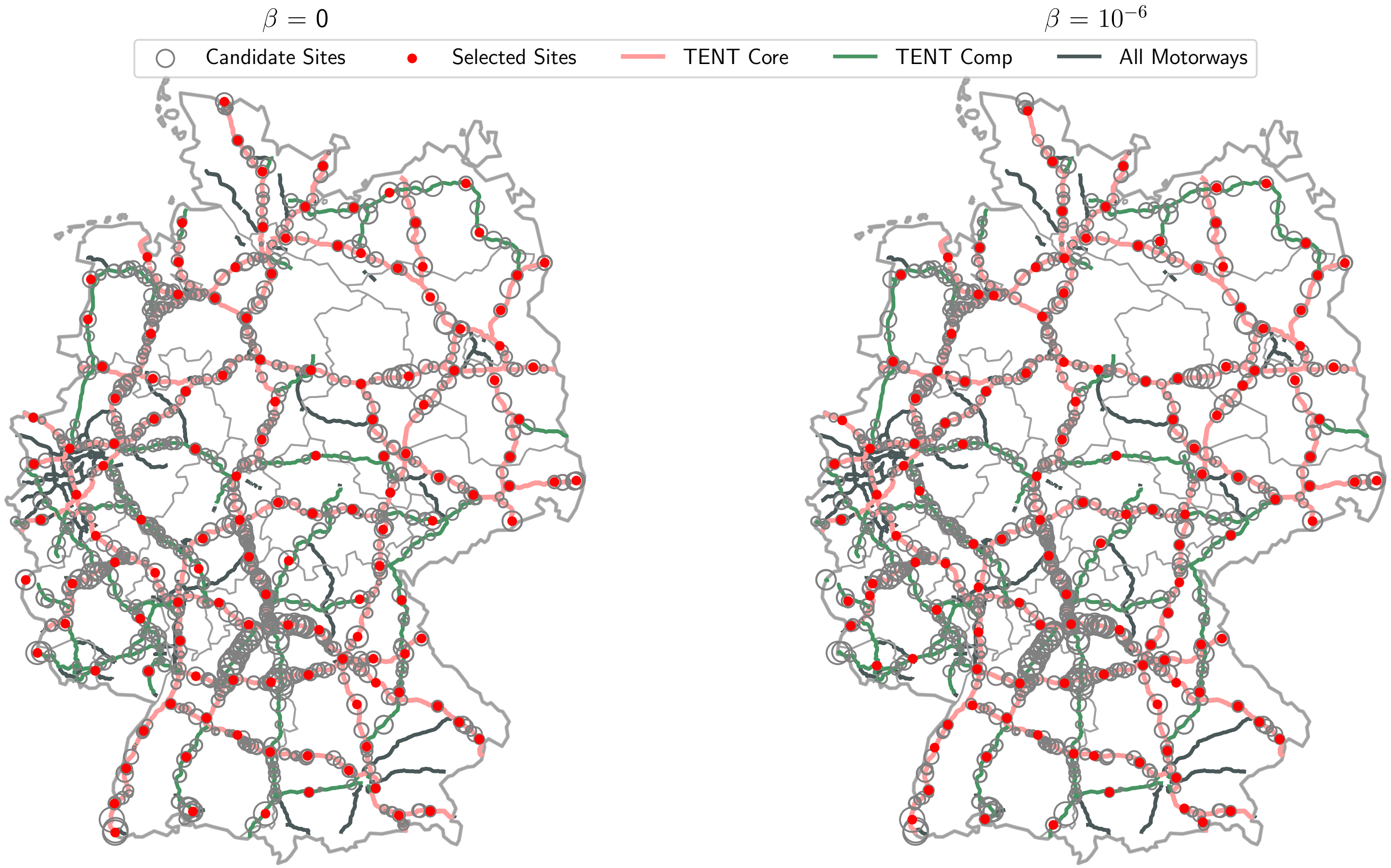

Figure 3.11: Two configuration of optimized charging networks using Equation 3.2. $N_c = 135$, for $\beta = 0$ and $\beta = 10^{-6}$. The hollow circles denote candidate sites for charging infrastructure. Greater circle diameters indicate higher adjusted distance from the high-voltage grid (using $\alpha_{\text{sub}} = 5$). In the left configuration, the grid connection is ignored, and energetically unattractive sites are frequently selected. ($d_{adj} = 1174\,\text{km}$, $d_{sub} = 1359\,\text{km}$, $d_{line} = 899\,\text{km}$) In the right configuration, the energetic attractiveness is the only optimization goal; significant improvements can be achieved. ($d_{adj} = 788\,\text{km}$, $d_{sub} = 916\,\text{km}$, $d_{line} = 556\,\text{km}$)

4 Dynamic Model

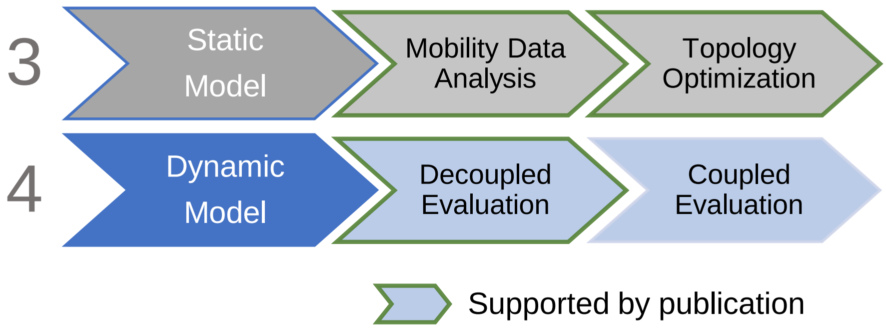

Figure 4.1: Overview of the core methodology and results - consisting of Chapter 3 and Chapter 4.

The dynamic model encompasses the evaluation of the charging networks conceived in Chapter 3. In a first step, Section 4.1 presents an approach to calculate the performance of the system consisting of vehicle, charging infrastructure, and operational strategy without considering the interaction or queuing between trucks. It amends a prior publication [83]*. A brief summary of the publication is provided, followed by the original publication and subsequently, the updates and amendments to the original method and results.

The second step Section 4.2 is directly consecutive, and its aim is to answer questions related to temporal effects within the system, e.g. the concurrency of trucks driving, charging and queuing during typical operation. Furthermore, the sizing of the charging locations to serve the prospective demand in a growing BET market is calculated and discussed in detail. For this purpose, a MATSim model is developed, to simulate the parallel operation of trucks on the German road network.

4.1 Decoupled Evaluation

The article [83]* proposes an integrated framework to evaluate the system consisting of BET, operational strategy, and charging network. Although several BET are entering the market, widespread adoption depends on the availability of high-quality public charging infrastructure along key routes. To address this need, requirements for a charging network to support a widespread adoption of BET are systematically determined. A simulation model is conceived, key performance indicators derived, and two charging networks from the literature for Germany, namely Close Meshed Network (CMN) and Wide Meshed Network (WMN), are evaluated thoroughly.

The approach follows five steps that, similarly to the V-model, first disaggregate the system and then aggregate the partial results again. The core of the methodology is a full-factorial approach that simulates every origin-destination pair among Germany's 401 Nomenclature of territorial units for statistics (NUTS)-3 regions. First, the OD relations of trucks in Germany are projected onto a map and routed using an A* algorithm. Then the routes are joined spatially with the charging network under investigation. In the following step, the dynamic programming optimization Battery Electric Truck Operational Strategy (BETOS) [102, 117]* determines the optimal operational strategy for each truck. Step 4 scales the results according to the OD-flows, and in step 5, the results are then aggregated again to yield system-level KPI, mainly the total time loss compared to diesel trucks and the rate of routes that are infeasible to drive electrically.

The two charging networks extracted from literature are a wide-meshed network (WMN) consisting of 130 charging sites and a close-meshed network (CMN), both adapted from [70]. The CMN represents an advanced stage of the charging network, whereas the CMN is designed to provide a start-up configuration to be reached early on.

Results show that both WMN and CMN offer excellent coverage of over $95\,\%$, even when facing moderate charging station outages. The relative time loss increases with a coarser charging network, yet the influence is small compared to other design parameters. On the surveyed routes $>240\,\mathrm{km}$, the trucks still experience a $5\,\%$-$9\,\%$ time loss compared to conventional vehicles, due to charging time exceeding break times. Higher charging infrastructure power (e.g., $1.5\,\mathrm{MW}$) is the most promising course of action to mitigate the time loss. This highlights that the then announced 1st Generation MCS chargers of $700\,\mathrm{kW}$ do not reach the limits of battery cells' C-rate and are thus the limiting factor.

4.1.1 Contributions

I conceived the initial idea and conceptualized the research together with Maximilian Zähringer, Jakob Schneider, and Markus Lienkamp. Maximilian Zähringer and I then developed the methodology and software, with me being responsible for steps routing, mapping, scaling, and aggregation, and Maximilian Zähringer being responsible for the simulation. Data acquisition, curation, and software deployment were my responsibility. I validated the results in collaboration with Jakob Schneider. The initial draft of the manuscript was prepared by me with contributions from Maximilian Zähringer, after which Jakob Schneider, Markus Lienkamp reviewed and improved it.

4.1.2 Connecting the Dots: A Comprehensive Modeling and Evaluation Approach to Assess the Performance and Robustness of Charging Networks for Battery Electric Trucks and Its Application to Germany

Georg Balke, Maximilian Zähringer, Jakob Schneider and Markus Lienkamp
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Publication Notes

The article titled *Connecting the Dots: A Comprehensive Modeling and Evaluation Approach to Assess the Performance and Robustness of Charging Networks for Battery Electric Trucks and Its Application to Germany* is presented in the following. The article is published in the World Electric Vehicle Journal [83][*]. The annotations and names of the article's reviewers are publicly available in the Review Report due to the adoption of an open review process.

World Electric Vehicle Journal

Article

Connecting the Dots: A Comprehensive Modeling and Evaluation Approach to Assess the Performance and Robustness of Charging Networks for Battery Electric Trucks and Its Application to Germany

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Abstract: The successful introduction of battery electric trucks heavily depends on public charging infrastructure. But even as the first trucks capable of long-haul transportation are being built, no coherent fast-charging networks are yet available. This paper presents a methodology for assessing fast charging networks for electric trucks in Germany from the literature. It aims to establish a quantitative understanding of the networks' performance and robustness to deviations from idealized system parameters and identify crucial charging sites from a transportation planning perspective. Additionally, the study explores the quantification of adaptation effects displayed by agents in response to charging site outages. To achieve these objectives, a comprehensive methodology incorporating infrastructure, vehicle and operational strategy modeling, simulation, and subsequent evaluation is presented. Factors such as charging station locations, C-rates, mandatory rest periods, and vehicle parameters are taken into account, along with the distribution of traffic according to publicly available data. The study aims to offer a comprehensive understanding of charging networks' performance and resilience. This will be applied in a case study on two proposed networks and newly created derivatives. The proposed network offers over 99% coverage for long-haul transport but leads to a time loss of approximately 7% under reference conditions. This study advances the understanding of the performance and resilience of proposed charging networks, providing a solid foundation for the design and implementation of robust and efficient charging infrastructure for electric trucks.

Keywords: battery electric trucks; charging network; open data; infrastructure optimization; operational strategy; green logistics; electrification; freight transport; simulation; methodology

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1. Introduction

The global goal of decarbonizing the industrial sector includes the aspect of transporting goods. The EU Commission has played a significant role in this area by publishing a draft law aimed at reducing emission limits for the coming years. Notably, the law stipulates that, by 2040, vehicle emissions must be reduced by 90%. While electric passenger vehicles started claiming significant market shares throughout all major markets worldwide [1], non-fossil-fueled trucks are still a niche product [2].

A promising solution for the commercial vehicles sector is the use of battery electric trucks (BETs), which are noted as being one of the most ecologically and economically beneficial options available [3]. Several truck OEMs, including Volvo, MAN, and Daimler, have already introduced BETs to the market [4,5]. However, the most prominent challenge that persists is the scarcity of public charging options for these electric trucks [6], with only a few adapted passenger vehicle options like the Aral charging corridor and Milence charging being available [7,8]. In response to the challenges in charging infrastructure, the EU introduced Alternative Fuel Infrastructure Regulation (AFIR). This regulation mandates the establishment of a public charging network, initially requiring charging facilities every 120 km. This network density will be intensified to every 50 km in subsequent phases [9]. The planning of such a charging network entails several challenges. Firstly, aligning the build-up of the charging network with the actual demand is essential. Factors such as the high volume of European transit traffic and the uneven distribution of industrial areas in Germany imply that not every region will have the same frequency of BET usage. Additionally, the longer charging times of trucks compared to private cars require even more parking space. This requirement calls for developing new areas for charging points and utilizing existing service sites. The high number and energy demand of vehicles generally require new medium and high-voltage grid connections, further increasing the need for long-term planning of the charging network [10]. From the perspective of drivers and logistics companies, practicality is a crucial factor. For instance, a low density in the charging network can lead to inconvenient charging breaks, resulting in significant additional time expenditure and thus reduced turnover for BETs compared to conventional trucks [11].

In this publication, we aim to create a better understanding of how a performant and resilient public fast-charging infrastructure for heavy commercial vehicles must be designed. By integrating vehicle, infrastructure, and operational strategies into a single simulation model, we incorporate various nonlinear effects and compute system-level key performance indicators (KPIs). Its core contributions lie in quantifying charging time loss and spatial coverage of charging networks, modeling self-optimizing vehicle behavior, nonlinear charging curves, time-optimal routing, and evaluating the networks' necessary design parameters like density and installed power. In short, we aim to simulate electric trucks on all routes between German counties and scale with the respective traffic flows in order to evaluate the systems holistically. The study presents a comprehensive methodology applied to two charging networks from the literature proposed for Germany. The data sources, however, are selected to be applied seamlessly throughout Europe. Ultimately, this research enhances the understanding of the effectiveness and resilience of proposed charging networks, which are crucial for successfully integrating battery electric trucks into transportation systems. It is structured as follows: After this Section 1, the second section (Section 2) covers related research on the electrification of trucks and system-level evaluation. Special emphasis is placed on the publications that are incorporated and evaluated during the analysis, and the research gap this article fills is identified. In Section 3, a comprehensive description of the simulation and analysis steps conducted is provided, along with a graphical representation of the method Figure 1. The fourth section (Section 4) covers the findings of the case study networks and their variations, while the final section (Section 5) focuses on their critical evaluation and contextualization. Finally, proposed future work is provided in Section 6.

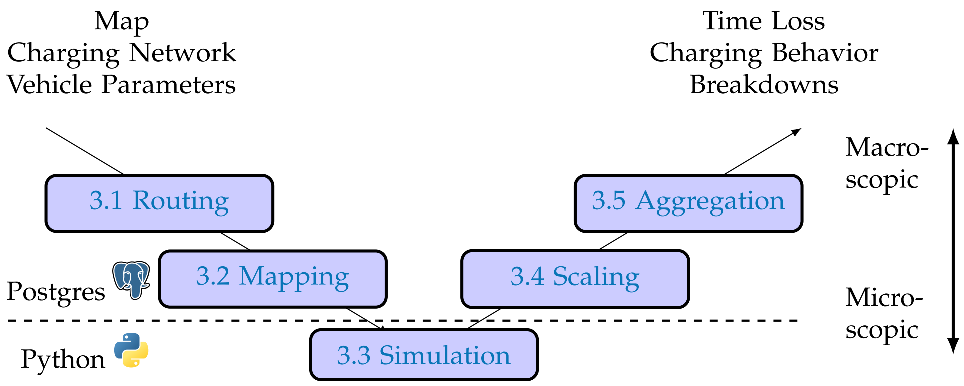


Figure 1. Visual abstract of the method presented. The data processing and geographical operations were carried out on a PostgreSQL 15 cluster using the PostGIS [12] and pgRouting [13] extensions. Simulation tasks were fetched by 19 different hosts and computed in parallel in Python, after which results were sent back to the PostgreSQL cluster for storage, evaluation, and aggregation.

2. Related Work

2.1. Electric Vehicle Charging Infrastructure Planning

The design of charging networks, especially but not exclusively for private electric cars, has been subject to extensive research [14–16]. Considering the optimization targets, the most prominent objectives are infrastructure cost (investment and operation), economical electricity grid integration, and the maximization of the traffic flows captured by the charging infrastructure [14] (p. 15f). This cost also includes the monetized waiting time due to limited site capacities [14] (p. 17). Among the less frequently addressed KPIs are the location relative to the desired routes and the routes accessible due to network coverage, which is especially important for commercial usage [14] (p. 18). Al-Hanahi et al. [16] highlight the specific challenges of charging infrastructure for commercial vehicles, such as medium- and heavy-duty trucks. They point out that the logistics processes of these vehicles can significantly constrain the possible charging process at the infrastructure [16]. Therefore, they review two separate operational strategies to include charging: the return-to-base model and the en-route charging model [16]. Metais et al. [15] emphasize the need for strategic deployment of charging infrastructure, considering both the environment and the behavior patterns of electric vehicle users. They discuss the importance of sizing charging stations according to the type of targeted route, allowing fast charging stations to be placed where a quick charge is most useful. Yet we previously demonstrated that even in charging networks of unlimited site capacity, infrastructure placement as well as power and charging stop strategy significantly impact the resulting time loss compared to conventional vehicles [11].

The time loss of EVs within a given real charging network is evaluated by Hecht et al. [17], using the existing German fast-charging network for private electric cars. The study analyzes travel durations for five typical EVs on 60 routes throughout Germany, considering factors such as non-linear and state-of-charge-dependent charging power, and non-linear velocity-dependent energy consumption. The routes were sampled to be coverage-oriented and later weighted according to traffic counting stations along the routes. Notably, as there are no mandatory breaks for private cars, Hecht et al. [17] applied the rest-time regulation of trucks to the private car scenario. The charging strategy, i.e., the selection of charging locations and energy amounts, was optimized numerically. The findings show that travel time increases by approximately 8% compared to conventional driving without refueling, but it is strongly dependent on route length. Extreme cases through areas with unsuitable infrastructure result in 30% more driving time. A sensitivity analysis identified the most influential factors as the initial state of charge (SOC), as well as the low energy efficiency and battery capacity of the car.

Charging networks designed specifically for trucks thus have to be balanced to fit the vehicles' technical properties. The design of such networks on national and European levels is currently of special research interest [18–24].

Hurtado et al. [22] highlight the importance of spatial coverage for proposed charging networks by evaluating Geographic Information Systems (GIS) data on the highway and power transmission network of the United States. Existing service areas are considered the solution space for localizing high-power charging infrastructure. Between 18% and 81% of spacial coverage of the contiguous US could be achieved by electrifying service stations in a 5-mile proximity to the interstate network. The study varied the area served by a charging site, as well as the maximum permissible distance to high-voltage transmission lines.

Borlaug et al. [20] evaluate 330 Mio km of recorded trips by semi-trailer trucks. By simulating overnight as well as en-route charging scenarios, the requirements of local, regional, and long-haul trucks are accommodated. In all scenarios, higher battery capacities reduced the dependence on en-route charging. Also, a shift to rural chargers with higher capacities for all operational ranges could be observed. For long-haul applications and electric ranges of 300 miles, 70% of the electric energy was replenished in en-route fast charging events.

Speth et al. model fast charging networks on the German [19] and European [18] levels. The charging stations are similarly placed at regular intervals of either 50 km or 100 km. Both studies use traffic count data and on-site queuing models and consider locations along major highways as candidate sites for the charging stations. While [19] includes the locations of manual traffic counts as candidate charging sites, Ref. [18] (p. 6) includes every node in the road network as a possible site. The models consider a future scenario where a certain percentage of the trucking fleet is battery electric (15% [19] and 5%/15% [18]). In the Germany-focused paper, the model considers 142 charging locations for a coarser start-up network (Wide-meshed Network (WMN)) and 267 charging locations for a denser expansion network (Close-meshed Network (CMN)). The European networks consist of 660 stations for the WMN and 1468 stations for the CMN expansion network.

Shoman et al. [21] present a simulation based on European freight flow data obtained from the ETISplus dataset, aggregated according to [25]. The freight flow is filtered for long-haul routes, which rely heavily on public charging, and subsequently split into trip chains compliant with EU break time regulations. Similar to [20], charging events are assigned to their geographical location without explicit modeling of a charging network [21]. However, the spatial assignment implies a dense coverage of 25–35 km between charging stations. Using only 45 min breaks instead of the permitted 15/30 min split, it can be demonstrated that a 750 kWh battery is required to fulfill the transport tasks of European long-haul freight transport.

Using a demand-oriented approach, Menter et al. [26] simulate a charging network with charging points (CPs) at every rest and service area in Germany using the framework MATSim. The usage of chargers in different electrification levels ranging from 1% to 20% is researched in detail. The agents do not split their 45 min breaks and charge at 720 kW constant power (1500 kW in the extrapolation scenario). In an initialization step, CPs are unlimited at each site, while in further iterations, the quantity is capped at the 70th percentile of simultaneously charging agents during initialization. With increasing electrification rates, the allocation of agents to the CP becomes more efficient, and queue duration decreases, while charging time remains constant due to the static strategy.

In previous works, we identified the time loss of BETs (compared to conventional drivetrains) as a key to the success of electric road freight transport and demonstrated the influence of infrastructure properties and drivetrain parameters on this time loss [11,27]. Adaptive strategy can help to mitigate these time losses [11]. In real driving data, rest time splits can also be observed [28].

2.2. Research Gap and Contributions

To summarize, different approaches have been presented to design fast-charging networks on (at least) a national scale. The main performance aims are maximized spatial coverage [21,22,29], speed of en-route charging [11,17,20,27], and charging queues [18,19,26], while costs are commonly considered in terms of installed infrastructure and grid integration.

In this article, we address multiple shortcomings of the current state of the art: By connecting vehicle, infrastructure, and operational strategy, the realistic system performance can be assessed. The increased modeling depth of the vehicle and operational strategy incorporates multiple nonlinear effects. Finally, the system-level KPI calculation enables a comparative assessment of proposed charging networks. In brief, this article's core contributions are as follows:

1 Quantification of time loss and spatial coverage.

We simultaneously quantify the time loss due to charging- and rest times, as well as the spatial coverage of different scenarios concerning vehicle and charging infrastructure.

2 Greater modeling detail.

Incorporated into the simulation are a self-optimizing charging strategy, nonlinear charging curves, and time-optimal routing on real road networks, as well as the allowance of a 15/30 min rest time split.

3 A case study examining two networks published by Speth et al. [19] in detail.

Our study contributes a case study of previously published charging networks, which—in combination with the greater modeling depth—enhances the understanding of their performance and adds new aspects to the analysis.

4 Newly derived networks to quantify required network density and robustness to outages.

By pruning out certain charging sites from [19], we derive charging networks of lower density. This creates an understanding of the necessary network density for a good system performance, as well as the degree of resilience towards site maintenance, technical faults, and other outages that will certainly occur in the infrastructure in real applications.

5 Charging strategy adaptation behavior.

In this study, the adaptation of the strategy to the available charging infrastructure is researched. The role of multi-stop strategies for time-optimal movement is highlighted in realistic scenarios in particular.

6 Microscopic resolution of a charging site's role within a network.

Through the presented method, it is possible to quantify the impact a single charging site has on the network level and identify regions of origin and destination that are served.

7 Identification of control levers to optimize system performance.

We assess and compare multiple approaches for future technology development to mitigate time loss and increase spatial coverage, including increased battery size, network density, and increased charging power

3. Methodology

In the proposed methodology, a macroscopic system consisting of a vehicle configuration, its strategy, and the charging network is analyzed by full factorial analysis of the possible routes within Germany. In our terminology, a *route* thus denotes the quickest path between two regions. A single *simulation* thus only comprises a single vehicle configuration simulated on a single route. In contrast, a *scenario* describes the collection of all possible routes in Germany simulated using a combination of a charging network and vehicle configuration.

Each simulation is broken down to the perspective of a single vehicle: the specific route and charging sites along it are isolated and simulated. Subsequently, the behavior is calculated and the selected rest and charging processes are logged. Then, the results are scaled according to the traffic flows (trucks per day) in 2019 on the simulated route [25]. Finally, the massively parallelized simulations' results are aggregated again per scenario, to provide system-level performance indicators. It should be noted that in all research scenarios, the same routes and the same traffic flows are simulated. A visual overview of the method is provided in Figure 1. The varied parameters are described in short in Table A2. The upcoming section explains the details of each step of modeling.

3.1. Routing

The first task in the modeling process is to determine the route a truck takes to get from an origin to a destination. First, the road network is modeled as a graph using the open-source software osm2po [30]. For the sake of simplicity and performance, minor roads such as residential roads were neglected. Speed limits are selected from specific labels provided in the Open Street Maps (OSM) data if present; otherwise, they are selected from the default values listed in Table A1.

Figures 2 and 3b show the results of the routing process: motorways and major highways are mainly restricted to a speed limit of 80 $\mathrm{km\,h^{-1}}$. The majority of the remaining roads allow movement at 60 $\mathrm{km\,h^{-1}}$. Slower speeds are mainly observed at links and junctions connecting motorways and highways. Following this, the travel times along the links are applied as costs, as freight forwarders are generally optimizing their main assets' utilization. This means that trucks should complete as many transport tasks in a given amount of time as possible. Dynamic speed limits, traffic lights, or traffic conditions are not considered in this model. Finally, the A* algorithm, in its implementation from the [13] project, is used to determine the time-optimal route through the network.

The routes are determined in full factorial sample for all possible origins and destinations among the 401 NUTS level 3 regions of Germany. These European statistical regions are equivalent to German counties (German: Kreise und kreisfreie Städte). Discarding relations in which origin equals destination, this yields $401 \cdot 401 - 401 = 160{,}400$ distinct routes through Germany. As an example, all routes leading to the City of Munich are visualized in Figure 2.

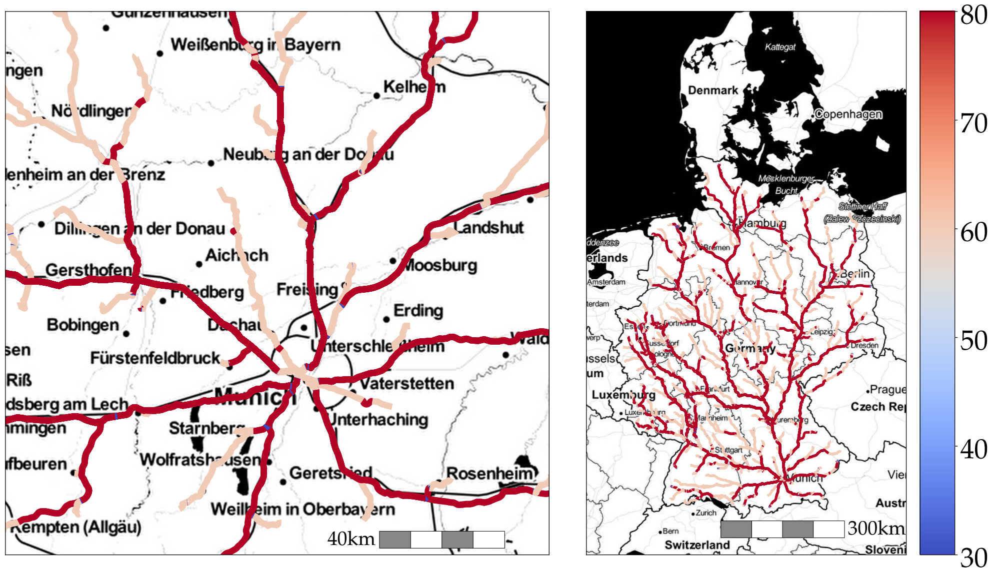
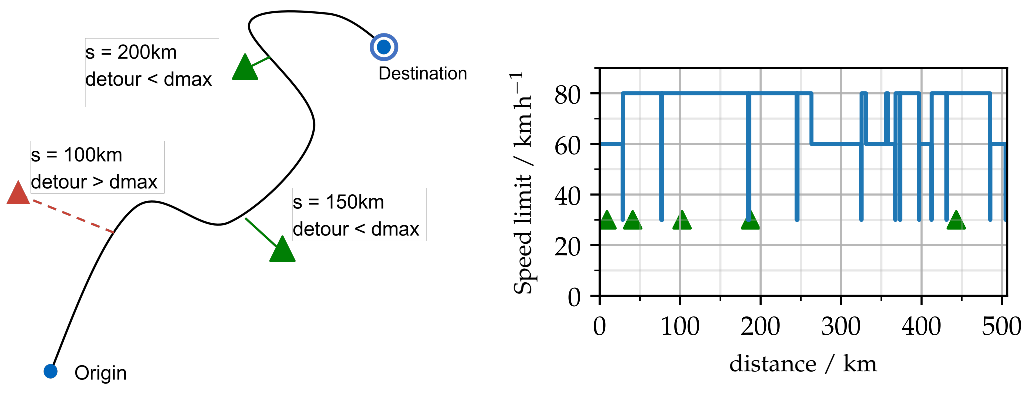


Figure 2. All time-minimizing routes leading to to Nomenclature of Territorial Units for Statistics (NUTS)-3 region DE211, the City of Munich. The speed limit is mostly 60 or 80 km h^{-1}, apart from links and junctions. Most traffic flows are captured by motorways after a few kilometers on regular highways. Attribution: Map tiles by Stamen Design, CC BY 3.0—Map data © OpenStreetMap contributors.



(**a**) (**b**)

Figure 3. Schematic overview of the mapping process. (**a**) Chargers are projected onto the route, using the shortest distance method. Chargers deviating from the route by more than 10 km are discarded. (**b**) Route sample: speed limits along the Gera–Plön route. Available chargers are displayed as green markers. Motorway changes are visible as short segments with 30 km h^{-1} speed limits.

3.2. Mapping

The routes, now present as polylines, are then mapped to the available charging stations of the charging network used in the simulation. Figure 3a visualizes this process: chargers within a parametric maximum distance to the original route are selected as possible rest locations. These are projected onto the original route orthogonally, and their distance from the starting point is saved for the simulation. It should be noted that, in the following simulation, detours are thus limited, but not further incorporated into the optimized driving strategy. By combining the results of the routing, distances, speed limit profile, mapping, as well as the position and properties of charging sites along the route, the input data for the simulation are complete. An example is shown in Figure 3b.

The charging network applied can be freely defined by providing only the geographic location. In this article, two networks, both defined by Speth et al. [19], are compared and varied. The WMN represents an initial charging network in Germany to accommodate domestic and transit traffic. The mean distance between charging stations is about 100 km and charging sites provide an average of 720 kW [19] (p. 8). The CMN is a network with a 50 km average distance between sites, which represents a more advanced state with higher electrification rates. In order to reflect the charging speed with the applied nonlinear charging curves (Figure A2) and provide comparable charging timea, the peak power of charging stations was increased to 1 MW. Both base networks are visualized in the appendix in Figure A1. In consecutive scenarios, the derivatives of the CMN and WMN are created and simulated by pruning out random sites from the charging network.

3.3. Simulation

Each individual route simulation is carried out using our separately published framework for the optimized truck charging strategy Battery Electric Truck Operational Strategy (BETOS) [31]. This ensures that each BET selects an individually optimal solution. In real applications, this would be equivalent to a navigation system incorporating charging speeds that are being consulted before departure. Thus, more realistic behavior is displayed and the performance and robustness of the charging network can be assessed more effectively. The base framework published in [31] remains unchanged; thus, in this section, we focus on the adaptations and input parameters specific to this publication. Since the metric for evaluating the charging networks in this work is chosen as the resulting time loss compared to diesel trucks, we use the total time required to complete the route as the optimization target for the charging strategy. It should be noted that chargers are always assumed to be free, to represent the primary charging demand at a site, as in the initialization run of [26].

In addition to the environment constraints (Figure 3b), vehicle parameters are used as inputs to the simulation framework. The analyzed scenario defines the starting battery state SOC_0 and the desired state SOC_{dest} at the end of the tour. In addition to these conditions, the minimum and maximum possible battery states $SOC_{min} = 0.15$ and $SOC_{max} = 1$, as well as the maximum possible battery C-rate of $3\,\mathrm{h}^{-1}$, are selected for this work. This corresponds with common values for the usable energy content of automotive battery systems. The charging capability of the vehicle is nonlinear, with a plateau of 3C between SOC 0.1 and 0.5 and the subsequent constant-voltage phase, as depicted in Figure A2. The actual charging speed is thus limited by the nonlinear charging capability of the vehicle and the power of the charger, which are constant throughout a scenario.

The global optimization for determining the optimal charging strategy ensures that the desired state of charge (SOC) is maintained on arrival. However, suppose the scenario requires that the starting SOC and the SOC on arrival are identical, and the charging network does not provide a point of interest (POI) along a route due to insufficient density. In that case, this condition cannot be met. Therefore, we formulated this condition as a soft constraint to consider such routes. For this purpose, the charging time required at the destination to reach the prescribed SOC is added to the total time t_{op} as a penalty. A charging power of $P_{dest} = 350$ kW is assumed for this recharging, so the additional time t_{add} is calculated based on the truck's battery capacity C_{bat}, as follows.

$$t_{add} = \max(0, SOC_{dest} - SOC_{end}) \cdot C_{bat} / P_{dest} \tag{1}$$

Each simulated route returns a set of summarizing values of the simulated trip, comparable to a trip logbook. Total time, energy consumption, and SOC constraint violations are recorded, as well as relevant parameters regarding breaks that took place during the trip. Each break is described by the ID of the charging site, the amount of energy charged, the arrival time, and the rest time at the site. It should be noted that, in some cases, breaks without charging are required to fulfill the mandatory rest periods. In other cases, both processes take place simultaneously.

As a single simulation takes, on average, 27.6 s to run on a single thread of an Intel Xeon Silver 4214R, so the sequential computation of 160,400 routes for only one scenario is prohibitively expensive. This conflict is resolved by massive parallelization across 19 heterogeneous virtual machines with up to 20 threads each. A full simulation of a scenario takes approximately 6 h.

3.4. Scaling

In order to incorporate the actual traffic flows, freight flow data from 2019, aggregated according to [25], are utilized. The dataset describes the OD matrix of traffic flows in trucks for European NUTS-3 regions and is visualized in Figure 4. It can be observed that the most frequented relations occur within a respective country (near the main diagonal). Some countries, like Cyprus, Finland, and Türkiye, are only loosely connected to the other European regions via road transport. Within Germany, all regions are relatively strongly interconnected. Particular clusters can be found in DE1 and DE2 (Southern Germany) and from DE9 to DEC (economic centers along the Rhine, Ruhr, and into Lower Saxony). In this study, only relations starting and ending in Germany are considered. This reduces computational effort, enables more scenarios to be compared, and is sufficient to build up the methodology. It can be observed that the German matrix is densely populated with traffic flows, which are roughly symmetric, reflecting the decentralized economic structure of the country. Domestic traffic accounts for approximately 85% of the mass of transported goods in Germany [26], with foreign traffic having higher market shares in long-haul transport.

The results of single-simulation runs are thus scaled according to the respective traffic flow between its origin and destination NUTS-3 regions. The breakdown of a single truck due to low SOC is weighted multiple times according to the corresponding traffic flow. The charging process is proportionally scaled in terms of kilowatt-hours (kWh). Finally, an electrification share s_{BET} and an annualization factor of $\frac{1}{286.3}$ adjust the annual values of the underlying data to the level of an average weekday (Monday–Friday). The factor is calculated from averaged hourly traffic count data from 2108 stations along the German motorways from 2020, available on [32]. On an average weekday, $\frac{1}{286.3}$ of the annual truck traffic was registered at the counting stations; on weekend days, on average, only $\frac{1}{1223.5}$ of the annual traffic passed the stations.

3.5. Aggregation

This section explains the process of aggregating the 160,400 routes between the 401 NUTS-3 regions per scenario to meaningful performance indicators. Depending on vehicle parameters and the charging network, each simulated vehicle can either succeed and reach its destination or violate the lower SOC boundary, in which case the route would be infeasible to drive. Thus, each simulated route contributes either a time loss (which may be zero) or a number of vehicles that could not reach the destination in the total scenario results. The two effects shall be decoupled and evaluated separately: for the evaluation of time loss, only routes that were completed successfully in all comparable scenarios are considered. The cumulative excess time divided by the cumulative driving and mandatory rest time yields the *relative time loss*. The sum of the traffic flow that is assigned to routes where the lower SOC constraint was violated, compared to the total simulated traffic flow, yields the *share of infeasible traffic flow*. To which category a route belongs may vary between scenarios: A scenario with a higher payload and increased consumption may lead to a vehicle on a certain route not making it to the next charging site. On another route with higher charging site density, increased consumption may only increase the charging time and may not render completing the route infeasible.

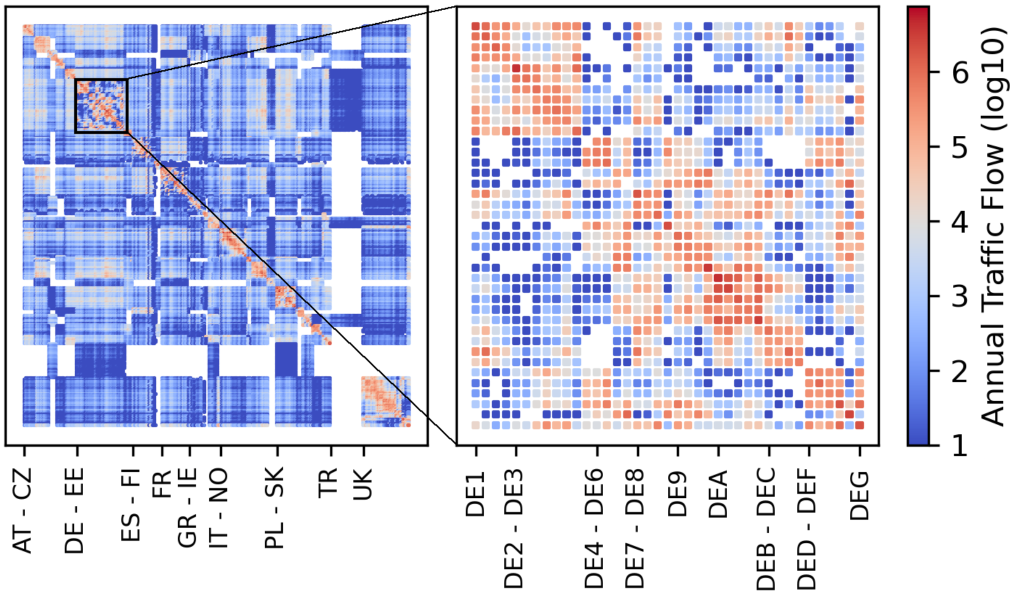


Figure 4. OD matrix of traffic flows in Europe (**left**) and Germany (**right**) per NUTS-2 region. Own visualization based on data from [25]. Colors indicate the intensity of traffic flow; domestic traffic for each country can be found near the main diagonal. Legend is X/Y symmetrical. Left: European countries (NUTS-0). Right: German regions (NUTS-2). The regions are provided in the 2006 revision of NUTS regions and are thus mapped to the closest NUTS-3 region of 2021 for this article.

The strategy BETOS calculates for the trucks is also evaluated: the number of *stops per route*, weighted according to the traffic flow on the route and by taking non-charging stops into account, provides insights about the strategy that is chosen. Another quantity of interest is the dwelling time at a rest location: to this end, the rest times are sorted into bins with the boundaries 0.4 h, 0.6 h, 0.8 h, and 1.2 h. Each stop is counted according to the traffic flow on the route and summed up to the *rest events by duration*.

By rearranging the trips according to the charging points used, network-level quantities can be computed. As each charger is characterized by a unique ID, the charging processes can be traced back to the location where the charging took place. An example is provided in Figure 5. The charging processes at a site in southern Germany in an exemplary scenario are caused by trips originating in central, western, and southwestern Germany, with the origins widely distributed. The destinations are strongly concentrated within the Munich Metropolitan Area, with Munich being responsible for 30% of the energy charged.

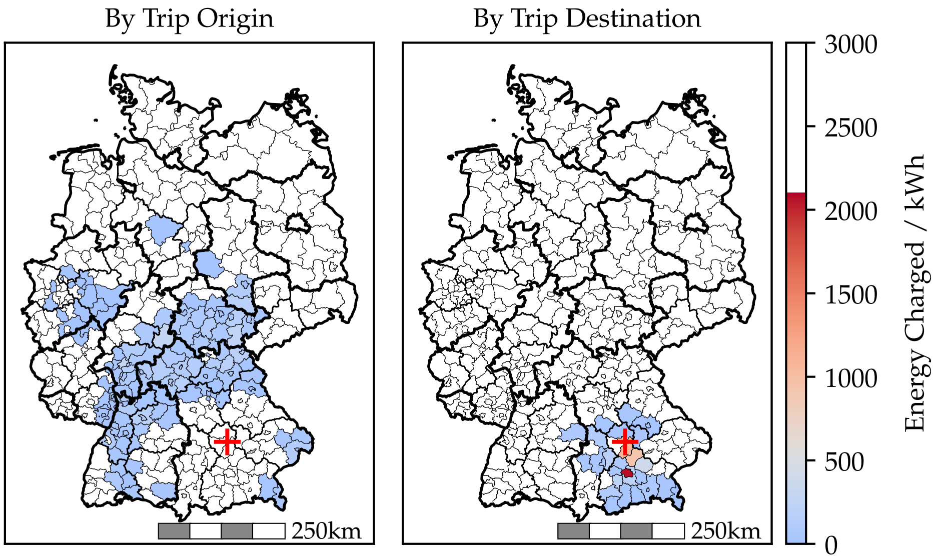


Figure 5. Origin and destination of trucks responsible for charging events at site ID 2102 in an exemplary scenario. The site is marked by a red cross and is located just south of Ingolstadt (Bavaria). The color scale indicates the energy aggregated by the NUTS-3 region of destination/origin.

4. Results

Multiple scenarios are simulated, representing reference scenarios as well as parameter variations of them. Infrastructure, strategy and vehicle parameters are varied; a detailed overview of all parameters is provided in Table A2.

The two charging networks, WMN and CMN, are simulated in reference cases where all trips start and end with a battery SOC of 50%. This setup ensures that trucks meet their energy needs en route, allowing for continuous long-haul transport without dependence on private charging infrastructure.

Each scenario varies a single parameter from the base cases. Changes in battery capacity of ± 100 kWh are explored in different scenarios. The impact of a high 24 t payload versus an average 13.6 t payload is examined in other specific scenarios. Charging power limitations are assessed in further scenarios, considering the announced first-generation MCS chargers at 700 kW and a proposed increase to 1.5 MW, meeting the limits of 3C-capable battery cells at 500 kWh.

The study also investigates the effect of unavailable charging stations, a real-world issue caused by technical problems, communication network issues, or construction work. A 95% availability rate for car charging infrastructure is considered based on German data. Advanced scenarios simulate a 5% station outage, while others explore the effects of up to a 50% outage rate. We aim to further understand optimization potentials within the network under these varying conditions.

4.1. Network Performance

The system performance of the simulation scenarios without charging site outages is visualized in Figure 6. It should be noted that only routes of at least 240 km (equivalent to 3 h of motorway driving) are included in the visualization to focus on long-haul transport. The method of aggregation is described in detail in Section 3.5. Globally, it can be observed that the network coverage in all scenarios is excellent, as more than 98% of the simulated routes are feasible without violation of the SOC constraint of 15%. The order of magnitude is in line with the findings by Menter et al. [26] (p. 15) of 0.3%. The time loss due to charging varies between 5.5% and 8.8%.

Among scenarios of a similar base network, an increase in charging power has the greatest impact on time loss and can cut time loss by about one fifth. Yet there is no impact on the share of infeasible routes, as gaps in the network remain unchanged, and insufficient traction energy can thus not be compensated. The effect of an increased battery capacity in the vehicle manifests as a marginally lower time loss combined with a lower infeasibility share. In contrast, lowered battery capacity and lowered charging power below the baseline of 500 kWh or 1 MW, respectively, show significant detrimental effects. This can be traced back to shorter driving legs and more necessary charging stops.

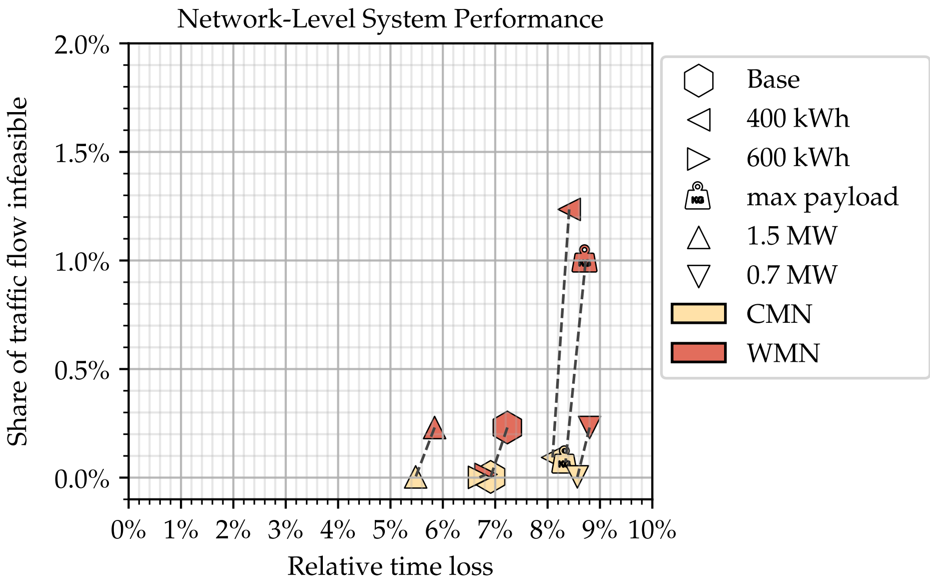


Figure 6. System performance of unilaterally time-optimized trucks operating within proposed charging networks. Each shape represents a single parameter variation of vehicle or infrastructure. The color indicates the network density of the base network (CMN vs. WMN). The KPI calculation is explained in detail in Section 3.5.

In the baseline scenario, all trucks carry 13.6 t of payload, far below their carrying capacity. It can be observed that the increased fuel consumption at a payload of 24 t renders some routes infeasible in wide-meshed networks. In contrast, the excess consumption can be remedied by refueling using the extra charging stations in CMNs. On both networks, logistics operators face an additional time loss of approximately 1.3%.

Comparatively, close-meshed networks perform strictly better in all corresponding scenarios: The increased number of charging stations offers better coverage and better synchronization of charging time with mandatory rest time. Also, a higher robustness to sub-optimal system parameters can be observed. This leads to the hypothesis that a network of higher density can also better compensate for site outages. Consequently, the specific system robustness to outages will be examined in detail in the following section.

4.2. Network Resilience

Figure 7 depicts the results of simulation runs with increasing random charger outages. The time loss is visualized to the left, whereas the right plot describes the effect on route infeasibility. Error bars in the plots indicate the standard deviation across multiple random draft scenarios, providing a measure of variability in the simulation outcomes.

The first key finding is the monotonic increase in time loss across derivatives from both base networks as outage levels increased. This is plausible because, by removing options from the agents, less preferable sites have to be selected. Bad synchronization with mandatory rest time and charging to higher SOC levels associated with slower charging are the main mechanisms of this time loss. Notably, the speed in the WMN without outages is on par with that in the close-meshed network at a 50% outage level. At the same time, both configurations have comparable numbers of charging sites and thus network density. This, again, demonstrates the correlation between network density and time loss.

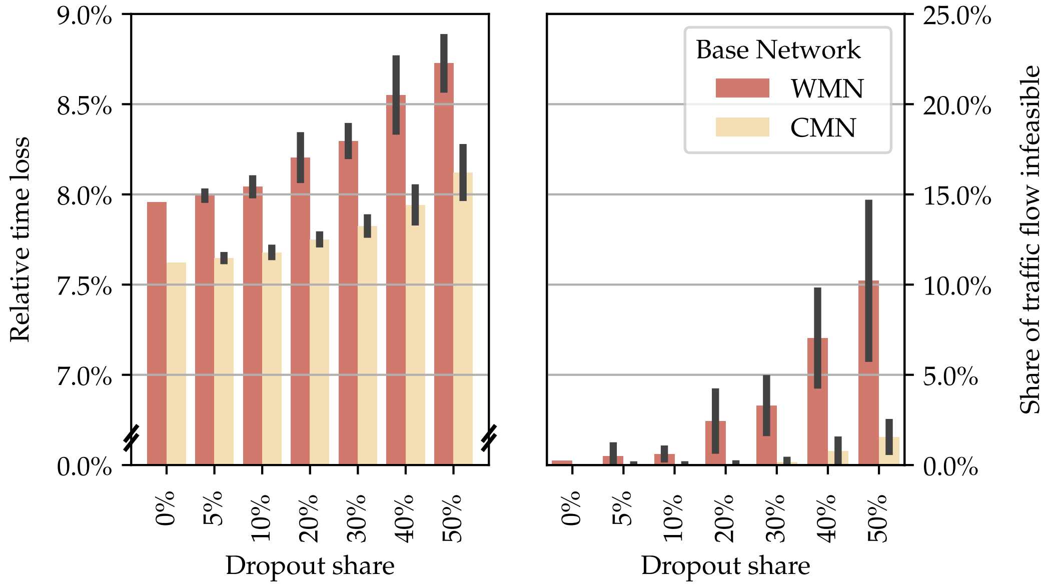


Figure 7. Network-level system performance of networks derived from CMN and WMN through random site removal. At higher dropout rates, the time loss increases as more unfavorable charging stops have to be factored in. Also, certain routes become infeasible to drive due to the amount of energy left. The KPI calculation is explained in detail in Section 3.5.

In real-world availability scenarios, represented by a 5% outage, the performance loss was marginal but measurable, indicating that both networks are robust to minor disruptions. Moreover, the small standard deviation indicates a certain degree of redundancy in the system. Generally speaking, the influence on time loss in low-to-mid outage level scenarios was smaller than in the system parameter variations of Figure 6. This can be traced back to the fact that the effective network density of the configurations is higher than their nominal value: the base networks are designed to reflect the alternative fuel infrastructure regulation (AFIR) guidelines of 50 km/100 km distance between charging sites [19]. But by counting sites along the simulated routes and weighting the observations by the traffic flow, it can be proved that average site distances of 34.53 km and 59.77 km, respectively, could be achieved. This is due to sites at intersections serving a larger part of the network than in hypothetical, purely linear configurations.

The analysis of traffic flow rendered infeasible reveals that close to zero breakdowns occur in CMNs, even at a 50% outage, displaying their high resilience towards outages. Derivatives of the WMN, however, translate the outage share into route infeasibility, starting at a 20% share. Nevertheless, networks at 60% availability of the original offer more than 90% coverage for long-haul transport. The calculated effective network density is measured at 103.86 km for this configuration.

To conclude, both networks display certain degrees of resilience towards outages, with the CMN providing far larger margins for outages. An important factor in this resilience is the strategic adaptations of the trucks, which pre-plan their respective strategies in the simulation optimally, even under outage scenarios. The mechanism of adaption is further examined in the following section.

4.3. Strategy

In the following analysis, only routes of at least 360 km are included, corresponding to a driving time of at least 4.5 h at an average speed of 80 km h^{-1} on motorways. These routes definitely require a mandatory break of 45 min. The results are visualized in Figure 8.

It should be noted that it is both legal and implemented in the BETOS to split the break into a 15 min break followed by a 30 min one.

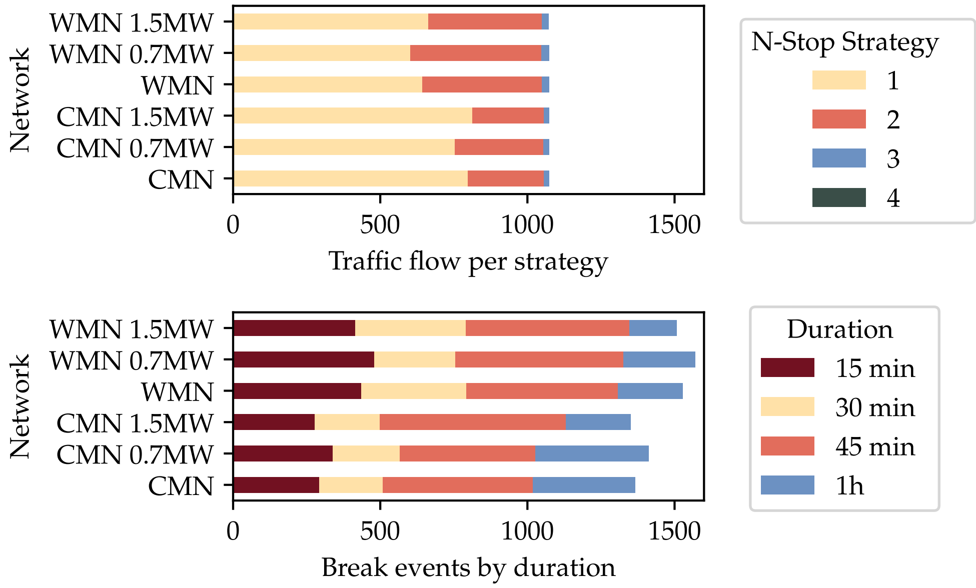


Figure 8. Evaluation of the strategies selected in varying infrastructure scenarios on long-haul routes of at least 360 km. (**Upper**) plot: number of scheduled stops in a trip. 4 stops are only required in edge cases. (**Lower**) plot: duration of the stops, binned at 0.2 h, 0.6 h, 0.8 h and 1.2 h. No stops above these limits were scheduled.

In order to isolate the effect of network density on the strategy, again, the base case simulations of CMN and WMN are evaluated. Additionally, the influence of increasing and decreasing available power is assessed by the inclusion of the derived 700 kW and 1.5 MW networks.

Throughout our simulations, the same predefined routes are utilized, ensuring consistency across all scenarios. Consequently, the upper graph of Figure 8 exhibits consistent stacked lengths, while the second plot exhibits varying numbers of pauses due to different strategies.

It can be observed that with a greater abundance of charging infrastructure associated with the CMN, it becomes more likely for a perfectly fitting 45 min stop to be integrated into the strategy. This behavior can save the 6 min of plug time that is required on each break. Furthermore, a weak tendency towards longer breaks with higher power levels and, conversely, shorter breaks with lower power levels is visible. Notably, 45 min breaks account for only 36% to 46% of the rest events in all scenarios, calling into question the commonly modeled neglection of the allowed rest time split, as this not time optimal in most scenarios. [19,21,26]

5. Discussion

The method presented comprises a vehicle model, charging infrastructure, and a modeled operational strategy in a real application context. Within this article, we demonstrate the individual influence of all the components on the overall system performance. In order to evaluate the performance, two key performance indicators are evaluated: time loss and spatial coverage.

This article focuses on the time loss component due to charging and mandatory rest periods, while other components have to be addressed separately: The queuing of trucks at charging sites can significantly increase their travel time and has to be addressed through a separate time-forward simulation. The power demand at large sites can reach several megawatts; thus, the electric grid capacity may not be sufficient. A sufficient electric grid connection or, conversely, the limitations of power drawing may represent two solution approaches and may lead to markedly increased investment costs or increased time loss, respectively.

Our study highlights the suitability of both CMN and WMN networks [19] for long-haul transport within Germany due to their extensive spatial coverage of over 99.5%. However, wide-meshed networks have notable limitations: 1% of the routes can not be operated at a full payload, and a residual time loss of 7.2% on remaining long-haul routes remains, even without the need for queuing at the charging site. Improvements can be achieved by increasing the charging station power, resulting in shorter charging times and possibly more sessions at a site, which is particularly valuable when space is constrained. Conversely, the CMN network showcases comparably small performance benefits. From a system perspective, we thus conclude that increased charging power at a site is a better expansion strategy than densifying the network beyond the WMN.

Hecht et al. [17] analyzed time-optimal routes for private electric cars on German motorways, assuming a comparable rest time model as for trucks. Significant findings [17] (p. 18) are supported by this study: a residual time loss of 8% is in line with our estimation of about 7% (Figure 6). Yet differences in the scenario definition demonstrate the sensitivity to system parameters: when starting at only 50% SOC, the a median of 20% time is lost compared to conventional vehicles [17]. It should be noted that the ranges of private vehicles are about 25% lower and the average C-rates about twofold higher. The charging power is thus almost exclusively limited by the car, which is not the case in our simulation. The importance of multiple short stops, in comparison to fewer long charging sessions, is also highlighted by the short average charging times [17] (Figure 21).

By focusing on the public charging aspect of the system, it is possible to analyze the specific requirements of long-haul transport, especially in applications where private or public destination charging infrastructure at the origin and destination is not available. This aspect is especially important to highlight, as it is commonly modeled that trucks start their day fully charged and end with a depleted battery [17,20,26,27]. Our model shows that, in such cases on domestic routes, only 0.6% of the consumed traction energy on routes over 300 km is drawn en route. With an average length of 343 km among those routes and an electric range of approximately 400 km, this is plausible. In related scenarios (100%/58% ensuring round-trip capability and 50%/50% ensuring infinite long-haul usage), our public charging share reaches 37% and 100%, respectively. Menter et al. [26] (Table 4) reach a public charging share of approximately 70%, which can partially be traced back to two modeling paradigms: the static charging strategy of charging up to 80%, whether needed or not for completing the driving task, increases charging demand, while foreign traffic puts more emphasis on long-haul routes. We conclude that quasi-stationary behavior should be achieved in future works so that public charging infrastructure is neither over- nor undersized, and temporal charging demand can be modeled more precisely.

The routing of trucks in this model reflects the current routes of conventional trucks: it optimizes driving time egoistically and statically under the neglection of dynamic constraints like queues at the charging hub. In this particular area, a routing engine that includes charging infrastructure parameters like power and density on different routes might further improve the speed of trucks. Queues at charging sites, describing dynamic components of the time loss, have been extensively studied in other research and will be considered in future iterations of the model. In the scope of this article, infrastructure parameters are assumed to be known at the moment of departure. This is a sound assumption for static information like the installed power and number of plugs at a site. For outage scenarios, an information system to communicate live availability would be required, however. Without this information, unknown site outages might result in significantly higher time losses or even the breakdown of vehicles. The increased travel time in outage scenarios was also highlighted by Hecht et al. [17], with approximately 2% to 7% excess time loss under varying outage scenarios, in line with our estimates of 0% to 10% on derivatives of the WMN.

Finally, the scope of the presented model is limited to Germany and intra-German traffic. Through the inclusion of European transit traffic, we expect that the focus will shift towards long-haul traffic in general, and spatially on the main routes of the TEN-T network in particular. The presented model offers these capabilities, as all data sources were picked and processed such that it is consistent throughout Europe.

6. Conclusions

This study advances the understanding of the interaction between battery electric trucks (BETs), their operational strategy, and fast charging infrastructure. Through simulation and evaluation, the research provides a detailed analysis of the performance and resilience of proposed charging networks and possible derivatives.

A crucial finding is that all analyzed networks are sufficient in terms of coverage to support electric trucks in Germany, even with reasonable security margins. Yet a time loss of 5.5% to 8.9% remains and can be mitigated most effectively through increased charging power. In contrast, the potential of improved battery capacity is found to be lower. This study also examines how outages in the network induce an adapted strategy. By shifting towards multiple shorter charging stops, time loss can be limited to an additional 0.12% at a 10% outage rate on a coarse charging network. The network density can be reduced by another 30% while still maintaining a coverage of over 90%.

While the case study was executed on two existing networks and their derivatives in Germany, the methodology and insights offer a widely applicable method of assessing the quality of service of charging networks throughout Europe.

In summary, this research significantly contributes to charging infrastructure planning, offering practical guidance for the development of efficient and resilient charging networks. However, its findings are equally relevant to regulatory bodies and logistics operators responsible for determining the efficiency of the system of electric goods transport.

Author Contributions: Conceptualization, G.B., M.Z., J.S. and M.L.; methodology, G.B. and M.Z.; software, G.B. and M.Z.; validation, G.B. and J.S.; data curation, G.B.; writing—original draft preparation, G.B., J.S. and M.Z.; writing—review and editing, G.B., J.S. and M.L.; visualization, G.B. and M.Z.; supervision, M.L.; project administration, G.B., M.Z. and J.S.; funding acquisition, M.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AFIR	Alternative Fuel Infrastructure Regulation
BET	Battery Electric Truck
BETOS	Battery Electric Truck Operational Strategy
CMN	Close-meshed Network
CP	Charging points
GIS	Geographic Information Systems
MCS	Megawatt Charging System
NUTS	Nomenclature of Territorial Units for Statistics
OSM	Open Street Maps
POI	Points of Interest
SOC	State of Charge
TEN-T	Trans-European Transport Network
WMN	Wide-meshed Network

Appendix A. Details of the Presented Model

Appendix A.1. Charging Network

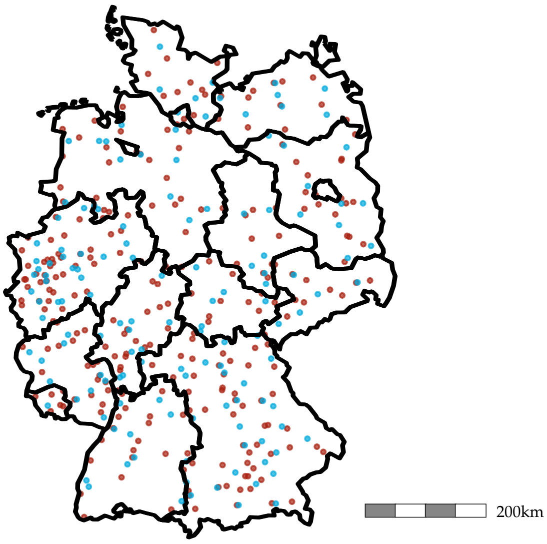

Figure A1. Overview of the simulated charging networks adapted from Speth et al. [19]. Red: CMN. Blue: WMN.

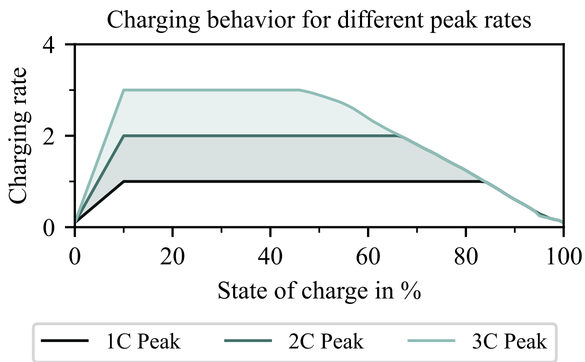

Figure A2. Charging curves of different cell models as in [31]; this article exclusively simulates a 3C peak C-rate.

Appendix A.2. Highway Network

Table A1. OSM street types and respective default speed limits used, in accordance with German laws. Speed limits are overridden if a specific speed limit for trucks (key: "maxspeed:hgv") is provided.

Values of "Highway" Key	Max Speed	Specific Edge Cost in h km $^{-1}$
motorway, trunk	80 km h^{-1}	0.01250
primary, secondary, tertiary	60 km h^{-1}	0.01667
motorway_link, trunk_link, primary_link, secondary_link, tertiary_link motorway_junction	30 km h^{-1}	0.03333
road	50 km h^{-1}	0.02000

Appendix A.3. Simulation Parameters

Table A2. Overview of simulation parameters and variations. Default parameter value marked with an asterisk.

Parameter	Values
Base network	WMN * CMN *
Battery capacity	400 kWh 500 kWh * 600 kWh
Charging power (max.)	700 kW 1000 kW * 1500 kW
SOC at start/end	100%/50% 100%/15% 50%/50% *
Payload	13.6 t * 24 t
Outage	Random 50% Random 40% Random 30% Random 20% Random 10% Random 5% 0% *

References

1. Razmjoo, A.; Ghazanfari, A.; Jahangiri, M.; Franklin, E.; Denai, M.; Marzband, M.; Astiaso Garcia, D.; Maheri, A. A Comprehensive Study on the Expansion of Electric Vehicles in Europe. *Appl. Sci.* **2022**, *12*, 11656. [CrossRef]
2. European Automobile Manufacturers' Association (ACEA). New Medium and Heavy Commercial Vehicle Registrations by Fuel Type, European Union. Available online: https://www.acea.auto/files/ACEA_Trucks_by_fuel_type_full-year-2022.pdf (accessed on 8 March 2023).
3. Wolff, S.P. Eco-Efficiency Assessment of Zero-Emission Heavy-Duty Vehicle Concepts. Ph.D. Thesis, Technische Universität München, Munich, Germany, 2023.
4. Daimler Truck AG. Der Man Etgx Elektrifiziert Den Fernverkehr. Available online: https://www.man.eu/de/de/lkw/alle-modelle/der-man-tgx/der-man-etgx/uebersicht.html (accessed on 27 November 2023).
5. MAN Truck & Bus SE. Der neue eActros | 600 Charged to Change. Available online: https://eactros600.mercedes-benz-trucks.com/de/de/eactros-600/showroom.html (accessed on 27 November 2023).
6. Sugihara, C.; Hardman, S.; Kurani, K. Social, technological, and economic barriers to heavy-duty truck electrification. *Res. Transp. Bus. Manag.* **2023**, *51*, 101064. [CrossRef]
7. Aral Aktiengesellschaft. Dekarbonisierung des Schwerlastverkehrs: Aral Eröffnet Europas Ersten Ladekorridor für Elektrische Lkw. Available online: https://www.aral.de/de/global/retail/presse/pressemeldungen/pm-2023-aral-eroeffnet-europas-ersten-ladekorridor-fuer-elektrische-lkw.html (accessed on 27 November 2023).
8. Commercial Vehicle Charging Europe B.V. Milence and Port of Antwerp-Bruges Reach an Agreement to Develop a 30-Bay Charging Hub for Heavy-Duty Vehicles. Available online: https://milence.com/press-release/milence-and-port-of-antwerp-bruges-reach-an-agreement-to-develop-a-30-bay-charging-hub-for-heavy-duty-vehicles/ (accessed on 22 November 2023).
9. Council of the EU and the European Council. Fit for 55: Towards More Sustainable Transport—Consilium. Available online: https://www.consilium.europa.eu/en/infographics/fit-for-55-afir-alternative-fuels-infrastructure-regulation/ (accessed on 14 August 2023).
10. NOW GmbH—National Centre for Charging Infrastructure. Einfach Laden an Rastanlagen | Auslegung des Netzanschlusses für E-Lkw-Lade-Hubs. Available online: https://nationale-leitstelle.de/wp-content/uploads/2022/09/Leitstelle_LKW-Netzstudie.pdf (accessed on 27 November 2023).
11. Zähringer, M.; Wolff, S.; Schneider, J.; Balke, G.; Lienkamp, M. Time vs. Capacity—The Potential of Optimal Charging Stop Strategies for Battery Electric Trucks. *Energies* **2022**, *15*, 7137. [CrossRef]
12. PostGIS Project Steering Committee and Others: PostGIS, Spatial and Geographic Objects for postgreSQL. Software Version 3.3.2. Available online: https://postgis.net (accessed on 7 April 2023).

13. pgRouting Project—Open Source Routing Library. Software Version 3.5.0. Available online: https://pgrouting.org/ (accessed on 14 August 2023).
14. Deb, S.; Tammi, K.; Kalita, K.; Mahanta, P. Review of recent trends in charging infrastructure planning for electric vehicles. *WIREs Energy Environ.* **2018**, *7*, e306. [CrossRef]
15. Metais, M.; Jouini, O.; Perez, Y.; Berrada, J.; Suomalainen, E. Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options. *Renew. Sustain. Energy Rev.* **2022**, *153*, 111719. [CrossRef]
16. Al-Hanahi, B.; Ahmad, I.; Habibi, D.; Masoum, M.A.S. Charging Infrastructure for Commercial Electric Vehicles: Challenges and Future Works. *IEEE Access* **2021**, *9*, 121476–121492. [CrossRef]
17. Hecht, C.; Victor, K.; Zurmühlen, S.; Sauer, D.U. Electric vehicle route planning using real-world charging infrastructure in Germany. *eTransportation* **2021**, *10*, 100143. [CrossRef]
18. Speth, D.; Sauter, V.; Plötz, P. Where to Charge Electric Trucks in Europe—Modelling a Charging Infrastructure Network. *World Electr. Veh. J.* **2022**, *13*, 162. [CrossRef]
19. Speth, D.; Plötz, P.; Funke, S.; Vallarella, E. Public fast charging infrastructure for battery electric trucks—A model-based network for Germany. *Environ. Res. Infrastruct. Sustain.* **2022**, *2*, 025004. [CrossRef]
20. Borlaug, B.; Moniot, M.; Birky, A.; Alexander, M.; Muratori, M. Charging needs for electric semi-trailer trucks. *Renew. Sustain. Energy Transit.* **2022**, *2*, 100038. [CrossRef]
21. Shoman, W.; Yeh, S.; Sprei, F.; Plötz, P.; Speth, D. Battery electric long-haul trucks in Europe: Public charging, energy, and power requirements. *Transp. Res. Part D Transp. Environ.* **2023**, *121*, 103825. [CrossRef]
22. Hurtado-Beltran, A.; Rilett, L.R.; Nam, Y. Driving Coverage of Charging Stations for Battery Electric Trucks Located at Truck Stop Facilities. *Transp. Res. Rec.* **2021**, *2675*, 850–866. [CrossRef]
23. Danese, A.; Garau, M.; Sumper, A.; Torsæter, B.N. Electrical Infrastructure Design Methodology of Dynamic and Static Charging for Heavy and Light Duty Electric Vehicles. *Energies* **2021**, *14*, 3362. [CrossRef]
24. Çabukoglu, E.; Georges, G.; Küng, L.; Pareschi, G.; Boulouchos, K. Battery electric propulsion: An option for heavy-duty vehicles? Results from a Swiss case-study. *Transp. Res. Part Emerg. Technol.* **2018**, *88*, 107–123. [CrossRef]
25. Speth, D.; Sauter, V.; Plötz, P.; Signer, T. Synthetic European road freight transport flow data. *Data Brief* **2022**, *40*, 107786. [CrossRef] [PubMed]
26. Menter, J.; Fay, T.A.; Grahle, A.; Göhlich, D. Long-Distance Electric Truck Traffic: Analysis, Modeling and Designing a Demand-Oriented Charging Network for Germany. *World Electr. Veh. J.* **2023**, *14*, 205. [CrossRef]
27. Schneider, J.; Teichert, O.; Zähringer, M.; Balke, G.; Lienkamp, M. The novel Megawatt Charging System standard: Impact on battery size and cell requirements for battery-electric long-haul trucks. *eTransportation* **2023**, *17*, 100253. [CrossRef]
28. Balke, G.; Adenaw, L. Heavy commercial vehicles' mobility: Dataset of trucks' anonymized recorded driving and operation (DT-CARGO). *Data Brief* **2023**, *48*, 109246. [CrossRef] [PubMed]
29. Asamer, J.; Reinthaler, M.; Ruthmair, M.; Straub, M.; Puchinger, J. Optimizing charging station locations for urban taxi providers. *Transp. Res. Part D Policy Pract.* **2016**, *85*, 233–246. [CrossRef]
30. Moeller, C. Osm2po-OpenStreetMap Converter and Routing Engine for Java. Software Version 5.5.6. Pinneberg, Germany. Available online: https://osm2po.de/ (accessed on 14 August 2023).
31. Zähringer, M.; Wolff, S.; Schneider, J.; Balke, G.; Lienkamp, M. Essential for battery electric long-haul trucks: An optimal dynamic charging strategy. *eTransportation* **2024**, *under review*.
32. Bundesanstalt für Straßenwesen BaSt. Automatische Dauerzählstellen auf Autobahnen und Bundesstraßen. Available online: https://www.bast.de/DE/Verkehrstechnik/Fachthemen/v2-verkehrszaehlung/Verkehrszaehlung.html (accessed on 2 November 2023).

4.1.3 Updates to the Published Work

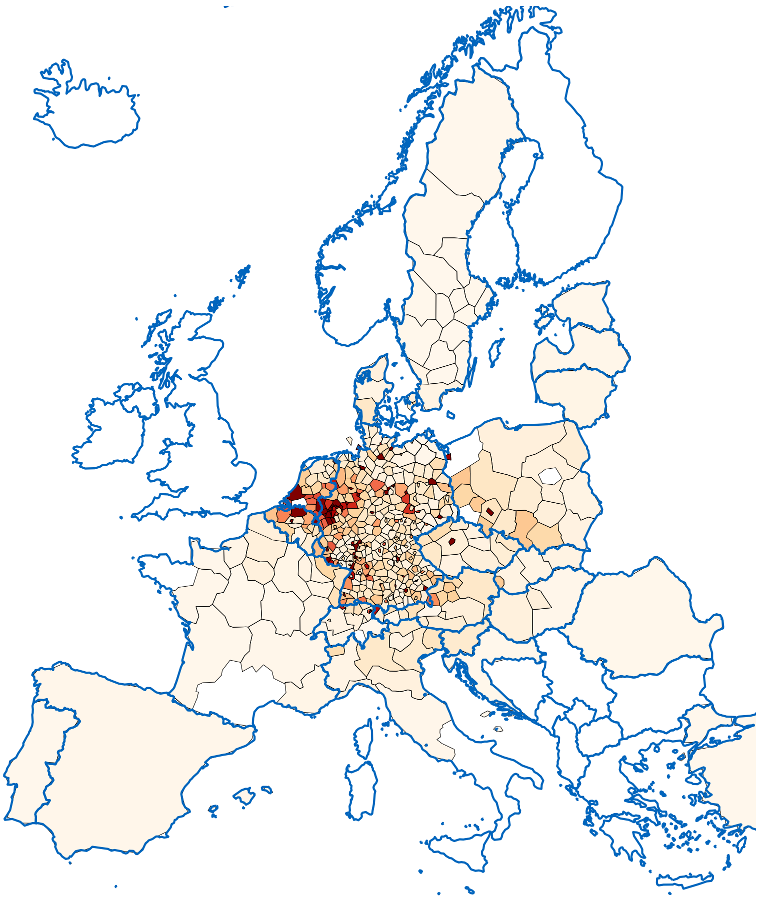

Figure 4.2: Map of Europe visualizing the yearly traffic performance on German roads departing from a region. Own visualization based on traffic flow data in [96], routing based on [83]*, filtered for long-haul traffic (>$200\,\mathrm{km}$). The color of a region corresponds to the traffic performance divided by its area, to correct for unequal region sizes. Cut-off for color scale above $1\,\mathrm{t\,km\,m^{-2}}$.

The methodology presented within [83]* is at the core of the following analyses. Yet limitations that remained at the time of publication will be addressed within this thesis: The publication [83]* only considered German domestic traffic, yet international traffic constitutes a significant share of the traffic flow. The main limitation, the neglect of site capacities and queuing, will be addressed in Section 4.2.

In 2023, $12.8\,\%$ of the transported freight mass in Germany was transported by foreign vehicles [118]. Yet in the same year, these trucks were responsible for $45.7\,\%$ of the traffic performance [118]. This is explicable by foreign vehicles contributing disproportionately large market shares to long-haul transport. To visualize this, Figure 4.2 depicts the dependency between the origin region of freight in Europe, and the corresponding traffic performance caused on German motorways: Strong economic ties with all neighboring countries are clearly visible. Yet certain regions, especially around the large deep-sea ports in Antwerp and Rotterdam, generate exceptional traffic, even higher than domestic industrial centers. But the international traffic does not only contribute to the road depreciation: Via fuel taxes and kilometer-based tolls, every truck on the motorways and federal highways is contributing to the maintenance of the road network. According to toll statistics, in 2020, $40.2\,\%$ of kilometers were driven by foreign-registered vehicles [119]. By far the largest foreign country of origin was Poland, followed by Czechia and Romania.

The need to include international traffic is thus obvious. The initial publication [83]* connects all 401 administrative NUTS-3 regions of Germany in a full-factorial way. To expand this approach directly to the approx.

2000 European NUTS-3 regions would increase the computational load quadratically, due to the generally longer routes to simulate, even more. Thus, a more efficient approach has to be conceived.

This computational problem will be addressed now, and a methodology for the efficient integration of international and transit traffic will be incorporated into the dynamic simulation framework. Following this, the two charging networks developed Section 3.2 will be thoroughly evaluated and the previously formulated hypothesis H.2 tested. Finally, the newly created charging networks will be compared against the state of the art, namely charging networks presented in Speth et al. [70].

Methodology

In order to reduce the computational effort of the traffic assignment and simulation, two steps are implemented. These steps reassign the OD matrix of Europe down to the partial road network in Germany. The two steps are:

1. the aggregation of regions to reduce the number of OD relations,
2. and the cropping of routes to the cordon area to reduce computational effort.

As the first step, the regions of higher proximity to Germany and stronger traffic interconnection should be resolved in greater detail within the model. These considerations have already been made within the German Verkehrsverflechtungsprognose (forecast of transport interconnectivity) (VVP) 2030 [98], which forecasts traffic as OD-flows for the years until 2030. Here, a heterogeneous resolution is implemented [98]. This is

Figure 4.3: Visualization of route ID 369659 (BE10 Brussels to CZ01 Prague) cropped to the German road network, along with chargers from E-OPT network. Source basemap: Maptiler.

also visualized in Figure 4.2 by the thin black lines separating regions. In this aggregation, Germany is fully resolved up to NUTS-3 level [98]. Remote countries like Spain, Norway, or Romania are resolved only on the national state level (NUTS-0), no differentiation regarding the exact origin or destination of traffic is made [98]. In between, regions are individually resolved on NUTS-1, NUTS-2 or NUTS-3 level, like in Poland, France, or Austria. This approach reduces the number of regions to 632, or 399424 relations in a full-factorial model. The application of this aggregation to the presented dynamic model has been implemented within a student project by Nguyen [120].

In the second step, the routes from origin to destination are calculated and cropped to the German road network. Germany, here is modeled as a cordon area. Traffic flows entering and exiting are resolved, but movements outside the cordon are not considered further. Within the work of Nguyen [120], it could be demonstrated that traffic counts on the road network indicate a higher usage proportion of motorways to highways, compared to the presented method [83][*]. So to improve the model accuracy of the routing algorithm, an updated parameter set for the cost of traveling on certain route types compared to [83][*] is used, in which non-motorway roads are assigned a speed penalty, so that stronger motorway usage is encouraged. Table A.1 lists these final parameters. The final result, including the cropping, is visualized as an exemplary route in Figure 4.3: There, the route from Brussels to Prague is selected, which has a total distance of $899\,\mathrm{km}$. This distance could be reduced to only the $598\,\mathrm{km}$ spent on the German road network, decreasing computational effort by $34\,\%$.

When comparing the simulated traffic flows to the measurements at counting stations, as in Figure 4.4, there is a stronger correlation ($R^2 = 0.484$) between the simulated traffic flows and the measurements of tractor-trailer combinations on the motorways than in the related literature [73, Fig. 12] ($R^2 = 0.008$, $R^2 = -1.66$). On average, the traffic flow in the simulation is 1.29-fold higher than the tractor-trailer combinations observed

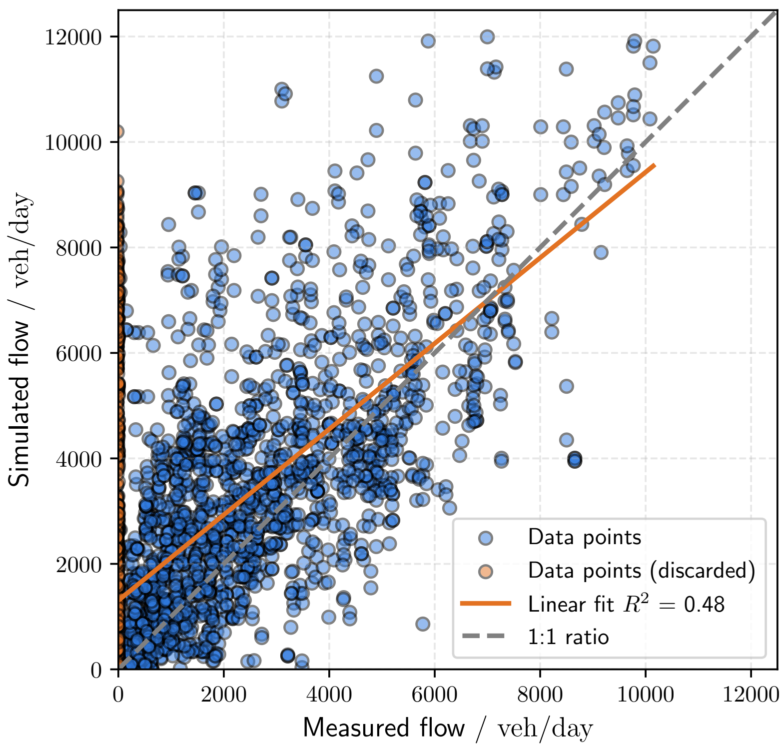

Figure 4.4: Average Tuesday traffic at 2077 counting stations [121] along the German motorways in 2021. $15.17\,\%$ of real counting stations are discarded as they did not count a single vehicle over a year. Only observations of tractor-trailer combinations at physical counting stations were evaluated. In 2021, there were no public holidays on Tuesdays.

at counting stations [121]. The apparent overestimation can be made plausible, as tractor-trailer configurations dominate long-haul freight transport [116][*], but are, e.g., rivaled by rigid trucks with additional trailers in volume-constrained applications. At the same time, not every tractor-trailer in the counting stations undertakes truly long-haul journeys, which strengthens the argument for an overestimation of the traffic performance.

The remainder of the analysis - especially the V-Model of routing, mapping, simulation, scaling, and aggregation remains as presented in [83][*].

The first of the following sections will examine the spatial coverage of the presented charging networks. The research question is, how many missions can not be completed due to gaps in the charging network, and whether there is a systematic bias among these infeasible missions.

The second part of the analysis is dedicated to time loss: Time loss in this context describes the additional time a BET needs to complete a certain transport task in comparison to a Diesel truck. The calculation has already been introduced in [33][*] and includes the mandatory rest times all truck drivers in Europe have to follow. Thus, time loss mainly occurs in three contexts:

1. When the charging power is too low, the charging time exceeds the mandatory rest time. This excess time is then counted as time loss.

2. Secondly, insufficient battery capacities lead to additional charging stops that a Diesel truck would not have needed at all.

3. Queues at charging stations increase the required dwelling time.

All three aspects are closely related to infrastructure design:

1. The charging power is limited not only by the vehicle, but also by the available charging power due to charging point or load management limitations. This excess time is then counted as time loss.

2. Large gaps within the charging network require trucks to bridge the gaps with charging breaks before and after, instead of charging when convenient.

3. The number of plugs per site has to be sufficient to avoid excessive queuing.

Aspects one and two will be analyzed within the decoupled model in this section, while the analysis of aspect three requires the coupled model presented in the following Section 4.2.

Results and Discussion

Within this section, multiple charging networks and vehicle configurations are being compared. These will mainly be referred to by their shorthand label. The labels along with the main characteristics of the scenarios are presented in Table 4.1, while the maps of the charging networks can be seen in the appendix in Figure A.1.

Table 4.1: Overview of the simulated scenarios. INIT-U, INIT-A: Initial charging network at unserviced areas / all areas as published in [61]. In all scenarios, initial and terminal SOC are kept at 50 %, which leads to the long-haul transport charging its complete energy demand at public fast charging stations. Deviations from this model are discussed in [83, p. 14] and [84, Fig. 4].

Scenario Label	Charging Network	Battery Capacity	Start SOC	End SOC	Max Charging Power	Number Charging Sites
M-OPT	M-OPT	500 kWh	50 %	50 %	1000 kW	135
E-OPT	E-OPT	500 kWh	50 %	50 %	1000 kW	135
WMN	WMN	500 kWh	50 %	50 %	1000 kW	141
INIT-U	INIT-U	500 kWh	50 %	50 %	1000 kW	125
INIT-A	INIT-A	500 kWh	50 %	50 %	1000 kW	352
400kWh	E-OPT	400 kWh	50 %	50 %	1000 kW	135
600kWh	E-OPT	600 kWh	50 %	50 %	1000 kW	135
1.5MW	E-OPT	500 kWh	50 %	50 %	1500 kW	135

Figure 4.5 provides a comparison of the performance of the new M-OPT and E-OPT networks, as well as the WMN adapted from Speth et al. [70], the initial charging networks at unserviced rest areas (INIT-U), and at all areas (INIT-A) [61]. The evaluation considers time loss and routes infeasible to drive electrically. Networks M-OPT, E-OPT, WMN, and INIT-U have a similar density, while INIT-A consists of significantly more charging sites.

It is immediately visible that WMN, M-OPT, and E-OPT show comparable characteristics in general, consistent with their equivalent average density and equal installed charging power. The initial charging network has a slightly lower density at 92.5 % of E-OPT and M-OPT, contributing to a time loss more severe than in all other charging networks. The scenario already assumes 1000 kW of available charging power, yet only 800 kW are mandated during demand surges by the public tender [61]. The similar performance of M-OPT and E-OPT can certainly be attributed to the rigid constraints that the AFIR sets. This alone is a significant finding, as it confirms that the legislation does set targets that are guaranteed to result in a charging network of high quality. The time loss has a noticeable gradient, with the M-OPT network having a slight edge over E-OPT, and a more pronounced advantage over the WMN. While this level of time loss seems insignificant overall, it is a direct measure of the productivity loss of a truck and, thus, can mean the difference between operating at a profit or at a loss in the price-competitive freight transport market. Notably, the INIT-A network exhibits no better time loss performance compared to E-OPT and M-OPT despite its high density, which hints at a saturation effect in practice, where even higher density does not improve the performance anymore.

Considering the infeasible routes, Figure A.1 in the appendix provides a detailed overview of the specific routes that are rendered infeasible in certain scenarios. The center plot of Figure 4.5 displays coverage rates of 99.7 % and 100 % for M-OPT, E-OPT, WMN, and INIT-A generally in the expected range considering [83, Fig.7]. The initial charging network at unserviced areas INIT-U achieves markedly worse coverage at only 75 %. Figure A.1 demonstrates that large stretches of main routes are not serviced by any charging site, e.g., along the A1 between Münster and Kiel, but also A3 or A4. The extension to serviced areas as planned is thus badly needed for the success of BET in long-haul transport and the fulfillment of the legal AFIR requirements.

Among the three theoretical networks, interestingly, the WMN leads before E-OPT and M-OPT networks, with more vehicles reaching their destination. An examination of the underlying data confirms that mainly routes along minor north-south axes are affected by breakdowns, especially along the A61 motorway

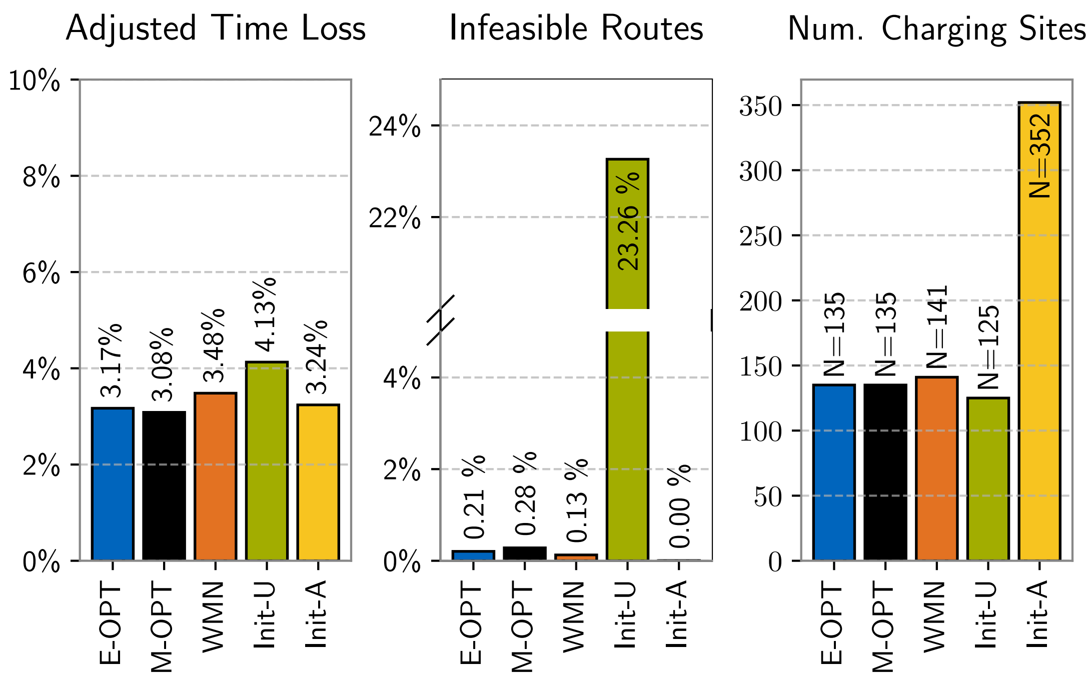

Figure 4.5: Quantitative comparison of charging network performance of different charging networks. Sources: E-OPT and M-OPT conceived in Section 3.2 based on Balke et al. [84]*, WMN adapted from Speth et al. [70]. INIT-U and INIT-A adapted from [61]. Adjusted time loss and infeasible routes computed as presented in Balke et al. [83]*. Public Charging share indicates that slightly more electric energy is charged than consumed due to discretization errors. This is corrected for through the time loss adjustment. Also refer to Figure A.1 for a visualization of infeasible routes.

from Mannheim to the Netherlands and the A71 motorway from Nuremberg to Erfurt. Both are TEN-T comprehensive motorways that are served by charging sites on larger core motorways. In practice, of course, these problems are known ahead of the journey and could be mitigated through several strategies: An adapted route choice, following motorways with more charging sites, would be the intuitive solution, but it would require detours. Charging more energy ahead of time (possibly on private charging infrastructure) is also possible. Both of these solutions would transform the infeasible route into a route with significant time loss, though. Finally, a fleet operator could also resort to using a truck with a higher range, although this directly requires a larger financial investment, or continue operating ICE trucks.

With these findings, hypothesis H.2 can be partly confirmed: Both newly created networks demonstrate excellent coverage and low time loss, meeting the goals of the AFIR. The results suggest that both proposed networks are well-suited to support the widespread adoption of BET in long-haul freight transport. Yet the small differences in time loss between the networks likely do not outweigh the significant economic and energetic benefits of a better connection to the high-voltage grid. An easier connection comes with reduced investment costs, but also potentially with a greater peak load that can be drawn from the grid. It thus facilitates the market growth and also the adaptation of higher-power charging infrastructure than $1\,\mathrm{MW}$. So, from a topology perspective, a layout that prioritizes proximity to the high-voltage grid is the dominant strategy. It has a marginal trade-off in service from a mobility perspective, and the reduced investment costs leave room to compensate for that effect by increasing charging power. The residual time loss and mitigation strategies for it shall be examined in detail next.

Figure 4.6 resolves the time loss on all simulated routes on two different scales: In the upper plot, the absolute time loss on all routes (in minutes) is provided as a probability distribution. This is beneficial to identify the specific mechanisms that lead to time loss. All scenarios generally exhibit the same profile: A high density at $0\,\mathrm{min}$ time loss reflects the fact that approx. A third of driving tasks can be carried out with no time loss at

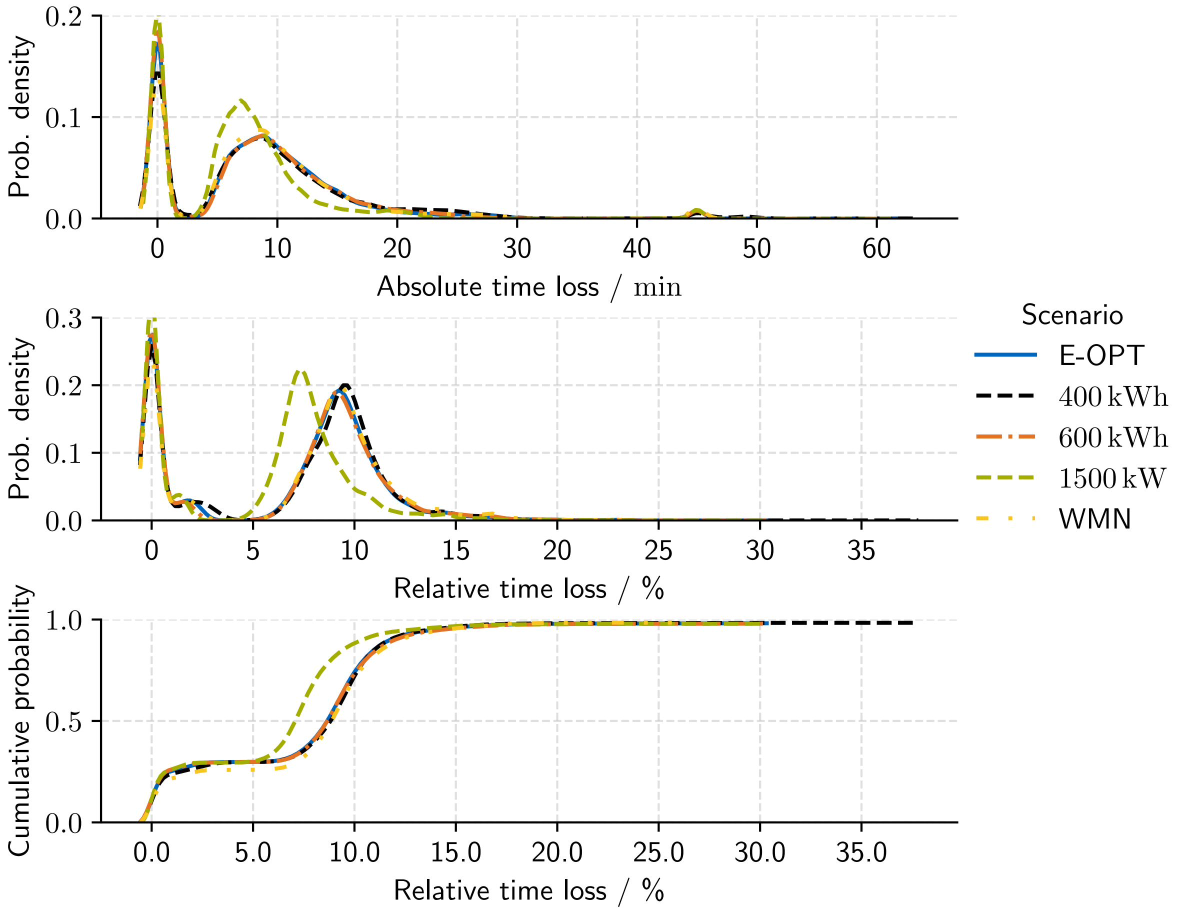

Figure 4.6: Distribution of time loss on all simulated routes, weighted by the average annual daily traffic (AADT).

all. This is followed by a high density of routes with time loss below 20 min. In edge cases, a 45 min time loss is observed, when necessary charging can not be aligned with mandated breaks. These occur only on extremely long routes, as the average operation time of routes exhibiting this anomaly is 11.6 h.

The center and lower plots display the relative time losses, so the time loss is in relation to the driving time. The majority of cases reflect the first of the three mechanisms presented in the previous section: Here, the charging time exceeds the legally required break time. In other words, the driver has to wait for the truck to finish charging. An effective mitigation strategy would thus move this peak in the diagram as far left as possible. Among the strategies tested, increased or decreased battery capacity has equally marginal effects. The share of traffic that has a low time loss (<5 %) can only be increased from 31.56 % to 31.6 % by increasing the battery capacity, as charging power instead of range is the limiting factor here. The network configuration has a measurable impact, too: The M-OPT network configuration provides low time loss service to 33.28 % of trucks, while the WMN configuration is at 27.39 %.

But the greatest technical lever is the available charging power: By increasing the charging power to 1.5 MW, the share raises to 31.95 %, and even more importantly: The time losses above 5 % decrease significantly, as can be seen in the cumulative density distribution in the lower plot of Figure 4.6.

This leads to the conclusion that in real-world long-haul applications that rely solely on public charging, the charging power is a greater lever than the battery capacity. A strong grid connection of the charging site facilitates higher charging powers generally, so this again gives rise to an energy-system-centered design of charging networks. On the other hand, this simulation simulates all trucks electrically – but in a free market, each fleet operator can decide whether to buy an electric truck or not. And in this case, fleet operators that would have to transport on high time loss routes, would likely decide against switching to a BET. In this case,

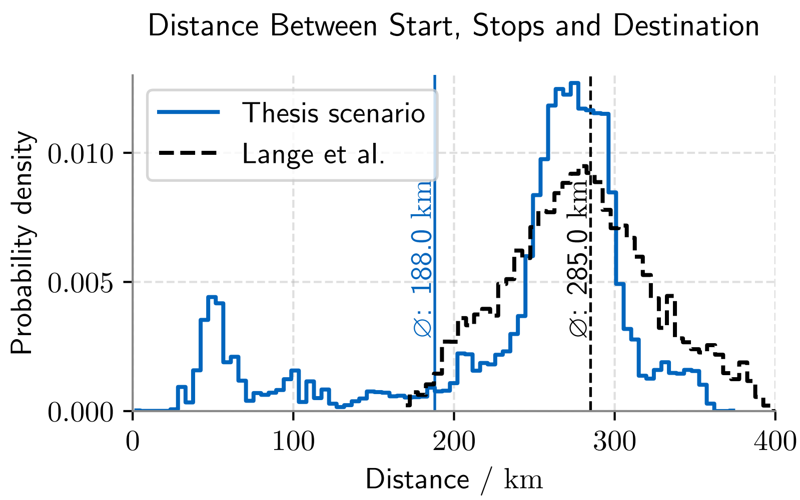

Figure 4.7: Distribution of driving distance between breaks in the simulated model (scenario: 80 % SOC at start, 20 % SOC at end) and adapted from Lange et al. [75].

the optimization of the charging network towards mobility (M-OPT network) would be the stronger strategy, as it maximizes the potential range of users of a BET.

The driving strategy Figure 4.7 corroborates these findings: The figure depicts the distribution of distances that the trucks drive between charging and between the start and the first charging. The presented model aligns well with the literature [75] in that it predicts a high probability of legs of approximately $280\,\mathrm{km}$ length. Yet it adds the complexity of multi-stop strategies that can be beneficial to exploit nonlinear charging curves [14][*]. Again, the model demonstrates that in practice, only in rare cases legs of more than $300\,\mathrm{km}$ have to be covered.

An increased battery capacity in the real world can still bring certain benefits, though: Especially if public charging is more expensive than private charging, the reduced reliance on public charging can offset higher investment costs [27]. But also reduced cyclic aging, or lower life cycle CO_2 footprint, can be arguments for higher battery capacities than required by this model [103]. This highlights that there is a macroscopic conflict between investments into the vehicle, typically done by a carrier, and investments into the charging infrastructure, which the charging point operator (CPO) has to provide. In both cases, though, government subsidies can shift the balance and change investment decisions.

4.2 Coupled Evaluation

After the decoupled evaluation, a last research question remains: How large do charging sites need to be in terms of installed plugs and power? The main goal of this section is to evaluate the concurrency of charging events and to derive recommendations for scaling charging sites. The key here is to consider the capacity of charging sites, as it limits the number of parallel charging sessions. For this purpose, an agent-based MATSim model is presented to simulate charging and queuing dynamics at these sites.

4.2.1 Method

A prototype of the MATSim model, especially the network, data pipeline, and first versions of the queuing model, was developed within the student project by Decarli [122]. The calibration of departure times was accomplished within the student project of Nguyen [120]. Parts of the methodology developed within these works are cited as such.

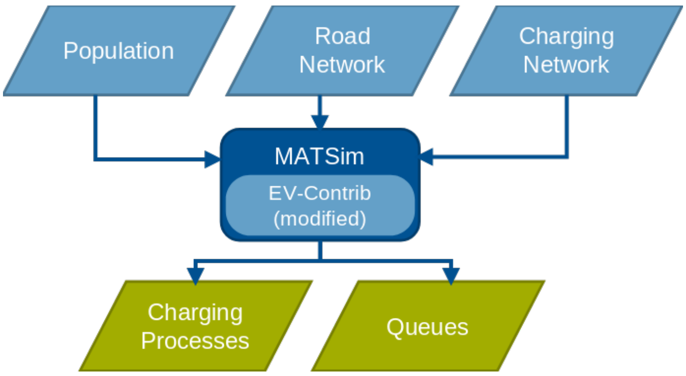

Figure 4.8: Model Overview

The simulation model is based on three primary input datasets, as visualized in Figure 4.8: the population, the road network, and the chargers. The population dataset contains a list of agents, each representing a transport task. It is specified with origins, destinations, and intermediate charging activities. The network dataset represents the road network, which has been converted from the data described in Section 4.1. Lastly, the chargers file defines the charging infrastructure, including the number of plugs available at each charging site. This agent-based model is only supposed to explain the behavior at charging sites; thus, the charging site utilization is the only output evaluated within this thesis.

Firstly, and simplest, the network file is derived from the road network described in Section 4.1. The representation of the road network is essential, as travel times between charging sites determine the arrival time and thus queuing of BET. The network has been cropped to Germany and converted as outlined in Decarli [122]. Travel times are assumed to be static and no traffic on the road is modeled, as the main purpose of this simulation step is to evaluate queuing behavior in a reproducible way [122].

Secondly, a population is defined based on the driving strategy that was computed from Section 4.1. Each agent within the population represents a truck, which is randomly drawn from the routes and charging strategies computed in Section 4.1 [122]. Crucially, the departure time of the agents is not yet known: For this purpose, a calibration process was implemented [120]. The calibration process ensures that the simulated traffic flows closely resemble observed real-world patterns. Observed traffic data, such as that from counting stations (Figure 4.9), provides a basis for this calibration. Yet it can only measure how many vehicles are present on the road, not when they departed. However, state-of-the-art methods [73] often assume that this probability distribution of vehicles passing through counting stations mirrors the departure distribution, which skews the traffic flow in the simulation: It occurs too late and is too spread out [120] (Figure 4.9).

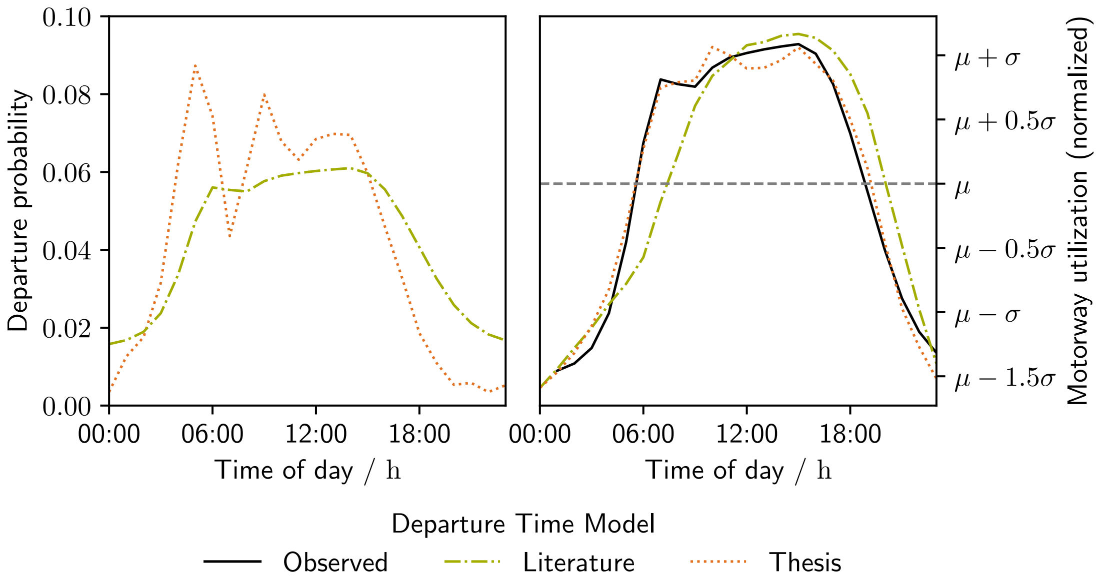

Figure 4.9: Simulated road utilization and modeled departure times. Own visualization based on data from Nguyen (model, [120]), Menter et al. (literature, [73]), and counting stations (observed, [121]).

To address this, [120] introduced a tailored approach, enabling a more realistic simulation of transport activity and to match the double-peak pattern seen in actual counting station data (Figure 4.9). It separates domestic and international traffic, and handles them separately [120]: For international traffic, the border crossing reflects the entry into the simulated area [120]. These entry times can thus be directly derived from counting stations at the borders [120].

For domestic traffic, this involves tuning the departure time distribution in an iterative approach, where departures of precomputed trips are scheduled iteratively. The gradient of hourly traffic volumes is used to infer departures: Iteratively and beginning at midnight, plans are sampled from the set of routes [120]. The approach simplifies the system, assuming that departure time and travel time are not correlated, which means that long-haul traffic may depart at any time of day with the same probability. The sampled plan is then subtracted from the measured road utilization until the simulated traffic volumes align with the observed data from counting stations [120]. The results of this improved calibration can be seen in Figure 4.9: The departure probability has two distinct peaks between 05:00 and 06:00, as well as around 09:00. The approach replicates this double-peak pattern observed in real-world data successfully [120]. While these departure times are calibrated to match the behavior of conventional trucks, BET are modeled next.

For this purpose, the MATSim module for the simulation of electric vehicles (EV-Contrib) was adapted. Charging plans, as generated from Section 4.1, are statically executed, instead of individually searching for suitable charging locations. After this step, a three-step approach is used to determine the sizing of the charging sites, comparable, e.g., to the sizing algorithm demonstrated in [73]. The approach ensures that the distribution of infrastructure is efficient and demand-oriented:

1. Open loop simulation: Infinite plugs are placed at each site, and the number of concurrent charging sessions is observed.
2. Observation: The distribution of parallel charging sessions at a site is computed.
3. The service level defines how many charging stations (plugs) are installed. This refers to a percentile of the distribution of parallel charging sessions at each site. A minimum of 2 plugs is ensured at all sites.

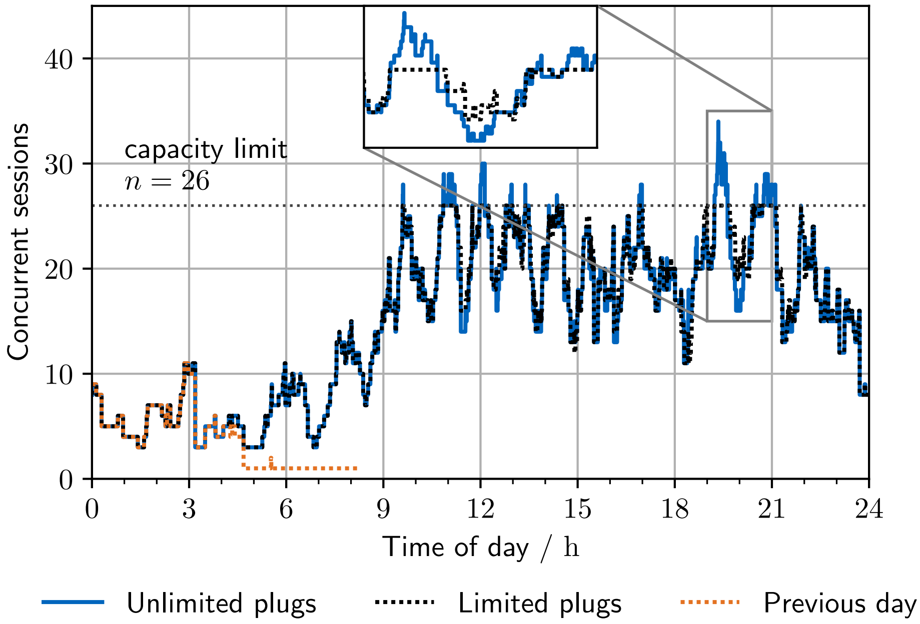

Figure 4.10: Parallel charging sessions at a single charging site: In iteration 1, no capacity is enforced. In iteration 2, the limit of available plugs is set to the 90th percentile of parallel charging sessions in iteration 1. The final result is projected onto one day.

4. Constrained simulation: The number of plugs is limited accordingly, and queuing/charging behavior is measured.

The charging sites are copied from the decoupled model Section 4.1, so the same simulation settings are used. Figure 4.10 visualizes this approach: The initial simulation at 100 % electrification rate yields up to 35 trucks charging in parallel in the afternoon. Yet in 90 % of cases, at most 26 trucks are charging in parallel, which sets the capacity limit to 26 charging stations.

4.2.2 Results

The parameters of the reference case simulation can be found in Table 4.2 and extend scenario 267 from Table 4.1. Here, the charging network M-OPT is selected, together with trucks with an available battery capacity of $500\,\mathrm{kWh}$. An electrification rate of $15\,\%$ represents a potential scenario for the year 2030 and ensures comparability with the literature [70].

Table 4.2: Simulation parameters and key metrics.

Parameter	Value
number of routes	$148\,177$
sampled plans	$18\,781$
charging network	M-OPT
service level	$90\,\%$
initial SOC	$50\,\%$
terminal SOC	$50\,\%$

The overall results of the simulation can be seen in Figure 4.11: It illustrates the total number of parallel charging sessions in Germany. The curve resembles a sine wave, with the peak occurring between 14:00 and 18:00 at up to 983 parallel fast charging sessions, and the valley at 239 charging sessions during the early morning hours, 04:00 to 06:00. This behavior is plausible, as few vehicles have to recharge shortly after departure, but rather later in the day. Because the agents in the simulation have to end their day at the same SOC as they started, late charging before arriving at the destination is the most time-efficient choice. The prolonged period of high energy demand until approx. 20:00 is thus a direct consequence of the optimized operational strategy. The sine wave pattern is comparable to Menter et al. [73, p 19], but more spread out, and later in the day. According to Menter et al. [73, p 19], the peak charging demand is located around 14:00 to 15:00. Notably, the simulated afternoon peak in Figure 4.11 coincides with the evening peak of electricity demand around 19:00 seen in the national electricity grid [123, 124]. It is crucial to acknowledge that *energy* demand of BET cannot be reduced significantly, as most efficiency measures in vehicle technology have already been applied even to ICE trucks. The only option is to shift the *power* to more beneficial times. So, to mitigate the impact of fast-charging trucks on the electricity grid, two main strategies can be conceived:

1. Incentivizing *fast* charging in off-peak hours: Dynamic pricing, capped charging power, or other incentives could be used to shift the fast charging demand into other hours of the day. However, this approach would lead to time loss, as the time-optimal charging strategy cannot be selected anymore. Also, the potential for a shift towards the night hours is limited.
2. Enabling overnight *slow* charging: A peak shift towards the night could be achieved if overnight charging at public or private charging stations is possible. The sharing of private charging infrastructure with third parties is actively pursued by industry [125] and research [110].

The total utilization rate on average is at $47\,\%$. This figure is in line with literature sources ([90, p. 14] $44\,\%$, [73, p. 15] $55\,\%$, [74, p. 12] $47\,\%$). Nevertheless, the efficient algorithmic allocation of plugs to charging sites can certainly not be achieved in a real-world scenario, and more plugs would have to be installed.

But what causes this singularly high demand at certain sites? Figure 4.12 presents the spatial distribution of chargers across Germany. Round, triangular, and square symbols represent charging sites of increasing size. There are only 5 charging hubs of more than 25 charging stations, 3 of which are located along the A2 motorway. This motorway connects eastern and western Europe and also contains the segment with the highest AADT in Germany [126], near Hannover, in immediate proximity to the by far largest charging site with 46 plugs. One other large hub is located along the A3 near Würzburg. A3 as well as A2 are important connections to the large deep-sea ports in Antwerp and Rotterdam, as discussed in Section 4.1. The fifth hub is located at the intersection of motorways A4 and A14 in Saxony, also in proximity to the Czech and Polish

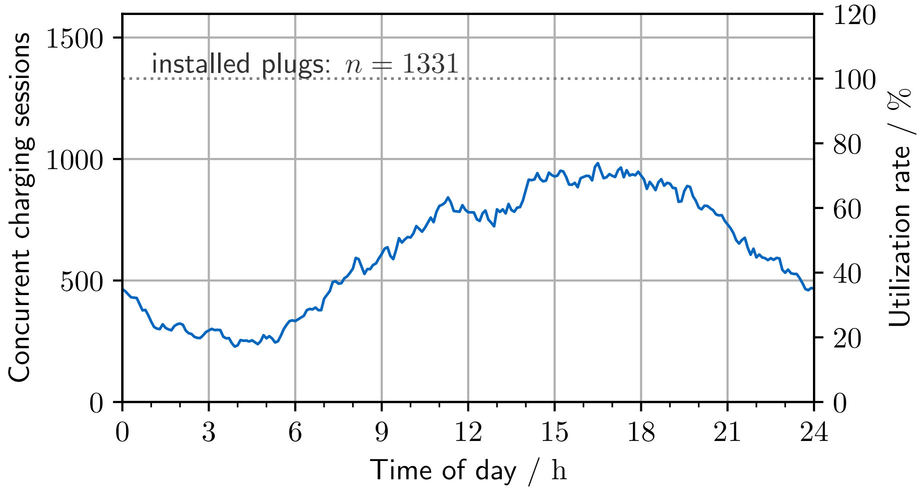

Figure 4.11: Number of concurrent charging sessions in the simulated scenario across the network. Compare also [73, Fig.21]

border. These anomalies highlight the huge impact of international traffic on the German infrastructure, and are congruent with the assessment by public authorities [41], that the largest demand for public fast charging occurs along international transport axes crossing Germany. However, the high demand at these locations depends on international BET traffic scaling at the same speed as the German domestic BET market. This is questionable, as international traffic requires all countries along the transport chain to provide public charging infrastructure. Likely, the application of BET in these cases will lag behind the usage in domestic scenarios.

Medium hubs (triangles) are more dispersed throughout the network. They predominantly grow along major transport corridors. Smaller hubs (dots) fill the gaps, especially on low-frequency routes in northern and eastern Germany. The findings of Figure 4.12 underline that slightly more than half of the charging stations are relatively small and can probably be connected to the medium voltage grid at first. Yet in a potential 2035-scenario at 50 % electrification (Figure A.2), most charging hubs along all major highways fall into the medium and large categories that likely have to be connected to the HV grid. This supports the design paradigm of the E-OPT network, where the grid connection is prioritized.

Each charging site from Figure 4.12 is represented in Figure 4.13 by a scatter point. It explores the connection between total daily charging time at a charging site and the total daily queuing time there. Large charging hubs on these plots are located on the right, in the areas of high connection times. At all sites, less than 5 % of queuing is added to the scheduled charging time at 90 % service level. Notably, small charging sites are the only ones to reach such high added time losses. This could indicate that the coordination of high charging demand at large charging hubs leads to a more stable behavior than small demand directed at small sites. Practically speaking, if only two plugs are occupied, an arriving third vehicle might have to wait out a full charging session until it can start charging.

Finally, Figure 4.14 quantifies the relationship between the share of BET, the total required plugs installed, and the queuing time at varying service levels. The queuing time is expressed as the share of time spent queuing relative to the total time spent at the charging site (including queuing, resting, and charging). As the service degree is gradually increased from 75 % to 100 %, the queuing time-share declines degressively from over 8 % to virtually 0. This trend is reproducible across the electrification degree; the results only diverge for high degrees of electrification coupled with low service levels. The number of plugs, in contrast, increases approximately linearly at first, but progressively for service levels over 90 %. While initial increases in service degree lead to substantial reductions in queuing time with moderate increases in plugs, the marginal benefit

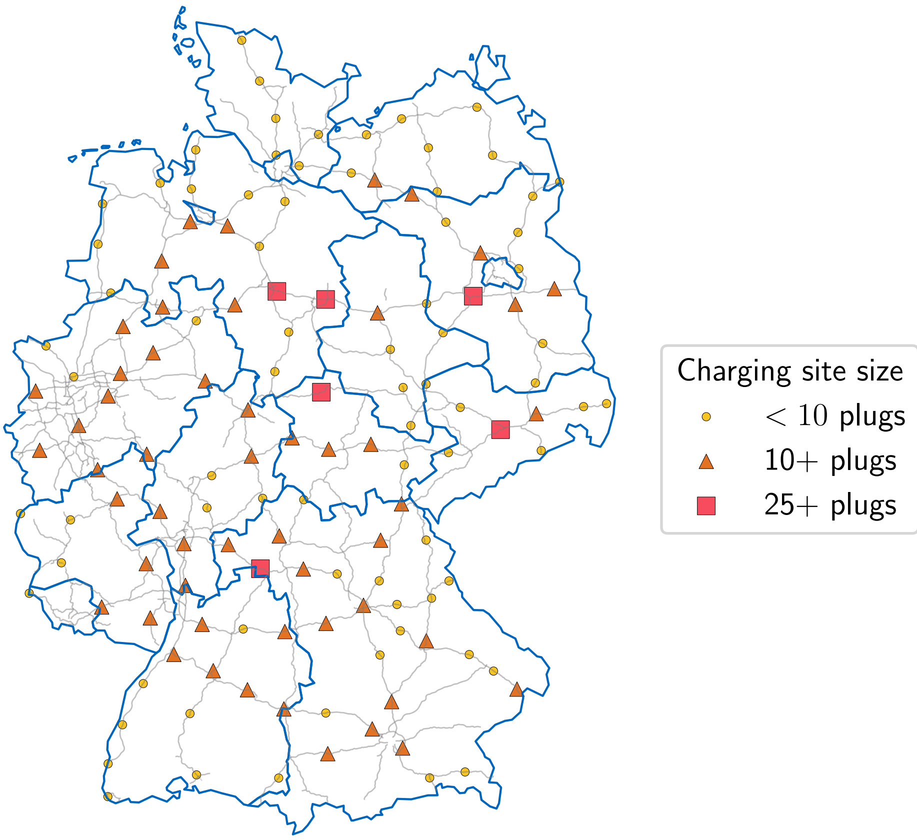

Figure 4.12: Charging network M-OPT with site dimensioning at 15 % electrification rate. In total, 1331 charging stations are placed. Refer to Figure A.2 for the 50 % scenario.

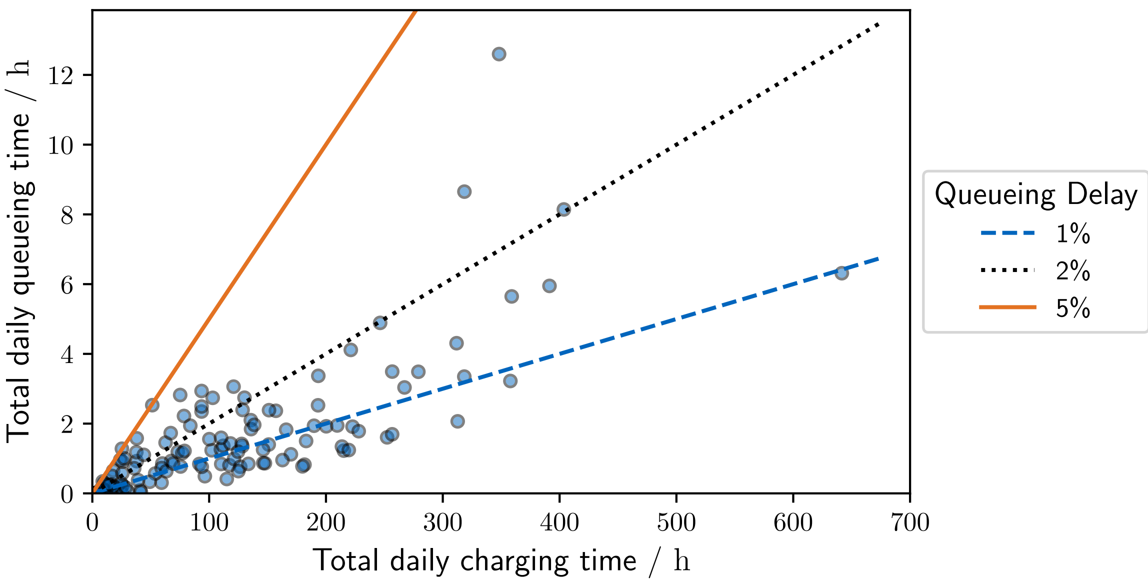

Figure 4.13: Comparison of total charging time and total queuing time at charging sites in scenario M-OPT at 90 % service level. Each scatter point represents a charging site. The lines are indicative of the relative share of the queuing time.

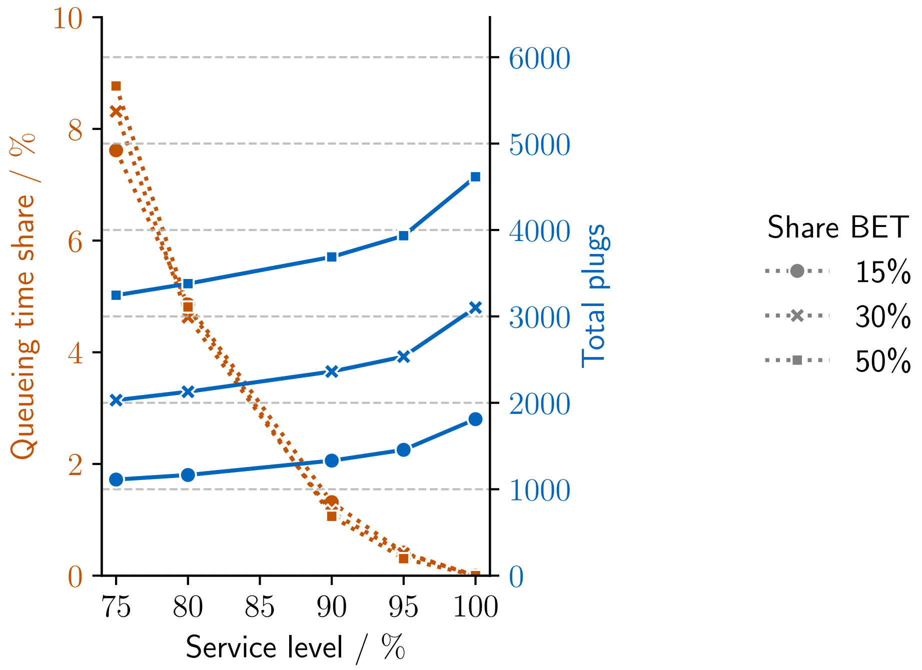

Figure 4.14: Total charging stations (plugs) across the charging network required to reach a certain service degree, alongside additional waiting time due to queuing. Higher service levels require more plugs, but decrease queuing behavior.

declines rapidly beyond 90 %. To put this into perspective, at 15 % BET share and 90 % service level, an increased service level requires 9.3 % more plugs, driving up the infrastructure costs. At the same time, the queuing time-share can only be reduced by 0.91 %, suggesting that an equivalent investment into higher charging powers could impact the efficiency of the charging site more from this reference point onwards. This suggests that, aiming for a 90 % service degree may represent an effective compromise.

A significant finding is that the demand for plugs due to growing market shares of BET grows sub-linear. At 90 % service level, a 2 or 3.3-fold electrification rate requires only a 1.78 or 2.78-fold number of plugs: These economies of scale facilitate the widespread market adoption of BET in a scenario after 2030, as the infrastructure investment cost per vehicle added to the system decreases. This effect is also reported in the literature [73, Table 4]. The number of chargers places in the 15 % BET share scenario is also comparable to literature values ([73, p. 15] 1148 at service level 76 %, [70, p. 11] 765 at 50 % public charging)

To conclude, the results of the simulation provide a fundamental understanding of charging site utilization, dimensioning, and its implications for charging infrastructure planning. The coupled simulation thus complements the decoupled evaluation with time-dependent information. Large charging hubs are concentrated along major international transport corridors, while smaller sites fill gaps in less frequented regions. For these smaller sites on the periphery, fewer than ten megawatt-charging stations suffice to serve the passing traffic. The findings suggest that a service degree at the 90$^{\text{th}}$ percentile of peak utilization is a reasonable economic compromise, ensuring efficient utilization and limited queuing delays. The daily electric load from BET fast charging reaches its peak in the late afternoon hours, coinciding with the national electricity demand peaks. For the future energy system, this raises the question of how the demand can be shifted away in order to reduce the load on the electric grid.

5 Discussion

This chapter discusses the contributions of this thesis along with its strengths and limitations, with a special emphasis on the applicability in the real world. Furthermore, it aims to put the thesis into a broader context, showing pathways for future scientific, technical, and regulatory action.

5.1 Demand and Degree of Electrification

Among the uncertainties within this work are the traffic flows: In the simulation, the origin-destination flows are assumed to be equal between the current, mainly ICE driven fleet and BET. Especially, the electrification rates (e.g., $15\,\%$, $30\,\%$, $50\,\%$ Figure 4.14) assume that for all market segments there is an equal share of BET within the market. This is certainly a simplification: Following the principles of efficient markets, it is to be expected that market segments where BET exhibit economic advantages shift to electrification earlier, while ICE trucks prevail where BET are less economically sensible. Thus, some arguments exist that would support a lower traffic performance of BET in long-haul applications than modeled, entailing lower fast charging demand:

- Market segments like distribution or regional haul offer a good setting from a technical perspective [94]: Low daily ranges lead to small battery sizes, slow overnight charging enables the battery to maintain a longer service life. With set electrification targets for the whole commercial vehicle market, a higher market share in distribution applications is to be expected.
- Parking space along motorways is extremely scarce. Acquiring ground and repurposing it for BET exclusively may prove impossible or at least costly, delaying public charging infrastructure projects.
- European transit traffic with BET is a substantial contributor to the charging demand in this model, yet it requires not only a charging infrastructure in one country, but a continuous charging network along the complete transport chain. If EU countries comply with the requirements set by the AFIR, at least a basic level of service would be assured, though. This effect will be discussed in greater detail in Section 5.2

Yet there are also arguments towards the opposite:

- Private charging infrastructure is a significant challenge for logistics companies. Especially in short-haul applications, each BET needs an overnight charging point at the depot, driving investment costs and likely requiring the costly upgrade of existing electric grid connections [127]. Long-haul operations that rely on public charging infrastructure may turn out to be a less investment and project management-intensive market.
- The high yearly mileage of long-haul trucks can generate higher revenue to compensate for the higher capital costs.

- Usage-based incentives like the existing toll exemption in Germany give BET in long-haul applications a comparative advantage.

Certain effects hold uncertainty in both directions:

- While this thesis is based on averaged traffic flows, the daily volumes fluctuate throughout the year. Within the counting station data, a standard deviation of $\sigma = 19\%$ of passing trucks can be observed during weekdays, and a residual $10\,\%$ excluding public holidays and core holiday seasons.
- Regulatory incentives can disproportionately shift the balance in either direction.
- The energy prices and grid fees for fossil fuels, electricity at private locations, and public charging prices carry high uncertainty. Especially dynamic pricing schemes can shift the charging demand, which will be examined in greater detail in Section 5.4
- Depending on the microeconomic costs of BET in long-haul application, a modal shift can occur. If the TCO of BET are lower than ICE trucks, a further modal shift from cargo transport via rail and inland waterways towards road freight transport is to be expected. The opposite shift can occur if higher transport costs render the alternatives more attractive.
- The demand for public fast charging is an endogenous variable of the provided charging infrastructure [62]. A high-quality supply induces demand, while the opposite can also occur.
- Soft factors, especially relating to the acceptance among drivers: BET can provide high acceleration, quiet driving experience, low noise, vibration, harshness (NVH), reserved parking spots for charging can be an advantage in times of overflowing rest areas. To the contrary, range anxiety, or e.g., time loss, but also attitudinal factors, can slow acceptance.

But to put the uncertainty into perspective: There is a wide consensus that BET are a mature and economically sensible technology, and it is likely that BET will take over as the dominant truck in the coming decade [5–9, 62, 63][11][*]. So the question of demand is more of a question *when* certain degrees of market penetration will be reached, not *if*. The results of this thesis, especially concerning the network dimensioning (Section 4.2), should thus be valid nonetheless, but the horizon in which $15\,\%$, $30\,\%$, $50\,\%$ electrification in long-haul is reached remains partly uncertain. For investments into public charging infrastructure, that means that momentarily overprovisioned infrastructure will reach its capacity in the future.

This thesis puts a special emphasis on Germany, yet it is crucial to also consider the embedding within the European Union in terms of regulatory, economic, and spatial connections. Crucially, the charging demand of European transit traffic relies on a continuous charging network throughout Europe. Thus, the next section explores the strategy of the EU, its member states, and private stakeholders to this end.

5.2 Coordinated European Strategy

A coherent strategic framework for public charging infrastructure is provided by the EU Alternative Fuel Infrastructure Regulation (AFIR). It ensures cross-border compatibility, harmonized standards, quality, and payment systems [20] and is accompanied by subsidies for infrastructure development [128]. As is demonstrated in Section 4.1, the targets for spatial coverage set by the AFIR are set high, as both AFIR compliant networks E-OPT and M-OPT showed superior coverage. In contrast, the requirements for the power of single charging points are low. Only $350\,\mathrm{kW}$ of charging power per plug is required at TEN-T core charging sites [20], significantly below the requirements of long-haul transport as demonstrated in Section 3.1, Section 4.1, and [33][*]. The installed power at a TEN-T core site in total has to reach $3.6\,\mathrm{MW}$ by 2030 [20]. To achieve

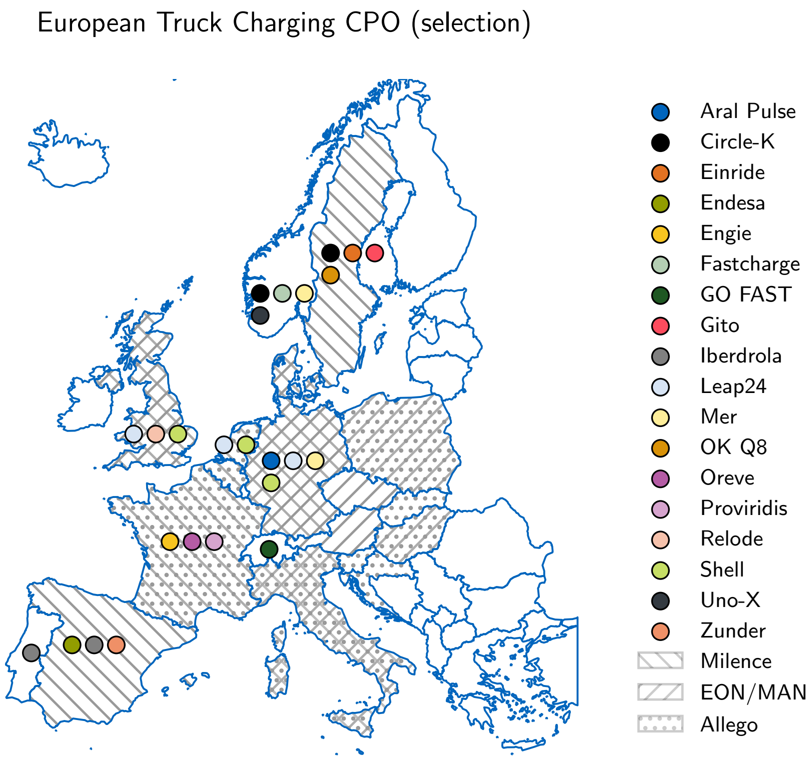

Figure 5.1: Overview of international and local European CPO for public truck charging infrastructure (built, planned, and announced). List non-exhaustive. Sources: [128, 133–141][142–148][149–155]

these targets, different countries have issued public tenders to build AFIR-compliant charging infrastructure. As many of these documents are not available in English, this analysis cannot claim completeness, but public funding in Germany, Denmark, France, Austria, and Poland could be confirmed, as is explained in the following.

The German *initial charging network* [61] exceeds these power requirements: Each station shall provide $1\,\mathrm{MW}$, and guarantee $800\,\mathrm{kW}$ even in load management constrained phases. Denmark also sets advanced targets for its public charging network tender. A total of 25 charging sites with 175 charging points and $133\,\mathrm{MW}$ in total are expected to be built from 2025 on [129]. This translates to an average of 7 charging points per site with $5.32\,\mathrm{MW}$ installed power, and an average charging station delivering $760\,\mathrm{kW}$. But other countries, such as France [130] and Austria [131], only aim for the legal minimum in their public tenders. Austria aims to install 1300 charging points for BET by 2035 [131], each of which has to provide only $350\,\mathrm{kW}$. In the same timeframe, France aims to install $13\,000$ charging points and supports the construction of each TEN-T core charging site with $2\,000\,000$€. Poland as well plans charging sites with the required $3600\,\mathrm{kW}$ installed power and $350\,\mathrm{kW}$ per plug and has put out a tender to build the charging infrastructure [132].

Public authorities are not the only stakeholders pushing for the construction of charging infrastructure. Private companies, on the other hand, have constructed, planned, or announced the construction of public truck charging infrastructure; an overview is provided in Figure 5.1. Chief among them are Milence (the joint venture of European OEM), the cooperation between MAN and E.ON, and Allego [133, 134, 147] that aim to create large cross-border networks. Other CPO address national markets or a few countries.

The most dynamic developments are taking place in Germany, Sweden, and the Netherlands in particular, which are also home markets of major truck OEM. There, transnational network operators as well as several private corporations both plan on building charging networks, promising dense and early coverage of the road network. Deficiencies are possible in the eastern EU, where no local private operators could be found, although foreign-language sources could not always be considered.

Notably, also few private providers have announced actual MCS charging infrastructure [133, 138, 152, 156], with most CPO installing off-the-shelf CCS solutions that also fulfill the AFIR requirements. Based on the findings of this thesis and previous publications, e.g., [14, 33]*, that charging power is key to the economic operation of BET, subsidies should be directed more towards projects building more future-proof MCS charging infrastructure.

It has been established that Germany plays a major role in the European freight transport market (Section 2.1). But by connecting the European perspective and the findings in Balke et al. [84]*, its importance may even be even greater for the success of BET. The previous publication [84]* demonstrates an optimized ramp-up strategy for the deployment of charging infrastructure tailored to domestic BET traffic in Germany. This strategy employed is a greedy algorithm that aims to select charging sites incrementally in order to maximize coverage of traffic flows. This results in the first stations forming a dense core network, before expanding towards the edges of the simulation area [84, Fig. 5]. Approximately $80\,\%$ coverage could be achieved with only $20\,\%$ of charging sites electrified. If such a center-to-edge approach can be projected to the European level, that means that Central European countries like Germany, Austria and the Netherlands play a pivotal role, and a quick charging infrastructure development there facilitates BET traffic across Europe.

Beyond charging infrastructure subsidies, there are also a number of other instruments that can serve to incentivize BET adoption. Crucially, only the EU Emissions Trading Scheme (EU ETS) provides a consistent framework for internalizing environmental costs. Apart from that, national policies such as petrol taxes, electrical energy taxes and fees, and toll systems vary significantly between member states. National toll exemptions for BET, as implemented in Germany, provide a strong incentive for long-haul electrification but may not exist in neighboring countries, reducing the competitiveness of BET in international traffic. To address this, a coordinated approach is needed to align these measures, ensuring that subsidies and incentives are harmonized across borders. This could involve setting minimum standards for toll exemptions, harmonizing energy tax structures, and integrating congestion pricing schemes to reflect the true external costs of transport.

5.3 Significance of High Voltage Grid Connections

One of the central questions that this thesis addresses in the design of charging infrastructure is the significance of high-voltage grid connections. Strong grid connections, especially to the HV grid, can support large charging hubs and, crucially, high charging powers that become relevant in the future. Higher charging power emerges from the results of this Section 4.1 as the best strategy to improve the performance of BET in long-haul operation. If the OEM indeed bring charging powers beyond $1\,\mathrm{MW}$ into the series production, the demand for high-voltage power lines would increase even more. However, this comes with significant grid expansion costs and may not be feasible in all locations. Figure 4.12 demonstrates that in a $15\,\%$ electrification scenario, the most frequented charging site reaches up to 46 parallel charging sessions, corresponding to approximately $35\,\mathrm{MW}$ of electrical power. Factoring in losses and reactive power, this means that a grid connection in the magnitude of $39\,\mathrm{MVA}$ is required [41, 42, 74]. Compared to other $15\,\%$ electrification simulations, this result is reasonable: Menter et al. [73, Tab.4, Fig.18] estimate a comparable number of chargers across the network (1148 [73] vs. 1331) yet have a lower maximum size load at 16 chargers. Speth et al. [74] place 2032 charging points with up to 30 plugs at a single site. Kippelt et al. [41] estimate for Prototype I locations (Hub at an international transit axis) in 2030 a required grid connection of $27.8\,\mathrm{MVA}$, also in line with the findings of this thesis. On the other hand, Figure A.2 demonstrates that certain peripheral locations, even in a progressive scenario of 50 % electrification, do not exceed 10 required charging points.

While the literature debates the relevance of high-voltage grid connections for charging hubs [40–42], this thesis sheds more light on the specific locations and time frames where these connections become relevant: Along major transit axes, as shown in Figure A.2, high-voltage grid connections will become a necessity. On the other hand, in rural and low-demand areas, medium voltage grid connections suffice even in a scenario beyond 15 % electrification. This underlines that the planning paradigm of the E-OPT is therefore a strong strategy, especially for large charging hubs and the expected increase in charging power. Future work could attempt to select between the planning paradigms of E-OPT and M-OPT for the main axes and peripheral routes to create an even more economical result.

5.4 Price Incentives and Charging Strategy

The energy market, as well as the transport sector, is highly competitive and economically driven: The offered goods are highly exchangeable, and the quality of the product is mostly homogeneous. It is therefore important to note that stakeholders from both sectors react strongly to price incentives to increase their respective economic benefit. From an energy market perspective, the integration of BET first and foremost poses a challenge. Highly fluctuating loads like BET charging paired with fluctuating energy generation from renewable sources induce volatility into the electric grid. Highly dynamic energy prices are the logical consequence. Fleet operators, on the other hand, will aim to minimize TCO by optimizing charging schedules to exploit low-price periods and avoid charging during high-price phases. High price elasticity, in turn, can contribute to leveling out price volatility, as it aligns demand and supply again. This dynamic interaction underscores the importance of incorporating energy market models into future research to better understand the economic implications of BET adoption. Essentially, the flexibility of BET in public and private charging settings is a valuable good.

The flexibility potential of BET and their dynamic charging coordination is a subject of recent research activity: Golab et al. [157] model the Austrian transport and energy system in a coupled simulation to evaluate the potential participation of electric vehicles, including BET, in the energy market. The main findings underline that dynamic pricing following the day-ahead energy market can significantly shift the load curves of BET into low-price zones around noon and midnight. Applied to Figure 4.11 this means, that the peak of grid strain in the evening hours can indeed be shifted though dynamic components in the pricing model. But the scheme has the downside that distinct peaks and regional load differences in the electric grid are created. These entail high redispatch costs within the grid. Another side effect is that dynamic pricing can also attract new customer groups not yet considered in the simulation. Deng et al. [158] model dynamic pricing at public charging sites in a distribution network. In this case, the demand for public charging increases with the adoption of dynamic pricing, as price gradients towards the public charging infrastructure can be exploited, causing the depot charging rate to drop from 90 % to 69 %. To summarize, dynamic pricing strategies are an option to shift electricity demand by BET, but they can lead to peak demands unfavorable from a grid perspective. An integrated approach to the expansion of the charging infrastructure and electric grid is likely required [157]. To build upon this thesis, future research could explore the development of coupled transport demand and energy market models. Coupled models would enable capturing the trading of flexibility between fleet operators and energy suppliers, as well as the influence of dynamic pricing, electric grid constraints, and market incentives on the system.

The business case of BET for its operator is a subject of ongoing research. The single most important influencing factor is the battery, as it is the single most costly component in purchase, but also determines the vehicle's dependence on public or private charging. Depending on payload requirements, available charging speed, and charging prices (public and private), different battery technologies as well as different battery sizes form the economic optimum from, as Schneider et al. [27] demonstrate. Future research should thus determine which use cases are especially advantageous for BET and derive recommendations for tailored vehicle configurations for these applications. As the economic feasibility also depends on the availability of public charging, this requires integrating extensive operational data with a close monitoring of development scenarios for public charging infrastructure density, quantity, and power, as outlined in this thesis.

A significant influence on the TCO is also attributed to the charging strategy. The strategy utilized in this thesis is presented in [102, 117]*, and assumed to be time-optimal but static. It represents, for example, a driver or dispatcher who plans a charging schedule ahead of each trip, but this schedule is executed statically. In reality, the strategy has to be adapted in real time to the dynamic environment: For example, queues at a charging station, traffic congestion, or deviations in the predicted energy consumption can all justify a deviation from the pre-planned strategy. These effects mark the system boundary towards microscopic models that can capture these interactions between the trucks and the environment, similar to the research of Karlsson and Grauers [90].

The charging strategy employed in this thesis also enforces that all energy required for driving has to be charged en route. This assumption is based on the tour lengths observed in long-haul transport [104]*, which make a significant contribution of private charging difficult. In practice, this means that the actual demand for fast charging is likely lower than modeled, as a certain percentage of private and semi-public or public overnight charging can only reduce the demand for public fast charging. For private charging to work on a vehicle level, though, an incentive influencing charging decisions would be required. A carrier should preferably charge to maximize its economic efficiency, so private charging would have to provide a price gradient or time advantage.

The equilibrium prices of public and private charging are still subject to major uncertainties, though: At present, and possibly subject to future changes, Milence, for example, offers static pricing throughout Europe [159]. In total contrast, the German *initial charging network* infrastructure allows for charging using 3rd party energy contracts [61] (German: *Durchleitungsmodell*) in combination with an infrastructure fee. This means that at a single charging point, varying charging tariffs, static as well as dynamic, may apply at the same time. Especially when the dynamics in the energy system grow due to the growing share of renewable energy and electric vehicles, the economic pressure to implement dynamic pricing strategies will grow, too.

5.5 Modeling Simplifications

Certain simplifying assumptions have been made in order to reduce the system's complexity. The time loss modeled in this thesis, e.g., is a simplification, as it mainly describes how well charging and mandatory breaks align. Time for plugging and unplugging is factored in, yet certain other factors would still increase the real-world time loss of BET: Reduced charging power due to load management in the infrastructure, as well as deficient pre-conditioning of the battery, increase the charging time. Vehicles in this simulation (Section 4.1) use 97 % of their break time for charging, and are thus efficient in using their time at the charging station. If in real-world scenarios, BET blocked the charging station longer than required, or used suboptimal strategies and charged longer than required, the queues would significantly increase.

On the other hand, the trip-based model used assumes that vehicles have to cover their energy demand on each trip, so they have equal initial and terminal states. If multiple trips are chained together, fewer charging sessions might suffice in many cases, and less time loss would occur. Also, the availability of private charging infrastructure, e.g., at unloading ramps, would reduce the en-route energy demand and thus charging time.

Another simplification is the construction process of a charging network. The charging site dimensioning Figure 4.14 assumes that a static demand can be measured and charging sites efficiently scaled to meet this demand. In reality, no charging site can be scaled freely; continually adding charging points to an existing hub would drive construction costs significantly. It is thus safe to assume that the required number of charging points computed is a lower estimate. Moreover, the fundamental process of building charging networks is a challenge, mainly due to the number of stakeholders involved: public authorities, transmission grid operators, energy suppliers and OEM interact on the system level, while on the charging site level charging point operators, landowners, distribution grid operators, logistics companies, and drivers have to act together for BET to become an economically successful technology. Long planning horizons are the consequence, meaning that for charging hubs along international transit axes, it may well be already too late to meet the expected demand in 2030.

6 Summary

While electric commercial vehicles are already widespread in urban distribution, long-haul applications present significant challenges due to high daily ranges, energy demand, and payload constraints. This thesis develops a comprehensive and strategic planning method for establishing a public fast-charging network for BET in long-haul freight transport, especially considering the interplay between vehicles, charging infrastructure, and the operational strategy.

Germany serves as a case study due to its central role in the European freight network and keystone function within the European TEN-T strategy, but international and transit traffic throughout Europe are integrated into the developed simulation models. Open data is used in all aspects of the methodology to ensure transparency and scalability across borders. Methodologically, this thesis closes a key research gap and addresses multiple shortcomings of the literature. It especially improves the modeling depth of the system, applying a systemic model scope from design to evaluation, and improving upon its own previous publications. The complex problem is addressed from multiple perspectives, namely the infrastructure operator, but also carriers, drivers, and distribution grid operators. The thesis is structured into a static model and a dynamic model. The static model's aim is to conceive an optimized charging network configuration that can then be evaluated within the time-forward simulations of the dynamic model.

The *static model* is based on the analysis of conventional trucks that were recorded during their operation in diverse use cases in six different fleets. The mobility data analysis demonstrates that operational patterns in short-haul are distinct from long-haul use cases. In regional and distribution transport, breaks often take place during loading and unloading, and there is simply no time for intermediate charging; the best electrification strategy is thus private charging infrastructure and especially overnight charging. In contrast, long-haul transport can only rely on private charging for a small share of its energy demand. Tours can reach multiple thousands of kilometers, and recharging during the driver's mandatory breaks, especially at rest areas along the motorway, is the best approach to avoid time loss and ensure cost-competitiveness of BET. The main users of the public fast charging network are likely trucks in long-haul operations.

On this basis, optimized charging network topologies are computed. The solutions have to fulfill the legal requirements set by the AFIR, as well as budget constraints. Two optimization paradigms are tested, an optimization from the mobility perspective competing with one from the electric grid perspective. Within the mobility-focused optimization, the spacing between charging sites is optimized, so drivers can freely align their rest schedules with the vehicle's charging time. The energy-focused optimization picks charging sites that are in close proximity to existing high-voltage electric grid infrastructure. This reduces infrastructure investments and facilitates larger charging hubs with higher charging power in the scaling stages of the market. By optimizing the location of charging sites relative to the electric grid, a total infrastructure savings potential of 354 000 000€ is estimated.

The *dynamic model* is utilized for the evaluation: Here, the complete traffic flow of European and German trucks is assigned to the network, and the system performance is evaluated. The first part of the model decouples all trips and evaluates four charging network configurations: The two optimized configurations, E-OPT and M-OPT, the WMN from the literature, and the initial charging network at unserviced rest areas currently on tender (INIT-U). It can be seen that the optimized networks exhibit strong performance, especially in terms of time loss. Though the number of charging sites is comparable in all cases, the spatial coverage of the newly created networks E-OPT and M-OPT is measurably higher than the coverage by the initial charging network INIT-U. The expansion stage INIT-A solves this deficiency at the cost of an almost threefold increase in charging sites. This confirms that solid planning of the charging network as a whole improves the performance and can save significant investment costs. It can also be concluded that the AFIR sets comparatively high standards for spatial coverage. A higher density of the charging network is unnecessary; the improvement of the maximum charging power would be a better strategy to provide better service to the BET.

The final element in the dynamic analysis is the coupled evaluation, where the queuing of trucks and concurrency of charging events are analyzed. A novel approach for the computation of departure times is integrated into the model to improve the estimation of required charging stations at the sites. In total, 1331 MCS charging stations are estimated to suffice for a possible 2030-scenario, where $15\,\%$ of the long-haul traffic is electrified. For the future, the demand for additional charging stations is expected to grow slightly less than the increase in BET market share.

Based on these findings, guidelines for technical, organizational, and regulatory action can be derived:

- Time loss due to charging is a major hurdle for the success of BET in long-haul applications. The strongest strategy to mitigate time loss on a system level is increased charging power. This requires improved vehicle and battery cell technologies, as well as high-power charging infrastructure and adequate electric grid connections. Higher network density or increased battery capacity have a limited impact on the residual time loss. The success on the system level is therefore dependent on multiple stakeholders cooperating.
- Consequently, future public subsidies in fast charging infrastructure should put particular emphasis on available charging power and prioritize MCS charging infrastructure with $1\,\mathrm{MW}$ upwards. In turn, an update to the AFIR is required, to increase the mandated charging power per plug to MCS levels.
- Two measures are especially suitable to reduce MCS charging demand: Private charging at the home base or during loading and unloading provides energy that does not need to be charged en route later. Even more importantly, overnight charging opportunities in public areas can reduce the dependence on public fast charging significantly compared to the simulated cases. It furthermore shifts the power demand into the night hours, away from peak load hours in the late afternoon. This system is especially efficient with a modular charging infrastructure that can be switched to MCS charging stations during the day.
- The increasing number of BET and the rising charging power per vehicle put strain on the electric grid. Especially along major TEN-T core routes, the electric grid connection can quickly become a limiting factor. Long planning horizons and sparse high-voltage grid coverage aggravate the issue. An early connection to the high-voltage grid, the planning of expansions, and possible temporary overprovisioning can be beneficial to meet future demand.

Future research should attempt to capture and model the actual usage patterns that the first BET entering the market exhibit: Do assumptions on the charging behavior, public charging quota, and the market share in long-haul applications hold up? The analysis of these parameters helps to fine-tune the models developed and to re-adjust the strategies for the technical development of vehicles and infrastructure. Though the overall results highlight the importance of a coordinated approach, it remains essential to scale up investments in electric road freight transport. The combination of financial resources and regulatory support provides guidance to the market and accelerates the transition.

This thesis's main aim is to shed light on the design of a public fast charging network, as high-quality public charging infrastructure serves as a key enabler for battery electric freight transport. It provides actionable guidelines for technical innovations, regulatory modifications, and synergy potentials between OEM, charging infrastructure operators, and distribution grid operators. Germany has a leading role within the European Union, as a node for six TEN-T corridors and as a traditional manufacturer of commercial vehicles, but the methods developed ensure scalability and transferability across borders. With the provided results, insights, and the generated knowledge about the system of Battery Electric Trucks (BET), public fast charging infrastructure, and the operational strategy, it can speed up the adoption of zero-emission vehicles in the logistics sector and make a major contribution to combating climate change.

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Bibliography

[1] Albert Arnold Gore Jr. “Nobel Prize Lecture," 2025. [Online]. Available: https://www.nobelprize.org/prizes/peace/2007/gore/lecture/ [visited on 06/12/2025].

[2] R. K. Pachauri - Intergovernmental Panel on Climate Change (IPCC). “Nobel Prize Lecture," 2025. [Online]. Available: https://www.nobelprize.org/prizes/peace/2007/ipcc/lecture/ [visited on 06/12/2025].

[3] European Commission. “*EU TRANSPORT IN FIGURES - STATISTICAL POCKETBOOK 2024*," 2024.

[4] European Commission. “Reducing CO2 emissions from heavy-duty vehicles," 2025. [Online]. Available: https://climate.ec.europa.eu/eu-action/transport/road-transport-reducing-co2-emissions-vehicles/reducing-co2-emissions-heavy-duty-vehicles_en [visited on 05/01/2025].

[5] Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung. “*Frühjahrsgutachten 2024*," 2024. Available: https://www.sachverstaendigenrat-wirtschaft.de/fruehjahrsgutachten-2024.html [visited on 01/08/2025].

[6] S. Link, A. Stephan, D. Speth and P. Plötz, “Declining costs imply fast market uptake of zero-emission trucks," *Nature Energy*, vol. 9, pp. 924–925, 2024, DOI: 10.1038/s41560-024-01555-1. Available: https://doi.org/10.1038/s41560-024-01555-1.

[7] H. B. Ben Sharpe, “A total cost of ownership comparison of truck decarbonization pathways in Europe," INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION, 2023. Available: https://theicct.org/wp-content/uploads/2023/11/ID-54-%E2%80%93-EU-HDV-TCO_paper_final2.pdf [visited on 05/30/2025].

[8] L. Mauler, L. Dahrendorf, F. Duffner, M. Winter and J. Leker, “Cost-effective technology choice in a decarbonized and diversified long-haul truck transportation sector: A U.S. case study," *Journal of Energy Storage*, vol. 46, p. 103891, 2022, DOI: https://doi.org/10.1016/j.est.2021.103891. Available: https://www.sciencedirect.com/science/article/pii/S2352152X21015565.

[9] J. Fleischmann, L. Bell and P. Kroyer. “*How batteries will drive the zero-emission truck transition*," 2024. Available: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/how-batteries-will-drive-the-zero-emission-truck-transition [visited on 09/18/2024].

[10] S. P. Wolff, “Eco-Efficiency Assessment of Zero-Emission Heavy-Duty Vehicle Concepts," PhD thesis, Technische Universität München, 2023.

[11] **G. Balke**, J. Schneider, M. Zähringer, T. Junior and M. Lienkamp, *Elektrifizierung des Güterverkehrs - Technologien und Handlungsempfehlungen*, Technische Universität München, 2024. Available: https://nefton.de/assets/NEFTON_report.pdf [visited on 05/15/2024].

[12] J. Bakker, J. Lopez Alvarez, J. Veldman and P. Buijs, “Strategic fleet replacement for the electrification of heavy-duty road freight transportation," *Applied Energy*, vol. 391, 2025, DOI: 10.1016/j.apenergy.2025.125935. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-105002768916&doi=10.1016%2fj.apenergy.2025.125935&partnerID=40&md5=263b79d288e5b20b02b4e7a22641ee97.

[13] I. Mareev, J. Becker and D. U. Sauer, “Battery Dimensioning and Life Cycle Costs Analysis for a Heavy-Duty Truck Considering the Requirements of Long-Haul Transportation," *Energies*, vol. 11, no. 1, 2018, DOI: 10.3390/en11010055. Available: https://www.mdpi.com/1996-1073/11/1/55.

[14] J. Schneider, O. Teichert, M. Zähringer, **G. Balke** and M. Lienkamp, “The novel Megawatt Charging System standard: Impact on battery size and cell requirements for battery-electric long-haul trucks," *eTransportation*, vol. 17, p. 100253, 2023, DOI: 10.1016/j.etran.2023.100253.

[15] MAN Truck & Bus SE. “Der neue MAN eTGX: Der eTruck für die Langstrecke: Der MAN eTGX elektrifiziert den Fernverkehr," 2025. [Online]. Available: https://www.man.eu/de/de/lkw/alle-modelle/der-man-tgx/der-man-etgx/uebersicht.html [visited on 01/16/2025].

[16] Daimler Truck AG. “Der neue eActros 600 – International Truck of the Year 2025 - Charged to change." 2025. [Online]. Available: https://www.mercedes-benz-trucks.com/de/de/trucks/eactros-600.html [visited on 01/22/2025].

[17] IVECO S.p.A. “Ihr neues IVECO S-eWay Rigid," 2025. [Online]. Available: https://www.iveco.com/germany/S-eWay-Rigid [visited on 05/25/2025].

[18] C. Werwitzke. “Deutschlands Lkw-Ladenetz nimmt Gestalt an," 2025. [Online]. Available: https://www.electrive.net/2024/09/19/deutschlands-lkw-ladenetz-nimmt-gestalt-an/ [visited on 05/26/2025].

[19] M. Hartmann and P. Vortisch, “A German Passenger Car and Heavy Vehicle Stock Model: Towards an Autonomous Vehicle Fleet," *Transportation Research Record*, vol. 2672, no. 46, pp. 55–63, 2018, DOI: 10.1177/0361198118782042. eprint: https://doi.org/10.1177/0361198118782042. Available: https://doi.org/10.1177/0361198118782042.

[20] Council of the EU and the European Council. “Fit for 55: towards more sustainable transport - Consilium," 2023. [Online]. Available: https://www.consilium.europa.eu/en/infographics/fit-for-55-afir-alternative-fuels-infrastructure-regulation/ [visited on 08/14/2023].

[21] F. Dohmen and S. Hage, “Gelber Weckruf: Weil Volkswagen, Daimler & Co. die Elektromobilität lange vernachlässigt haben, hat die Deutsche Post kurzerhand selbst ein E-Auto gebaut. Und blamiert damit die Fahrzeugbranche," *Der Spiegel*, no. 33, 2016. Available: https://www.spiegel.de/wirtschaft/gelber-weckruf-a-09ce9484-0002-0001-0000-000146269157?context=issue.

[22] Designwerk Technologies AG. “High Cab - Der E-LKW für weite Strecken," 2025. [Online]. Available: https://www.designwerk.com/elektro-lkw-high-cab/ [visited on 01/22/2025].

[23] DAF. “Der DAF XF Electric der neuen Generation - Fahren ohne Emissionen," 2025. [Online]. Available: https://www.daftrucks.de/de-de/lkw/new-generation-daf-xf-electric [visited on 01/22/2025].

[24] Volvo Trucks Deutschland. “Volvo FH Aero Electric," 2025. [Online]. Available: https://www.volvotrucks.de/de-de/trucks/electric/volvo-fh-aero-electric.html [visited on 01/22/2025].

[25] Renault Trucks Deutschland. “Renault Trucks E-Tech T Elektrisch," 2025. [Online]. Available: https://www.renault-trucks.de/product/renault-trucks-e-tech-t-elektrisch [visited on 01/22/2025].

[26] Scania Deutschland GmbH. “Elektro-Lkw - Die grüne Revolution in der Transportwelt," 2025. [Online]. Available: https://www.scania.com/de/de/home/products/trucks/battery-electric-truck.html [visited on 01/22/2025].

[27] J. Schneider, O. Teichert, M. Zähringer, K. Götz and M. Lienkamp, “Spoilt for Choice: User-Centric Choice of Battery Size and Chemistry for Battery-Electric Long-Haul Trucks," *Energies*, vol. 17, no. 1, 2024, DOI: 10.3390/en17010158. Available: https://www.mdpi.com/1996-1073/17/1/158.

[28] J. Schneider, “Economic, Ecological and Social Evaluation of Battery Systems for Electric Long-Haul Trucks (Dissertation)," 2025.

[29] O. Teichert, “Battery Design for Battery-Electric Long-Haul Trucks," PhD thesis, Technische Universität München, 2024. Available: https://mediatum.ub.tum.de/1705700.

[30] H. B. Ben Sharpe, “A meta-study of purchase costs for zero-emission trucks," INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION, 2022. Available: https://theicct.org/publication/purchase-cost-ze-trucks-feb22/.

[31] K. Abo Gamra, P. Bilfinger, M. Schreiber, T. Kröger, C. Allgäuer, et al., “Unlocking the full potential of electric vehicle fast-charging over lifetime through model-based aging adaptation," *Journal of Energy Storage*, vol. 99, p. 113361, 2024, DOI: 10.1016/j.est.2024.113361.

[32] N. Wassiliadis, J. Schneider, A. Frank, L. Wildfeuer, X. Lin, et al., “Review of fast charging strategies for lithium-ion battery systems and their applicability for battery electric vehicles," *Journal of Energy Storage*, vol. 44, p. 103306, 2021, DOI: https://doi.org/10.1016/j.est.2021.103306. Available: https://www.sciencedirect.com/science/article/pii/S2352152X21009981.

[33] M. Zähringer, S. Wolff, J. Schneider, **G. Balke** and M. Lienkamp, “Time vs. Capacity - The Potential of Optimal Charging Stop Strategies for Battery Electric Trucks," *Energies*, vol. 15, no. 19, 2022, DOI: 10.3390/en15197137.

[34] M. Zähringer, J. Schneider, **G. Balke**, K. A. Gamra, N. Klein, et al., “Fast track to a million: A simulative case study on the influence of charging management on the lifetime of battery electric trucks," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 9, p. 100731, 2024, DOI: https://doi.org/10.1016/j.prime.2024.100731. Available: https://www.sciencedirect.com/science/article/pii/S2772671124003115.

[35] University of Kassel. “New Research Project at the Department of LE: Project Beyond1kV," 2025. [Online]. Available: https://www.uni-kassel.de/eecs/en/infothek/sitemap-news-detail/2023/10/4/new-research-project-at-the-department-of-le-project-beyond1kv?cHash=e13a22be31b4e1f77e2cdd22f8249f5f [visited on 01/08/2025].

[36] MAN Truck & Bus SE. “Current Activities and Projects," 2025. [Online]. Available: https://emobilitaet.sh/file/forum2024_man_truck_bus.pdf [visited on 01/08/2025].

[37] F. Bussieweke, **G. Balke**, P. Rosner and M. Lienkamp. “*Automating and Electrifying Road Freight Logistics Using Transfer Hubs: An Agent-based Evaluation*," 2025. DOI: 10.13140/RG.2.2.10201.02406.

[38] D. Bönnighausen. “Brennerautobahn und Alpitronic nehmen Megawatt-Ladesystem in Bozen in Betrieb," 2025. [Online]. Available: https://www.electrive.net/2025/05/26/brennerautobahn-und-alpitronic-nehmen-megawatt-ladesystem-in-bozen-in-betrieb/ [visited on 05/29/2025].

[39] S. Schaal. “Kempower arbeitet an eigenem MCS-Produkt für Elektro-Lkw," 2025. [Online]. Available: https://www.electrive.net/2023/10/17/megawatt-laden-kempower-arbeitet-an-eigenem-mcs-produkt/ [visited on 01/10/2025].

[40] Forum Netztechnik/Netzbetrieb im VDE (FNN). “Netzanschlüsse für E-Lkw-Ladeparks. Orientierungshilfe für Verteilnetzbetreiber und Netzanschlussnehmer für die Bearbeitung von Netzanschlussanfragen für E-Lkw-Ladeinfrastruktur," 2025. [Online]. Available: https://www.vde.com/resource/blob/2347520/3490f979067fbbfd344729fcb61057ea/vde-fnn-impuls-netzanschluesse-fuer-e-lkw-ladeparks-data.pdf [visited on 04/09/2025].

[41] S. Kippelt, F. Probst, M. Greve and K. Burges, “Einfach laden an Rastanlagen. Auslegung des Netzanschlusses für E-Lkw-Lade-Hubs," Nationale Leitstelle Ladeinfrastruktur, 2022. Available: https://nationale-leitstelle.de/wp-content/uploads/2022/09/Leitstelle_LKW-Netzstudie.pdf [visited on 05/03/2025].

[42] K. Burges, S. Kippelt and F. Probst, “Grid-related challenges of high power charging stations for battery electric long haul trucks," in *5th E-Mobility Power System Integration Symposium (EMOB 2021)*, 2021, pp. 144–148, DOI: 10.1049/icp.2021.2517.

[43] badenovaNETZE GmbH, ED Netze GmbH, FairNetz GmbH, MVV Netze GmbH, MVV Netz GmbH, Netze BW GmbH, Netze ODR GmbH,Stadtwerke Ulm/Neu, Stadtwerke Karlsruhe Netzservice GmbH, Stuttgart Netze GmbH, Syna GmbH Überlandwerk Mittelbaden GmbH & Co. KG, “Regionalszenario 2023 | Planungsregion SÜDWEST," 2023.

[44] Y. Blume, M. Müller, A. Weiß and M. Hecker, “Einfluss des Hochlaufs batterieelektrischer Nutzfahrzeuge auf die Verteilnetzplanung," 2023. Available: https://www.ffe.de/veroeffentlichungen/einfluss-des-hochlaufs-batterieelektrischer-nutzfahrzeuge-auf-die-verteilnetzplanung/ [visited on 04/03/2025].

[45] Nationale Plattform Zukunft Mobilität. “Ladeinfrastruktur für batterieelektrische LKW," 2025. [Online]. Available: https://www.plattform-zukunft-mobilitaet.de/wp-content/uploads/2021/04/NPM_AG5_Ladeinfrastruktur_ELkw.pdf [visited on 04/09/2025].

[46] D. Battersby, A. Weiß and O. Baumann, “Beitragsreihe: Der Weg zum klimaneutralen Schwerlastverkehr – Die Symbiose aus MCS-Laden und der Photovoltaik – Was ist möglich?," 2024. Available: https://www.ffe.de/veroeffentlichungen/beitragsreihe-die-symbiose-aus-mcs-laden-und-der-photovoltaik-was-ist-moeglich/ [visited on 04/03/2025].

[47] Deutsche Energie-Agentur GmbH (dena), “Ausbau- und Innovationsbedarf der Stromverteilnetze in Deutschland bis 2030." 2012. Available: https://www.dena.de/fileadmin/dena/Dokumente/Pdf/9100_dena-Verteilnetzstudie_Abschlussbericht.pdf [visited on 05/02/2025].

[48] OpenStreetMap contributors. “Europe.osm.pbf dump retrieved from https://download.geofabrik.de/," 2022. [Online]. Available: %7Bhttps://download.geofabrik.de/%7D [visited on 11/24/2022].

[49] consentec. “Abschätzung der Kostenwirkung einer zunehmenden Verkabelung von 110-kV-Leitungen. Schlussbericht im Auftrag von Oesterreichs Energie, Brahmsplatz 3, A-1041 Wien," 2025. [Online]. Available: https://oesterreichsenergie.at/fileadmin/user_upload/Oesterreichs_Energie/Publikationsdatenbank/Studien/2020/Consentec_OE_Verkabelung110kV_Bericht_20201013.pdf [visited on 04/04/2025].

[50] B. Xiong, D. Fioriti, F. Neumann, I. Riepin and T. Brown, “Modelling the high-voltage grid using open data for Europe and beyond," *Scientific Data*, vol. 12, no. 1, p. 277, 2025.

[51] OpenStreetMap contributors. “Open Infrastructure Map," 2025. [Online]. Available: https://openinframap.org/ [visited on 05/28/2025].

[52] 123map GmbH & Co. KG. “flOSM Power Grid," 2025. [Online]. Available: https://www.flosm.org/en/powergrid.html [visited on 05/28/2025].

[53] DB Energie GmbH. “*Bahnstrom/Gleichstrom: Für Mobilität auf der Schiene*," https://web.archive.org/web/20170612085034/http://www.gartner.com/newsroom/id/1824919. 2011. [Visited on 02/10/2012].

[54] Intraplan Consult GmbH, TTS TRIMODE Transport Solutions GmbH, ETR Economic Trends Research GbR and MWP GmbH. “*Verkehrsprognose 2040 – Gesamtüberblick*," Forschungsbericht. Version 1.0. Robert-Schuman-Platz 1, 53175 Bonn, Oct. 2024.

[55] P. Wittenbrink, *Transportmanagement Kostenoptimierung, Green Logistics und Herausforderungen an der Schnittstelle Rampe*, Springer Gabler, 2014.

[56] Umweltbundesamt. “Fahrleistungen, Verkehrsleistung und Modal Split," 2025. [Online]. Available: https://www.umweltbundesamt.de/daten/verkehr/fahrleistungen-verkehrsaufwand-modal-split#guterverkehr [visited on 04/19/2025].

[57] European Commission, Directorate-General for Mobility and Transport. “Trans-European Transport Network (TEN-T)," 2025. [Online]. Available: https://transport.ec.europa.eu/transport-themes/infrastructure-and-investment/trans-european-transport-network-ten-t_en [visited on 05/25/2025].

[58] European Commission. “*TENtec Interactive Map Viewer*," 2024. Available: https://ec.europa.eu/transport/infrastructure/tentec/tentec-portal/map/maps.html [visited on 04/03/2024].

[59] Directorate-General for Mobility and Transport, European Commission. “Alternative Fuels Infrastructure Q&A on operating recharging infrastructure," 2025. [Online]. Available: https://transport.ec.europa.eu/news-events/news/alternative-fuels-infrastructure-regulation-qa-operating-recharging-infrastructure-2024-04-12_en [visited on 06/11/2025].

[60] Directorate-General for Mobility and Transport, European Commission. “File:Trans-European Transport Network (2024, not final).jpg," 2025. [Online]. Available: https://commons.wikimedia.org/wiki/File:Trans-European_Transport_Network_(2024,_not_final).jpg [visited on 04/19/2025].

[61] Bundesrepublik Deutschland, vertreten durch die Autobahn GmbH des Bundes, “Projektexposé: Planung, Errichtung und Betrieb von öffentlich zugänglicher Schnellladeinfrastruktur für E-Lkw an unbewirtschafteten Rastanlagen entlang der Bundesautobahnen in der Bundesrepublik Deutschland," Autobahn GmbH des Bundes, 2024. Available: https://www.autobahn.de/storage/user_upload/qbank/Projektexpose_Auschreibung_LKW-Schnellladenetz_unbewirtschaftete_Rastanlagen.pdf.

[62] Z. Raoofi, M. Mahmoudi and A. Pernestål, “Electric truck adoption and charging development: Policy insights from a dynamic model," *Transportation Research Part D: Transport and Environment*, vol. 139, p. 104515, 2025, DOI: https://doi.org/10.1016/j.trd.2024.104515. Available: https://www.sciencedirect.com/science/article/pii/S1361920924004723.

[63] e-mobil BW. “*Strukturstudie BW 2023: Kernergebnisse und Handlungsempfehlungen*," Online. 2023. Available: https://www.e-mobilbw.de/fileadmin/media/e-mobilbw/Publikationen/Studien/e-mobilBW_Strukturstudie_BW_2023_Kurzfassung.pdf [visited on 01/08/2025].

[64] European Automobile Manufacturers’ Association (ACEA). “NEW COMMERCIAL VEHICLE REGISTRATIONS, EUROPEAN UNION," 2025. [Online]. Available: https://www.acea.auto/files/Press_release_commercial_vehicle_registrations_Q1-2025-1.pdf [visited on 06/13/2025].

[65] S. Deb, K. Tammi, K. Kalita and P. Mahanta, “Review of recent trends in charging infrastructure planning for electric vehicles," *WIREs Energy and Environment*, vol. 7, no. 6, e306, 2018, DOI: 10.1002/wene.306. eprint: https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/wene.306.

[66] M. Metais, O. Jouini, Y. Perez, J. Berrada and E. Suomalainen, “Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options," *Renewable and Sustainable Energy Reviews*, vol. 153, p. 111719, 2022, DOI: 10.1016/j.rser.2021.111719.

[67] C. Hecht, K. Victor, S. Zurmühlen and D. U. Sauer, “Electric vehicle route planning using real-world charging infrastructure in Germany," *eTransportation*, vol. 10, p. 100143, 2021, DOI: 10.1016/j.etran.2021.100143.

[68] B. Al-Hanahi, I. Ahmad, D. Habibi and M. A. S. Masoum, “Charging Infrastructure for Commercial Electric Vehicles: Challenges and Future Works," *IEEE Access*, vol. 9, pp. 121476–121492, 2021, DOI: 10.1109/ACCESS.2021.3108817.

[69] B. Borlaug, M. Moniot, A. Birky, M. Alexander and M. Muratori, “Charging needs for electric semi-trailer trucks," *Renewable and Sustainable Energy Transition*, vol. 2, p. 100038, 2022, DOI: 10.1016/j.rset.2022.100038.

[70] D. Speth, P. Plötz, S. Funke and E. Vallarella, “Public fast charging infrastructure for battery electric trucks–a model-based network for Germany," *Environmental Research: Infrastructure and Sustainability*, vol. 2, no. 2, p. 025004, 2022, DOI: 10.1088/2634-4505/ac6442.

[71] D. Speth, V. Sauter and P. Plötz, “Where to Charge Electric Trucks in Europe - Modelling a Charging Infrastructure Network," *World Electric Vehicle Journal*, vol. 13, no. 9, 2022, DOI: 10.3390/wevj13090162.

[72] W. Shoman, S. Yeh, F. Sprei, P. Plötz and D. Speth, “Battery electric long-haul trucks in Europe: Public charging, energy, and power requirements," *Transportation Research Part D: Transport and Environment*, vol. 121, p. 103825, 2023, DOI: 10.1016/j.trd.2023.103825.

[73] J. Menter, T.-A. Fay, A. Grahle and D. Göhlich, “Long-Distance Electric Truck Traffic: Analysis, Modeling and Designing a Demand-Oriented Charging Network for Germany," *World Electric Vehicle Journal*, vol. 14, no. 8, 2023, DOI: 10.3390/wevj14080205.

[74] D. Speth, P. Plötz and M. Wietschel, “An optimal capacity-constrained fast charging network for battery electric trucks in Germany," *Transportation Research Part A: Policy and Practice*, vol. 193, p. 104383, 2025, DOI: https://doi.org/10.1016/j.tra.2025.104383. Available: https://www.sciencedirect.com/science/article/pii/S0965856425000114.

[75] J.-H. Lange, D. Speth and P. Plötz, “Optimized demand-based charging networks for long-haul trucking in Europe," *Environmental Research: Infrastructure and Sustainability*, vol. 4, no. 045004, 2024, DOI: 10.1088/2634-4505/ad889e. Available: https://doi.org/10.1088/2634-4505/ad889e.

[76] D. Speth, “Electrification of road freight transport – public fast charging infrastructure and the market diffusion of battery electric trucks," PhD thesis, Karlsruher Institut für Technologie (KIT), Karlsruher Institut für Technologie (KIT), 2024, DOI: 10.5445/IR/1000171485.

[77] L. C. Hunter, J. Scobie, C. McGarry and S. Galloway, “WattRoutes: smart planning for electric HGV charging infrastructure," *IET Conference Proceedings*, vol. 2024, pp. 6–11, 2025, DOI: 10.1049/icp.2024.3727. eprint: https://digital-library.theiet.org/doi/pdf/10.1049/icp.2024.3727. Available: https://digital-library.theiet.org/doi/abs/10.1049/icp.2024.3727.

[78] M. Kuby and S. Lim, “The flow-refueling location problemdocument.title=’ for alternative-fuel vehicles," *Socio-Economic Planning Sciences*, vol. 39, no. 2, pp. 125–145, 2005, DOI: https://doi.org/10.1016/j.seps.2004.03.001.

[79] A. Hurtado-Beltran, L. R. Rilett and Y. Nam, “Driving Coverage of Charging Stations for Battery Electric Trucks Located at Truck Stop Facilities," *Transportation Research Record*, vol. 2675, no. 12, pp. 850–866, 2021, DOI: 10.1177/03611981211031542.

[80] S. Narayanan and C. Antoniou, “Electric cargo cycles - A comprehensive review," *Transport Policy*, vol. 116, pp. 278–303, 2022, DOI: https://doi.org/10.1016/j.tranpol.2021.12.011. Available: https://www.sciencedirect.com/science/article/pii/S0967070X21003644.

[81] A. Danese, M. Garau, A. Sumper and B. N. Torsæter, “Electrical Infrastructure Design Methodology of Dynamic and Static Charging for Heavy and Light Duty Electric Vehicles," *Energies*, vol. 14, no. 12, 2021, DOI: 10.3390/en14123362. Available: https://www.mdpi.com/1996-1073/14/12/3362.

[82] E. Çabukoglu, G. Georges, L. Küng, G. Pareschi and K. Boulouchos, “Battery electric propulsion: An option for heavy-duty vehicles? Results from a Swiss case-study," *Transportation Research Part C: Emerging Technologies*, vol. 88, pp. 107–123, 2018, DOI: 10.1016/j.trc.2018.01.013. Available: https://www.sciencedirect.com/science/article/pii/S0968090X18300470.

[83] **G. Balke**, M. Zähringer, J. Schneider and M. Lienkamp, “Connecting the Dots: A Comprehensive Modeling and Evaluation Approach to Assess the Performance and Robustness of Charging Networks for Battery Electric Trucks and Its Application to Germany," *World Electric Vehicle Journal*, vol. 15, no. 1, 2024, DOI: 10.3390/wevj15010032.

[84] **G. Balke**, M. Zähringer, A. Paper and M. Lienkamp, "Navigating the Change: Optimization and Ramp-Up Strategy of a Charging Network for Battery Electric Heavy Trucks," in *IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*, 2024, pp. 1–7, DOI: 10.1109/ITSC58415.2024.10920217.

[85] P. Jochem, E. Szimba and M. Reuter-Oppermann, "How many fast-charging stations do we need along European highways?," *Transportation Research Part D: Transport and Environment*, vol. 73, pp. 120–129, 2019, DOI: https://doi.org/10.1016/j.trd.2019.06.005. Available: https://www.sciencedirect.com/science/article/pii/S1361920919300215.

[86] P. Jochem, C. Brendel, M. Reuter-Oppermann, W. Fichtner and S. Nickel, "Optimizing the allocation of fast charging infrastructure along the German autobahn," *Journal of Business Economics*, vol. 86, no. 5, pp. 513–535, 2015, DOI: 10.1007/s11573-015-0781-5. Available: https://doi.org/10.1007/s11573-015-0781-5.

[87] P. K. Rose, R. Nugroho, T. Gnann, P. Plötz, M. Wietschel, et al., "Optimal development of alternative fuel station networks considering node capacity restrictions," *Transportation Research Part D: Transport and Environment*, vol. 78, p. 102189, 2020, DOI: https://doi.org/10.1016/j.trd.2019.11.018. Available: https://www.sciencedirect.com/science/article/pii/S1361920919306479.

[88] B. Borlaug, M. Muratori, M. Gilleran, D. Woody, W. Muston, et al., "Heavy-Duty Truck Electrification and the Impacts of Depot Charging on Electricity Distribution Systems," *Nature Energy*, vol. 6, 2021, DOI: 10.1038/s41560-021-00855-0. Available: https://www.osti.gov/biblio/1807669.

[89] T. Dimatulac, H. Maoh and R. Carriveau, "An archetypal routing network model to help identify potential charging locations for long-haul electric vehicles in Ontario, Canada," *Transportation Research Interdisciplinary Perspectives*, vol. 19, p. 100825, 2023, DOI: https://doi.org/10.1016/j.trip.2023.100825. Available: https://www.sciencedirect.com/science/article/pii/S2590198223000726.

[90] J. Karlsson and A. Grauers, "Agent-Based Investigation of Charger Queues and Utilization of Public Chargers for Electric Long-Haul Trucks," *Energies*, vol. 16, no. 12, 2023, DOI: 10.3390/en16124704. Available: https://www.mdpi.com/1996-1073/16/12/4704.

[91] Amazon.com. "*Chalet: Charging Location for Electric Trucks*," 2024. Available: https://github.com/amzn/chalet-charging-location-for-electric-trucks [visited on 01/11/2025].

[92] P. Mishra, E. Miller, S. Santhanagopalan, K. Bennion and A. Meintz, "A Framework to Analyze the Requirements of a Multiport Megawatt-Level Charging Station for Heavy-Duty Electric Vehicles," *Energies*, vol. 15, no. 10, 2022, DOI: 10.3390/en15103788. Available: https://www.mdpi.com/1996-1073/15/10/3788.

[93] B. Nykvist and O. Olsson, "The feasibility of heavy battery electric trucks," *Joule*, vol. 5, no. 4, pp. 901–913, 2021, DOI: https://doi.org/10.1016/j.joule.2021.03.007. Available: https://www.sciencedirect.com/science/article/pii/S2542435121001306.

[94] D. Speth and P. Plötz, "Depot slow charging is sufficient for most electric trucks in Germany," *Transportation Research Part D: Transport and Environment*, vol. 128, p. 104078, 2024, DOI: https://doi.org/10.1016/j.trd.2024.104078. Available: https://www.sciencedirect.com/science/article/pii/S136192092400035X.

[95] M. J. Hodgson, "A Flow-Capturing Location-Allocation Model," *Geographical Analysis*, vol. 22, no. 3, pp. 270–279, 1990, DOI: https://doi.org/10.1111/j.1538-4632.1990.tb00210.x. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1538-4632.1990.tb00210.x. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1538-4632.1990.tb00210.x.

[96] D. Speth, V. Sauter, P. Plötz and T. Signer, "Synthetic European road freight transport flow data," *Data in Brief*, vol. 40, p. 107786, 2022, DOI: 10.1016/j.dib.2021.107786.

[97] E. Szimba, M. Kraft, J. Ihrig, A. Schimke, O. Schnell, et al. "*ETISplus Database Content and Methodology*," Nov. 2012. DOI: 10.13140/RG.2.2.16768.25605.

[98] M. Schubert, T. Kluth, G. Nebauer, R. Ratzenberger, S. Kotzagiorgis, et al., "Verkehrsverflechtungsprognose 2030," INTRAPLAN Consult GmbH and BVU Beratergruppe Verkehr + Umwelt GmbH, 06/2014. Available: https://daten.clearingstelle-verkehr.de/276/1/verkehrsverflechtungsprognose-2030-schlussbericht-los-3.pdf [visited on 04/18/2025].

[99] Gurobi Optimization, LLC. "*Gurobi Optimizer Reference Manual*," 2023. Available: https://www.gurobi.com.

[100] S. Li, Y. Huang and S. J. Mason, "A multi-period optimization model for the deployment of public electric vehicle charging stations on network," *Transportation Research Part C: Emerging Technologies*, vol. 65, pp. 128–143, 2016, DOI: https://doi.org/10.1016/j.trc.2016.01.008. Available: https://www.sciencedirect.com/science/article/pii/S0968090X16000267.

[101] O. Teichert, S. Link, J. Schneider, S. Wolff and M. Lienkamp, "Techno-economic cell selection for battery-electric long-haul trucks," *eTransportation*, vol. 16, p. 100225, 2023, DOI: 10.1016/j.etran.2022.100225.

[102] M. Zähringer, O. Teichert, **G. Balke**, J. Schneider and M. Lienkamp, "Optimizing the Journey: Dynamic Charging Strategies for Battery Electric Trucks in Long-Haul Transport," *Energies*, vol. 17, no. 4, 2024, DOI: 10.3390/en17040973.

[103] J. Schneider, S. Wolff, M. Seidenfus and M. Lienkamp, "Sizing up sustainability: Influence of battery size and cell chemistry on battery-electric trucks' life-cycle carbon emissions," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 9, p. 100656, 2024, DOI: https://doi.org/10.1016/j.prime.2024.100656. Available: https://www.sciencedirect.com/science/article/pii/S2772671124002365.

[104] **G. Balke** and L. Adenaw, "Heavy commercial vehicles' mobility: Dataset of trucks' anonymized recorded driving and operation (DT-CARGO)," *Data in Brief*, vol. 48, p. 109246, 2023, DOI: 10.1016/j.dib.2023.109246. Available: https://www.sciencedirect.com/science/article/pii/S2352340923003657.

[105] **G. Balke** and L. Adenaw. "*DT-CARGO dataset*," 2017. Available: https://github.com/TUMFTM/dt-cargo.

[106] T. Q. Nguyen, "Data Quality Assessment of Hybrid Mobility Data," Bachelor's Thesis, Technische Universität München, München, 2022.

[107] National Renewable Energy Laboratory. "*Fleet DNA Project Data*," 2024. Available: www.nrel.gov/fleetdna [visited on 01/14/2025].

[108] A. Paper, **G. Balke**, P. Rosborough and M. Lienkamp. "*Electrification potential of heavy-duty truck fleets using real-world GPS mobility data*," 2025. DOI: 10.13140/RG.2.2.32011.40483.

[109] T. Stuckenberger, "Data Based Analysis E-Mobility," IDP, Technische Universität München, München, 2023.

[110] Technical University of Munich. "SPIRIT-E: Shared Private Charging Infrastructure and Reservation for Bidirectionally Integrated Truck Electrification," 2025. [Online]. Available: https://spirit-e.de/ [visited on 05/17/2025].

[111] H. Sornn-Friese, "Interfirm linkages and the structure and evolution of the danish trucking industry," *Transportation Journal*, vol. 44, pp. 10–26, 2005, DOI: 10.5325/transportationj.44.4.0010.

[112] Dirk Lohre and Wilfried Stock and Frank Huster, "Stückgutlogistik in Deutschland, Studie zu Prozessen, Marktvolumen, Herausforderungen und Zukunftsentwicklungen eines logistischen Spezialsegments," 2021. Available: https://www.dslv.org/fileadmin/Redaktion/PDFs/07_Publikationen/DSLV_Studie_Stueckgutlogistik_2021-08-24.pdf [visited on 05/27/2025].

[113] F. Nilsson, H. Sternberg and T. Klaas-Wissing, “Who controls transport emissions and who cares? investigating the monitoring of environmental sustainability from a logistics service provider’s perspective," *The International Journal of Logistics Management*, vol. 28, pp. 798–820, 2017, DOI: 10.1108/ijlm-11-2015-0197.

[114] C. Peteranderl, M. Zähringer, **G. Balke** and J. Schneider. ““Megawatt charging as an enabler for battery-electric long-haul trucks – is that enough?”," in: *Commercial Vehicles 2023*. VDI Verlag, 2023, pp. 55–66. ISBN: 9783181024171. DOI: 10.51202/9783181024171-55.

[115] M. Unold, “Clustering of mobility data to identify mobility behaviour of heavy commercial vehicles," Master’s Thesis, Technische Universität München, München, 2022.

[116] S. Wolff, J. Schneider, **G. Balke**, M. Zähringer, S. Büttner, et al., “Applications – Transportation Applications | Hybrid Electric Buses and Trucks – Batteries," in *Encyclopedia of Electrochemical Power Sources (Second Edition)*, J. Garche, ed. Oxford: Elsevier, 2025, pp. 202–214, ISBN: 978-0-323-95822-6. DOI: https://doi.org/10.1016/B978-0-323-96022-9.00125-0. Available: https://www.sciencedirect.com/science/article/pii/B9780323960229001250.

[117] M. Zähringer, O. Teichert, **G. Balke**, J. Schneider and M. Lienkamp. “*BETOS Framework (Battery-electric Truck Operation Simulation)*," 2024. Available: https://github.com/TUMFTM/BETOS_Framework.

[118] Kraftfahrt-Bundesamt. “Güterbeförderung 2023," 2025. [Online]. Available: https://www.kba.de/DE/Statistik/Kraftverkehr/europaeischerLastkraftfahrzeuge/ve_Gueterbefoerderung/ve_Gueterbefoerderung_node.html [visited on 04/18/2025].

[119] B. für Logistik und Mobilität (BALM). “*Mautstatistik*," 2020. Available: https://www.balm.bund.de/SharedDocs/Downloads/DE/Statistik/Lkw-Maut/Jahrestab_19_20.pdf [visited on 07/18/2025].

[120] T. Q. Nguyen, “Model Calibration for Battery Electric Trucks," IDP, Technische Universität München, München, 2024.

[121] Bundesanstalt für Straßenwesen (BASt). “Automatische Dauerzählstellen - Beschreibung der CSV-Ergebnistabelle," 2025. [Online]. Available: https://www.bast.de/DE/Verkehrstechnik/Fachthemen/v2-verkehrszaehlung/pdf-dateien/DZ-Abkuerzungen-Beschreibung.pdf?v=11 [visited on 01/19/2025].

[122] M. Decarli, “Data Driven Engineering - Multi agent simulation of battery electric heavy duty vehicles," Semesterarbeit, Technische Universität München, München, 2024.

[123] M. Kuehnbach, A. Bekk and A. Weidlich, “Prepared for regional self-supply? On the regional fit of electricity demand and supply in Germany," *Energy Strategy Reviews*, vol. 34, p. 100609, 2021, DOI: 10.1016/j.esr.2020.100609.

[124] J. Smolen and B. Dudic, “Electricity Price and Demand Pattern Changes Due to Increases in Solar Generation in German Electricity Markets," *International Journal of Energy Economics and Policy*, vol. 9, pp. 168–173, 2019, DOI: 10.32479/ijeep.7067.

[125] J. Denzer. “KRAVAG startet Ladenetzwerk für Elektro-Lkw," 2025. [Online]. Available: https://www.ruv.de/newsroom/pressemitteilungen/2025-03-27-kravag-ladenetz-elektro-lkw [visited on 05/17/2025].

[126] Bundesamt für Logistik und Mobilität (BALM). “*Mauttabelle*," 2025. Available: https://www.balm.bund.de/DE/Themen/Lkw-Maut/Mauttabelle/mauttabelle_node.html [visited on 01/19/2025].

[127] F. Biedenbach and K. Strunz, “Multi-Use Optimization of a Depot for Battery-Electric Heavy-Duty Trucks," *World Electric Vehicle Journal*, vol. 15, no. 3, 2024, DOI: 10.3390/wevj15030084. Available: https://www.mdpi.com/2032-6653/15/3/84.

[128] European Climate, Infrastructure and Environment Executive Agency. “Fifth cut-off date of the Alternative Fuels Infrastructure Facility call for proposals - Cohesion and General envelopes," 2025. [Online]. Available: https://cinea.ec.europa.eu/document/download/8c09daa5-0d21-4dd4-92b9-39d6c16c36f6_en?filename=AFIF_Cut-off%205_List%20of%20projects_simple.pdf [visited on 06/22/2025].

[129] Transportministeriet. “25 nye ladeparker til ellastbiler," 2025. [Online]. Available: https://www.trm.dk/nyheder/2023/25-nye-ladeparker-til-ellastbiler [visited on 06/24/2025].

[130] ENGIE MOBILITES ELECTRIQUES. “*Soutenir le déploiement des infrastructures publiques de recharge dédiées aux poids-lourds pour atteindre les objectifs de décarbonation*," May 1, 2025. Available: https://conference-ambition-france.transports.gouv.fr/sites/default/files/documents/Engie_Soutenir%20le%20d%C3%A9ploiement%20des%20infra%20publiques%20de%20recharge%20PL.pdf [visited on 06/21/2025].

[131] L. Ungerboeck. “Asfinag schreibt Konzessionen für E-Auto-Ladeinfrastruktur aus," 2025. [Online]. Available: https://www.derstandard.at/consent/tcf/story/3000000218061/asfinag-schreibt-konzessionen-fuer-e-auto-ladeinfrastruktur-aus [visited on 06/21/2025].

[132] Generalna Dyrekcja Dróg Krajowych i Autostrad. “Plany rozwoju elektromobilności przy głównych szlakach w Polsce," 2025. [Online]. Available: https://www.gov.pl/web/gddkia/plany-rozwoju-elektromobilnosci-przy-glownych-szlakach-w-polsce [visited on 06/24/2025].

[133] Commercial Vehicle Charging Europe B.V. “Milence showcases Europe’s largest public charging network for heavy duty trucks at IAA Transportation 2024 in Hannover," 2025. [Online]. Available: https://milence.com/press-release/milence-showcases-europes-largest-public-charging-network-for-heavy-duty-trucks-at-iaa-transportation-2024-in-hannover/ [visited on 06/21/2025].

[134] MAN Truck & Bus SE. “E.ON AND MAN SET UP PUBLIC CHARGING NETWORK," 2025. [Online]. Available: https://www.man.eu/corporate/en/newsroom/stories/eon-and-man-build-public-charging-network-150208.html [visited on 06/21/2025].

[135] BP p.l.c. “bp pulse builds Europe’s first public charging corridor for electric trucks along major logistics route," 2025. [Online]. Available: https://www.bp.com/en/global/corporate/news-and-insights/press-releases/bp-pulse-build-europes-first-public-charging-corridor-for-electric-trucks-along-major-logistics-route.html [visited on 06/21/2025].

[136] com-a-tec GmbH. “OKQ8 expands truck charging facilities across Sweden," 2025. [Online]. Available: https://www.mobilityplaza.org/news/40803 [visited on 06/21/2025].

[137] Einride Technologies Germany GmbH. “Smart charging Europe," 2025. [Online]. Available: https://www.einride.tech/charging-network [visited on 06/21/2025].

[138] Fastcharge AS. “Our charging hubs," 2025. [Online]. Available: https://fastcharge.no/chargemap/%20(also%20MCS) [visited on 06/21/2025].

[139] Leap24 B.V. “Locaties," 2025. [Online]. Available: https://leap24.eu/ [visited on 06/21/2025].

[140] Ortec Group. “Oreve’s network," 2025. [Online]. Available: https://oreve.com/en/oreves-network/ [visited on 06/21/2025].

[141] GITO Heavy Charging Solutions AB. “Karta över våra publika laddstationer," 2025. [Online]. Available: https://gito.se/vart-laddnatverk/ [visited on 06/21/2025].

[142] Editorial Board EVBoosters. “Five countries lead Europe’s electric truck charging infrastructure," 2025. [Online]. Available: https://evboosters.com/ev-charging-news/five-countries-lead-europes-electric-truck-charging-infrastructure/ [visited on 06/21/2025].

[143] Infocap Communication & Publishing S.L. “Traton se alía con Zunder para facilitar la carga de sus camiones en el sur de Europa," 2025. [Online]. Available: https://www.rutadeltransporte.com/servicios/traton-alia-zunder-facilitar-carga_0_2000004608.html [visited on 06/21/2025].

[144] Gareth Roberts. “Power Park network to help decarbonise commercial vehicles," 2025. [Online]. Available: https://www.fleetnews.co.uk/news/power-park-network-to-help-decarbonise-commercial-vehicles [visited on 06/22/2025].

[145] Shell Deutschland GmbH. “E-Mobilität für Lkw-Fuhrparks," 2025. [Online]. Available: https://www.shell.de/geschaeftskunden/shell-card-tankkarten/nachhaltigkeit/elektro-lkw.html [visited on 06/22/2025].

[146] Gareth Roberts. “Shell opens first charger in the UK for electric trucks," 2025. [Online]. Available: https://www.fleetnews.co.uk/news/shell-opens-first-charger-in-the-uk-for-electric-trucks [visited on 06/22/2025].

[147] Allego N.V. “Allego Announces Successful Pilot Program for High-Powered Truck Charging; Initial 2024 Network Roll-out Planned," 2025. [Online]. Available: https://ir.allego.eu/events-publications/press-releases/detail/71/allego-announces-successful-pilot-program-for-high-powered#:~:text=On%20October%2012%2C%202023%2C%20Allego,hour%20for%20heavy%20duty%20trucks [visited on 06/22/2025].

[148] Enova. “Snart kjører elektriske lastebiler mellom byene i Sør-Norge," 2025. [Online]. Available: https://kommunikasjon.ntb.no/pressemelding/18031967/snart-kjorer-elektriske-lastebiler-mellom-byene-i-sor-norge?publisherId=17848299&lang=no [visited on 06/22/2025].

[149] Chris Randall. “Circle K launches truck charging network in Sweden," 2025. [Online]. Available: https://www.electrive.com/2023/06/22/circle-k-launches-truck-charging-network-in-sweden/ [visited on 06/22/2025].

[150] Mer Germany. “Elektrifizierung des Hamburger Hafens schreitet voran: Eröffnung neuer Schnellladepunkte," 2025. [Online]. Available: https://de.mer.eco/wp-content/uploads/sites/8/2024/11/Mer-Germany_Pressemitteilung_Hamburger-Hafen.pdf [visited on 06/22/2025].

[151] Brede Høgseth Wardrum. “Uno-X Mobility kjøper Tungbil Lading AS," 2025. [Online]. Available: https://www.yrkesbil.no/enova-ladeinfrastruktur-tungbil-lading-as/uno-x-mobility-kjoper-tungbil-lading-as/4094418 [visited on 06/22/2025].

[152] IBERDROLA, S.A. “Iberdrola | bp pulse to launch the first Megawatt Charging System (MCS) charger for heavy-duty vehicles in Southern Europe," 2025. [Online]. Available: https://www.iberdrolaespana.com/press-room/news/detail/240426-iberdrola-bp-pulse-to-launch-the-first-megawatt-charging-system-mcs-charger-for-heavy-duty-vehicles-in-southern-europe [visited on 06/22/2025].

[153] Endesa Energía, Endesa S.A. “Endesa and Gasolprice open 4 ultra-fast charging points on the A-2, very close to Zaragoza, for light and heavy vehicles," 2025. [Online]. Available: https://www.endesa.com/en/press/press-room/news/energy-transition/electric-mobility/gasolprice-inauguration-points-ultra-fast-recharging [visited on 06/22/2025].

[154] ENGIE MOBILITES ELECTRIQUES. “Recharge your electric trucks and vans with ENGIE Vianeo," 2025. [Online]. Available: https://www.engie-vianeo.com/en/etruck-charging-station/ [visited on 06/23/2025].

[155] GOFAST Ltd. “Ready even for heavy duty electric trucks," 2025. [Online]. Available: https://www.gofast.swiss/en/blog/press-release/ready-even-for-heavy-duty-electric-trucks [visited on 06/23/2025].

[156] F. Treiß. “Shell präsentiert Megawatt-Ladesystem für Lkw und Schiffe," 2025. [Online]. Available: https://www.electrive.net/2024/06/20/shell-praesentiert-megawatt-ladesystem-fuer-lkw-und-schiffe/ [visited on 06/23/2025].

[157] A. Golab, C. Loschan, S. Zwickl-Bernhard and H. Auer, “The value of flexibility of commercial electric vehicle fleets in the redispatch of congested transmission grids," *Energy*, vol. 316, p. 134385, 2025, DOI: https://doi.org/10.1016/j.energy.2025.134385. Available: https://www.sciencedirect.com/science/article/pii/S0360544225000271.

[158] J. Deng, H. Hu and L. Dai, “How will dynamic charging tariff affect electric truck fleet operation: A two-stage stochastic model," *J. Shanghai Jiatong Univ.*, vol. 29, no. 6, pp. 1050–1062, 2024.

[159] Laden & Bezahlen. “Milence and Port of Antwerp-Bruges reach an agreement to develop a 30-bay charging hub for heavy-duty vehicles," 2025. [Online]. Available: https://milence.com/de/charging-payment/ [visited on 05/30/2025].

Prior Publications

During the development of this dissertation, publications and student theses were written in which partial aspects of this work were presented.

Journals; Scopus/Web of Science listed (peer-reviewed)

[14] J. Schneider, O. Teichert, M. Zähringer, **G. Balke** and M. Lienkamp, “The novel Megawatt Charging System standard: Impact on battery size and cell requirements for battery-electric long-haul trucks," *eTransportation*, vol. 17, p. 100253, 2023, DOI: 10.1016/j.etran.2023.100253.

[33] M. Zähringer, S. Wolff, J. Schneider, **G. Balke** and M. Lienkamp, “Time vs. Capacity - The Potential of Optimal Charging Stop Strategies for Battery Electric Trucks," *Energies*, vol. 15, no. 19, 2022, DOI: 10.3390/en15197137.

[34] M. Zähringer, J. Schneider, **G. Balke**, K. A. Gamra, N. Klein, et al., “Fast track to a million: A simulative case study on the influence of charging management on the lifetime of battery electric trucks," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 9, p. 100731, 2024, DOI: https://doi.org/10.1016/j.prime.2024.100731. Available: https://www.sciencedirect.com/science/article/pii/S2772671124003115.

[83] **G. Balke**, M. Zähringer, J. Schneider and M. Lienkamp, “Connecting the Dots: A Comprehensive Modeling and Evaluation Approach to Assess the Performance and Robustness of Charging Networks for Battery Electric Trucks and Its Application to Germany," *World Electric Vehicle Journal*, vol. 15, no. 1, 2024, DOI: 10.3390/wevj15010032.

[102] M. Zähringer, O. Teichert, **G. Balke**, J. Schneider and M. Lienkamp, “Optimizing the Journey: Dynamic Charging Strategies for Battery Electric Trucks in Long-Haul Transport," *Energies*, vol. 17, no. 4, 2024, DOI: 10.3390/en17040973.

[104] **G. Balke** and L. Adenaw, “Heavy commercial vehicles’ mobility: Dataset of trucks’ anonymized recorded driving and operation (DT-CARGO)," *Data in Brief*, vol. 48, p. 109246, 2023, DOI: 10.1016/j.dib.2023.109246. Available: https://www.sciencedirect.com/science/article/pii/S2352340923003657.

Conferences, Periodicals; Scopus/Web of Science listed (peer-reviewed)

[84] **G. Balke**, M. Zähringer, A. Paper and M. Lienkamp, “Navigating the Change: Optimization and Ramp-Up Strategy of a Charging Network for Battery Electric Heavy Trucks," in *IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*, 2024, pp. 1–7, DOI: 10.1109/ITSC58415.2024.10920217.

[116] S. Wolff, J. Schneider, **G. Balke**, M. Zähringer, S. Büttner, et al., "Applications – Transportation Applications | Hybrid Electric Buses and Trucks – Batteries," in *Encyclopedia of Electrochemical Power Sources (Second Edition)*, J. Garche, ed. Oxford: Elsevier, 2025, pp. 202–214, ISBN: 978-0-323-95822-6. DOI: https://doi.org/10.1016/B978-0-323-96022-9.00125-0. Available: https://www.sciencedirect.com/science/article/pii/B9780323960229001250.

Journals, Conferences, Periodicals, Reports, Conference Proceedings and Poster, etc.; not Scopus/Web of Science listed

[11] **G. Balke**, J. Schneider, M. Zähringer, T. Junior and M. Lienkamp, *Elektrifizierung des Güterverkehrs - Technologien und Handlungsempfehlungen*, Technische Universität München, 2024. Available: https://nefton.de/assets/NEFTON_report.pdf [visited on 05/15/2024].

[37] F. Bussieweke, **G. Balke**, P. Rosner and M. Lienkamp. "*Automating and Electrifying Road Freight Logistics Using Transfer Hubs: An Agent-based Evaluation*," 2025. DOI: 10.13140/RG.2.2.10201.02406.

[108] A. Paper, **G. Balke**, P. Rosborough and M. Lienkamp. "*Electrification potential of heavy-duty truck fleets using real-world GPS mobility data*," 2025. DOI: 10.13140/RG.2.2.32011.40483.

[114] C. Peteranderl, M. Zähringer, **G. Balke** and J. Schneider. ""Megawatt charging as an enabler for battery-electric long-haul trucks – is that enough?"," in: *Commercial Vehicles 2023*. VDI Verlag, 2023, pp. 55–66. ISBN: 9783181024171. DOI: 10.51202/9783181024171-55.

Y. Schulze, F. Biedenbach and **G. Balke**. "*Online-Workshop: Bidirektionales Laden von Nutzfahrzeugen*," Vortrag vor 110 Teilnehmern aus dem Forschungsprogramm elektro-mobil. Nov. 2022.

S. Wolff and **G. Balke**. "*Unter Strom - Potentiale Batterieelektrischer Lkw*," Vortrag vor dem Sachverständigenrat für Gesamtwirtschaftliche Entwickung (Wirtschaftsweisen) inkl. wissenschaftlichem Stab. Mar. 2024.

Non-thesis-relevant publications; Scopus/Web of Science listed (peer-reviewed)

F. Waldner and **G. Balke** (shared authorship), F. Rech, M. Lellep and M. Lienkamp, "Data-Driven Insights into (E-)Bike-Sharing: Mining a Large-Scale Dataset on Usage and Urban Characteristics - Descriptive Analysis and Performance Modeling," (accepted), *Transportation*.

S. Krapf, L. Bogenrieder, F. Netzler, **G. Balke** and M. Lienkamp, "RID–Roof Information Dataset for Computer Vision-Based Photovoltaic Potential Assessment," *Remote Sensing*, vol. 14, no. 10, 2022, DOI: 10.3390/rs14102299. Available: https://www.mdpi.com/2072-4292/14/10/2299.

M. Seidenfus, T. Zacher, **G. Balke** and M. Lienkamp, "Out of Alignment: Fixing Overlapping Segments in German Car Classification through Data Driven Clustering," (in review process), *Future Transportation*, 2025.

Thesis-relevant open-source software

[105] **G. Balke** and L. Adenaw. "*DT-CARGO dataset*," 2017. Available: https://github.com/TUMFTM/dt-cargo.

[117] M. Zähringer, O. Teichert, **G. Balke**, J. Schneider and M. Lienkamp. "*BETOS Framework (Battery-electric Truck Operation Simulation)*," 2024. Available: https://github.com/TUMFTM/BETOS_Framework.

Supervised Student Theses

The following student theses were written within the framework of the dissertation under the supervision of the author in terms of content, technical and scientific support as well as under relevant guidance of the author. In the following, the bachelor, semester and master theses relevant and related to this dissertation are listed. Many thanks to the authors of these theses for their extensive support within the framework of this research project.

[106] T. Q. Nguyen, “Data Quality Assessment of Hybrid Mobility Data," Bachelor’s Thesis, Technische Universität München, München, 2022.

[109] T. Stuckenberger, “Data Based Analysis E-Mobility," IDP, Technische Universität München, München, 2023.

[115] M. Unold, “Clustering of mobility data to identify mobility behaviour of heavy commercial vehicles," Master’s Thesis, Technische Universität München, München, 2022.

[120] T. Q. Nguyen, “Model Calibration for Battery Electric Trucks," IDP, Technische Universität München, München, 2024.

[122] M. Decarli, “Data Driven Engineering - Multi agent simulation of battery electric heavy duty vehicles," Semesterarbeit, Technische Universität München, München, 2024.

F. Rech, “Data Analysis of the Bike Sharing Dataset," IDP, Technische Universität München, München, 2023.

Appendix

A Chapter Anhang

A.1 Academic Keywords

For the search of "Charging Infrastructure", the keyword "Charging infrastructure" is used. Publications in the category "Battery Electric Trucks" carry a keyword from the synonyms: "battery electric truck", "battery electric trucks", "battery-electric truck", "battery-electric trucks", "electric truck" and "electric trucks" The category "Fast Charging Trucks" unites matches of "megawatt charging" with any combination between "fast charging" and the BET synonyms.

A.2 Highway Network

Table A.1: Used OSM street types and respective default speed limits following German laws. Speed limits are overridden if a specific speed limit for trucks (key "maxspeed:hgv") is provided. Updated values compared to [83][*].

values of "highway" key	**max speed**	**specific edge cost in** $\mathrm{h\,km^{-1}}$
motorway, trunk	$80\,\mathrm{km\,h^{-1}}$	0.0125
primary, secondary	$50\,\mathrm{km\,h^{-1}}$	0.02
tertiary	$40\,\mathrm{km\,h^{-1}}$	0.025
motorway_link, trunk_link, primary_link, secondary_link, tertiary_link motorway_junction	$30\,\mathrm{km\,h^{-1}}$	0.033 33
road	$50\,\mathrm{km\,h^{-1}}$	0.02

A.3 Infeasible Routes per Charging Network

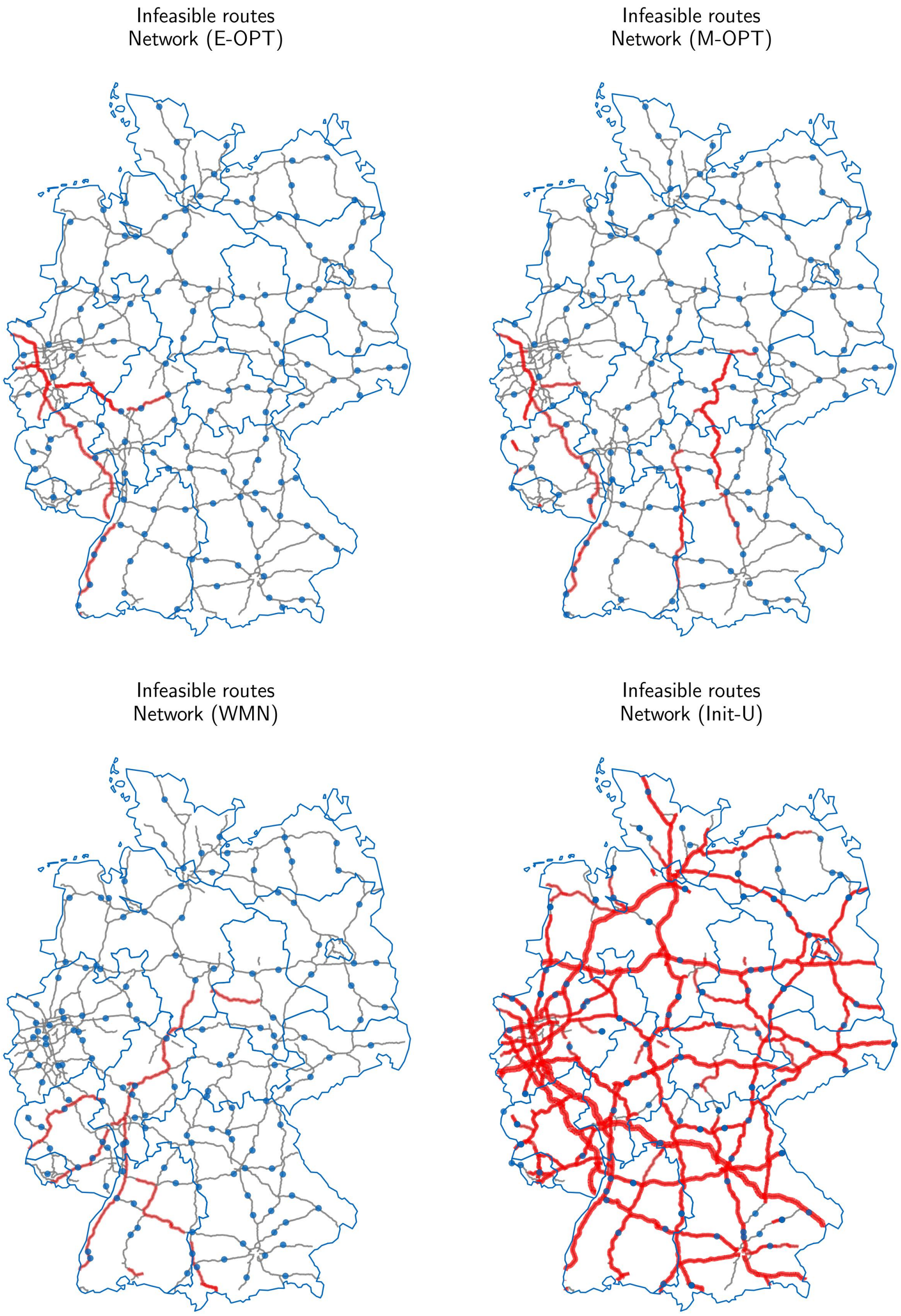

Figure A.1: Charging networks, motorways and the associated infeasible routes in scenarios 266 (upper left), 267 (upper right), 271 (lower left) and 275 (lower right).

A.4 Charging Network: Site Dimensioning at High Electrification Rate

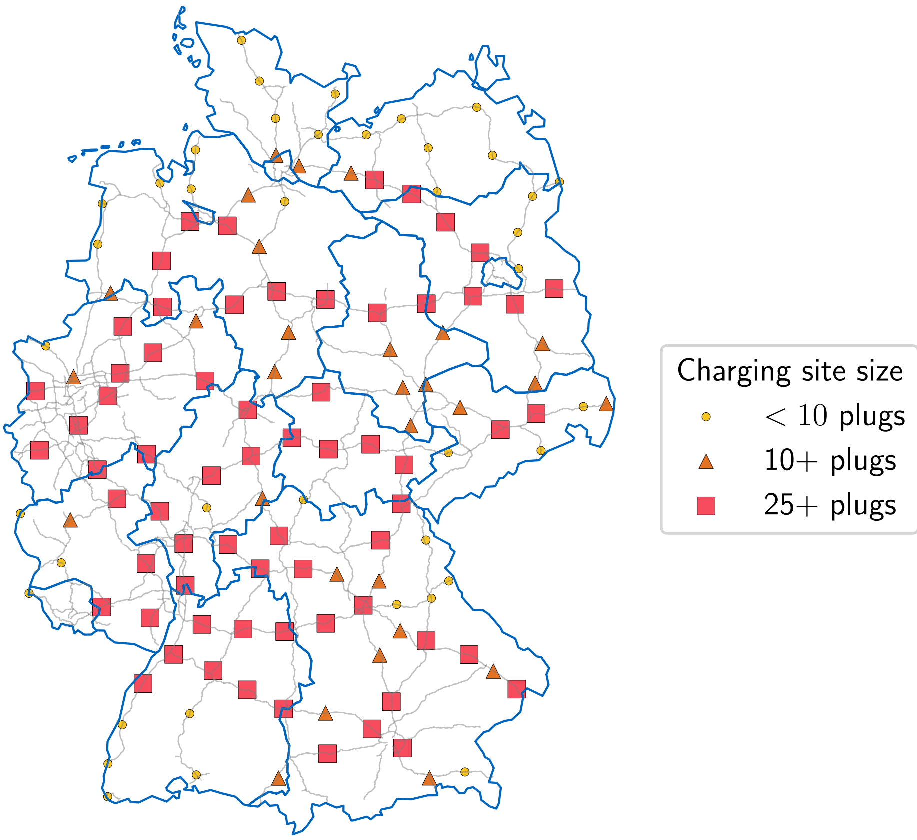

Figure A.2: Charging network M-OPT with site dimensioning at 50 % electrification rate. In total, 3688 charging stations are placed. Refer to Figure 4.12 for the 15 % scenario.