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Determining Charging Infrastructure Requirements for Electrified Long-Haul Freight Traffic on German Motorways: A Dual-Perspective Analysis

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Executive Summary

Road freight transport is a major contributor to greenhouse gas emissions in Europe, underscoring the need for sustainable alternatives to diesel-powered trucks. This study assesses the public charging infrastructure required along German motorways to support increasing levels of long-haul truck electrification, balancing the needs of logistics companies and charge point operators (CPOs). At 1% electrification, 519 high-power charging (HPC) points and 742 low-power charging (LPC) points are required, with HPC utilized during short driving breaks and LPC during extended rest periods. This demand grows to 2,155 HPC and 8,147 LPC points across 525 locations at 20% electrification. The charging power is not fixed but dynamically determined based on parameters such as charging duration and the vehicle's remaining state of charge (SoC). HPC utilization rises from 8% to 38% across these scenarios, while average waiting times remain between three and five minutes. The results demonstrate that efficient, scalable infrastructure can be deployed to meet rising electrification demands while maintaining service quality and operational viability for both stakeholder groups.

Keywords: Heavy Duty electric Vehicles & Buses, Optimal charging locations, Modeling & Simulation, Charging Business Models, Fast and Megawatt charging infrastructure

1 Introduction

As the global shift towards sustainable energy solutions accelerates in response to climate change, the transportation sector remains a key area of focus for emission reduction. In the context of decarbonizing road transport, the European Union (EU) has introduced stringent CO_2 emission performance standards for new heavy-duty vehicles [1]. Battery electric trucks (BETs) are emerging as a central technology in this transition, with high-power charging (HPC) during intermediate stops playing a critical enabling role. To support the deployment of such infrastructure, the EU has enacted the Alternative Fuels Infrastructure Regulation (AFIR), which sets minimum requirements for publicly accessible charging stations along the Trans-European Transport Network (TEN-T) [2].
Germany, as the EU member state with the highest annual volume of road freight transport, faces a particular challenge in electrifying long-haul operations and ensuring adequate public charging infrastructure [3]. Although slow depot charging (below 44 kW) is expected to meet the needs of most small and medium electric trucks [4], long-haul trucks are likely to obtain approximately 50% of their required energy from public chargers [5]. This makes analysis and optimization of the charging infrastructure for long-haul freight transport, defined here as trips exceeding 300 km, a critical priority. Moreover,

providing a robust data-driven foundation for infrastructure planning facilitates further techno-economic and environmental assessments, such as those demonstrated by [6].

Several studies have investigated the charging infrastructure requirements for BETs in long-haul freight transport.
[7] propose a demand-oriented charging network for Germany using an agent-based microscopic simulation, estimating 1,296 Megawatt Charging System (MCS) chargers at 457 locations to support 20% BET penetration. However, the study does not address overnight charging or apply an optimization approach. [8] enhance this model by refining route planning, break scheduling, and queuing behavior within the multi-agent simulation framework (MATSim [9]).
Alternative approaches avoid microscopic simulations. [10, 11] use node-based models with queuing theory, estimating infrastructure needs based on traffic volumes. Their analyses for a 15% BET share suggest charging networks with locations spaced every 50 or 100 km, but these models assume uniform daily mileage and do not consider existing rest areas or differentiate charging technologies in detail.
At the European scale, [12] employ a trip-chain model aligned with EU driving regulations, estimating Germany's infrastructure need at 10,300 Combined Charging System (CCS) and 1,360 MCS points for a 15% electrification level, without distinguishing between public and depot charging.
This study aims to comprehensively assess the public charging infrastructure needs for battery-electric long-haul freight transport along the German motorway network, incorporating the distinct perspectives of two key stakeholder groups: logistics companies and charge point operators (CPOs). To achieve this, the analysis builds upon the existing methodology explained in [13], which explicitly distinguishes between high-power (HPC) and low-power (LPC) charging, as well as between public and depot charging.

2 Methodology

The methodology described in [13] is outlined in Figure 1 and consists of multiple components. It combines multi-agent simulation (MATSim [9]) with evolutionary bi-objective optimization (NSGA-II [14]) to design efficient public charging infrastructure for long-haul battery-electric trucks in Germany. It simulates truck traffic and charging demand, then optimizes charger placement by balancing two goals: maximizing charger utilization (for CPOs) and minimizing user waiting times (for logistics companies). The optimization focuses on high-power chargers and evaluates each configuration through simulation-based performance metrics. For better understanding, important aspects of the methodology will be elaborated further beginning with the MATSim scenario.

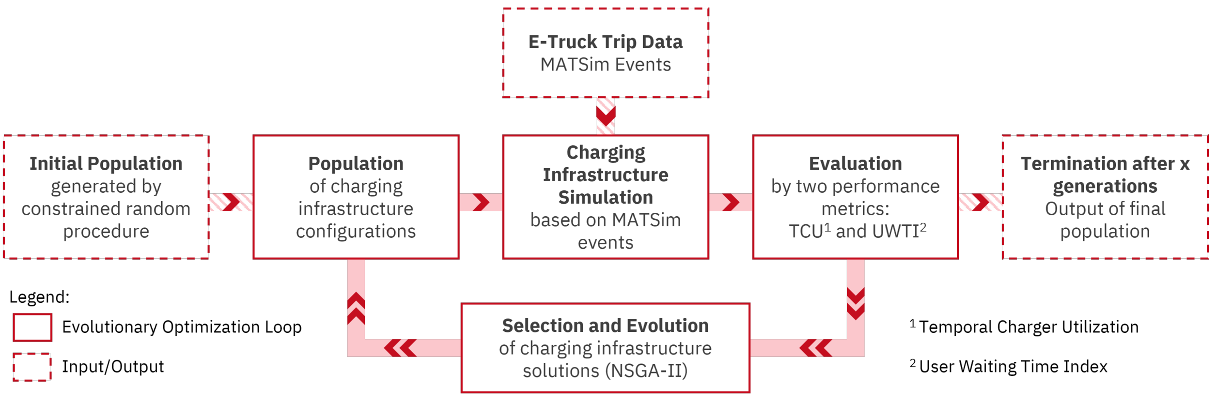


Figure 1: Schematic representation of the methodology outlined in [13], own presentation

The transport simulation software MATSim is employed to generate synthetic origin-destination trajectories (trip data) based on publicly available data as described in [7]. The specifications of the MATSim scenarios are provided in Table 1. The spatial and temporal distribution of truck trajectories is calibrated to realistically reflect long-haul freight traffic on the German road network, using traffic count data from 2020. The MATSim scenarios simulate freight movements at five different levels of fleet electrification, ranging from 1% to 20%, by varying the share of BET trips. Only BET-operated trips are considered within the simulation and at least the start or end of each trip is located within German borders. According to European regulations, trip plans include mandatory breaks, a 45-minute pause after 4.5 hours of driving followed by an 11-hour rest after 9 hours total driving time [15]. Based on OpenStreetMap data, these breaks are scheduled at one of 526 designated rest areas, each located within 1.5 km of the nearest motorway [7]. Charging activities occur exclusively during these breaks, and these rest areas also serve as candidate sites to deploy the charging infrastructure. To avoid route modification due to charging station availability, the scenario assumes unlimited charging capacity at each potential location, ensuring that all BETs can complete their trips without delay. Although the MATSim scenarios provide chronological trip and break data for BETs, they do not track individual vehicles, as a new agent is initialized for each trip [7]. All vehicles are uniformly modeled as semi-trailer trucks, each with a gross vehicle weight of 40 tons, a battery capacity of 600 kWh, and an energy consumption rate of 1.2 kWh per kilometer [8].

Table 1: Specifications of the MATSim scenarios (cf. [7])

Parameter	Specification	Parameter	Specification
Simulation area	Germany	Charging infrastructure availability	unlimited
Scenario year	2020	Usable battery capacity	600 kWh
Share of electrified trips	1%/5%/10%/15%/20%	Average vehicle energy consumption	1.2 kWh/km
Simulation period	Monday-Thursday (96 h)	Vehicle start SoC	100%
Potential charging locations	526		

In addition to the truck trip data, an initial population of charging infrastructure configurations, referred to as individuals, is required to initiate the evolutionary optimization process. This initial population is generated by randomly assigning charging points (CP) to the predefined set of potential charging locations. To ensure plausibility, the random assignment procedure is subject to a set of constraints that enforce basic feasibility criteria. In the charging infrastructure simulation, charging events occurring during the mandatory 45-minute breaks are classified as HPC, while those taking place during the 11-hour rest periods are treated as LPC. Notably, the duration of HPC processes is set to 40 minutes while charging time of LPC processes is set to nine hours. Additionally, the charging power of HPC and LPC is set to the required mean power to reach the target SoC of 100% at the end of each charging process while ensuring that the mean charging power can not exceed 900 kW. As the optimization procedure focuses solely on HPC infrastructure, the individuals in the evolutionary algorithm encode only the number of HPC points per location. Consequently, only the HPC infrastructure is subject to optimization.

For LPC charging, no decision-making process is involved during simulation. Trucks encountering an extended rest period are assumed to charge without incurring any waiting time. Given that overnight charging sessions occupy CP for extended durations and offer limited potential for efficiency optimization, the required number of LPC plugs per location is determined in a post-optimization step. This incorporates the influence of LPC on HPC requirements, ensures sufficient capacity for LPC and allows to determine reasonable numbers for required LPC plugs per location.

Both the generated individuals and the BET trip data serve as input to the charging infrastructure simulation. The simulation-based evaluation process assesses each individual by simulating truck charging behavior using MATSim trip data. It processes truck arrivals at charging locations chronologically, checking state of charge (SoC), waiting queue and break duration to determine whether a truck should charge. For each charging attempt, it calculates waiting time, charging power, and updates truck schedules accordingly. Based on these performance indicators, each individual is evaluated with respect to the two performance metrics. A genetic algorithm (NSGA-II) is then employed to evolve the population by selecting the best-performing individuals and using them to generate a new population through crossover and mutation operations. This iterative optimization continues for 700 generations, ultimately producing a final set of Pareto-optimal charging infrastructure configurations. These configurations represent different trade-offs between the evaluation criteria, thereby reflecting the diverse priorities of both logistics companies and CPOs.

The charging infrastructure scenarios are evaluated using two performance metrics: the Temporal Charger Utilization (TCU) and the User Waiting Time Index (UWTI) [13]. TCU quantifies the efficiency of infrastructure usage by measuring the proportion of time that charging points are actively in use relative to the total scenario duration. It is expressed as a percentage, with higher values indicating more effective utilization of the installed charging capacity. The UWTI, by contrast, serves as a user-centric metric aimed at capturing service quality and user satisfaction. It penalizes waiting times experienced by vehicles at charging locations. A waiting time of zero yields the optimal score, while increasing waiting durations progressively reduce the index. In particular, waiting times that exceed a predefined threshold incur a substantial penalty, reflecting their negative impact on operational efficiency and user experience. This methodological setup enables the inclusion of real-world factors such as driving breaks, waiting queues, energy consumption, and the locations of rest areas and depots. Moreover, it supports a comprehensive analysis of vehicle and charging infrastructure needs and helps evaluate load profiles to estimate grid connection requirements.

3 Results

In this section, the optimization results corresponding to these electrification levels are analyzed to derive insights into the charging infrastructure requirements necessary to support battery-electric long-haul freight transport on the German motorway network. Furthermore, the performance of the resulting infrastructure configurations is evaluated in relation to the objectives and constraints of both logistics companies and CPOs, allowing for an assessment of alignment with stakeholder perspectives.

3.1 Charging Infrastructure Demand of Investigated Electrification Levels

The electrification levels represent the proportion of trips conducted by BETs. The following section presents characteristics for each electrification level, focusing on the extent of required HPC and LPC infrastructure, the resulting waiting times, and the temporal charger utilization. Figure 2 [13] illustrates the final non-dominated set of solutions, including a reference solution for each electrification level. These reference solutions indicate the number of required HPC charging points assuming that every charging process occurs without waiting time, indicated by a waiting time of zero minutes.

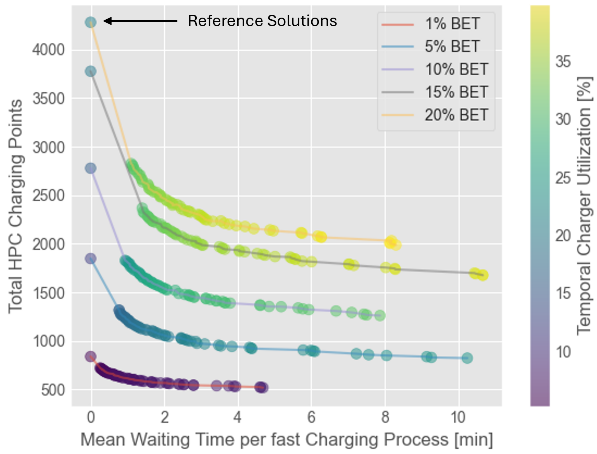


Figure 2: Final non-dominated set of each electrification level cf. [13]

The results indicate that the number of required HPC points does not increase linearly with the level of electrification. Rather, the rate of increase diminishes as electrification progresses. Moreover, the distance between the non-dominated set and the reference solution underscores the potential for optimization, with lower electrification levels (e.g., 1%) exhibiting comparatively limited potential. Additionally, the temporal utilization of chargers in the reference solution increases with higher electrification levels, even in the absence of optimization. The optimization procedure further amplifies this utilization trend. This effect is accompanied by rising waiting times, particularly when the number of charging points is reduced. Table 2 specifies the bounds of selected characteristics within the final non-dominated sets, as visualized in Figure 2.

Table 2: Boundary values of the final set of HPC solutions for each electrification level

Electrification level	Charging points (plugs) [pcs]	TCU [%]	Mean waiting time [min]
1%	519 – 722	6.11 – 8.26	0.26 – 4.69
5%	823 – 1,317	16.27 – 23.58	0.77 – 10.23
10%	1,261 – 1,828	23.41 – 31.33	0.94 – 7.86
15%	1,675 – 2,366	29.87 – 38.33	1.40 – 10.70
20%	1,987 – 2,824	30.39 – 39.87	1.10 – 8.30

For further analysis, a specific solution is selected from each electrification level that represents a balanced trade-off between the perspectives of logistic companies and CPOs. Similar to [13], a solution qualifies for selection if the mean waiting time per charging process is under five minutes and the proportion of charging attempts with a waiting time exceeding 90 minutes is below 0.5%. From the eligible solutions, the one closest to these criteria is chosen for each electrification level.
A detailed overview of these solutions is presented in Table 3. The 1% solution exhibits the highest mean waiting time per HPC charging process among the selected solutions and shows a relatively smaller improvement in the number of HPC plugs and TCU compared to the corresponding reference solution. The remaining solutions demonstrate much higher relative improvements in these characteristics, although there is a tendency that the lower limit of mean waiting times per charging process rises with the increasing number of electrified truck trips (Table 2). Additionally, the 1% solution has very low utilization, which increases by a factor of 4.6 when electrification reaches 20%. Despite the 20-fold increase in trips made by BETs, the required number of HPC plugs only increases by a factor of 4.2.

Table 3: Characteristics of the chosen charging infrastructure solutions for each electrification level

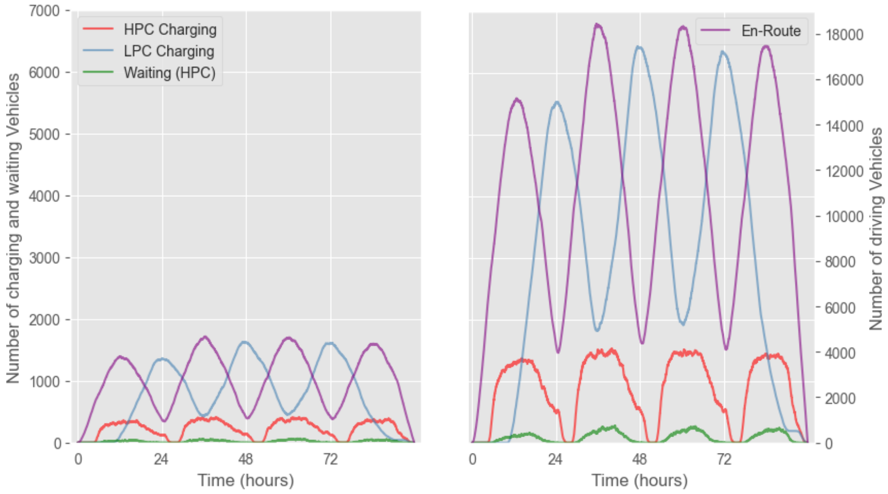
Electrification level	1%	5%	10%	15%	20%
Total trips [pcs]	6,940	34,482	68,854	114,968	138,563
Mean trip distance [km]	483.7	479.88	480.56	481.45	481.54
HPC plugs [pcs]	519	943	1,389	1,899	2,155
HPC sites [pcs]	491	520	525	525	525
LPC plugs [pcs]	742	2,525	4,446	6,874	8,147
LPC sites [pcs]	377	469	498	499	506
LPC/HPC plug ratio	1.42	2.68	3.2	3.62	3.78
Total HPC charging processes [pcs]	5,868	28,337	56,580	93,648	112,602
Total LPC charging processes [pcs]	1,350	6,582	13,098	22,019	26,576
Mean waiting time HPC [min]	4.69	3.84	3.79	4.53	4.44
TCU HPC [%]	8.26	21.88	29.68	35.9	38.02
TCU LPC [%]	21.37	28.26	32.03	35.05	36.07
Accumulated Energy at trip start [GWh]	4.16	20.69	41.31	68.98	83.14
Energy charged at public CPs [GWh]	2.6	12.63	25.2	41.85	50.37
Charged energy via public HPC [GWh]	2.11	10.21	20.4	33.77	40.61
Charged energy via public LPC [GWh]	0.49	2.42	4.81	8.08	9.76
Depot charging demand [GWh]	1.56	8.06	16.11	27.13	32.77
Share of public charging [%]	62.65	61.04	61.0	60.67	60.58

Furthermore, the demand for LPC infrastructure at various electrification levels is assessed. In this study, the impact of HPC infrastructure on LPC infrastructure occurs solely when vehicles are unable to charge and reach a state of charge (SoC) of 0% due to excessive waiting times. This is because subsequent rest periods, and thus LPC processes, are not considered once vehicles reach an SoC of 0%. Therefore, it is reasonable to derive the LPC demand from the reference solution for each electrification stage to avoid this underestimation. It is shown that the number of LPC plugs required is significantly higher than the number of HPC plugs. Although the LPC infrastructure is designed to ensure that every long charging process occurs without waiting time, the TCU is comparable to the TCU of HPC infrastructure in the optimized solutions. For low electrification levels from 1% to 10% LPC TCU is even higher than HPC TCU. This is caused by the high occupation time of the long charging processes. Considering the amount of energy charged at 20% electrification, LPC infrastructure is responsible for only 19% of the charged energy indicating that there is a potential use case for public LPC infrastructure but public HPC infrastructure is more relevant for both, users and CPOs.

Moreover, Figure 3 compares the number of fast charging, slow charging, waiting, and driving vehicles over time for electrification levels of 5% and 20%. The curves exhibit cyclical behavior between day and night, with the peak of vehicles using LPC occurring at night and the peak of vehicles using HPC occurring during the day. This suggests a correlation between the number of en-route vehicles and HPC processes. Furthermore, the peak of simultaneous LPC processes closely matches the peak of driving vehicles, while the peak number of simultaneous HPC processes is much lower. However, the total amount of HPC processes is over four times higher than the amount of LPC processes, as shown in Table 3. Despite the higher number of vehicles in the 20% scenario, the observed behavior over time between the 5% and 20% electrification levels remains very similar. Notably, the peak number of LPC processes increases more significantly with the rising number of driving vehicles compared to the peak number of HPC processes. This trend is highlighted in Table 3, which shows that the number of required LPC plugs increases more sharply with higher electrification levels than the number of required HPC plugs, while the ratio of energy charged with HPC and LPC remains constant. The ratio of LPC plugs to HPC plugs rises from 1.42 to 3.78, displaying an asymptotic behavior that suggests this ratio increases less as electrification exceeds 20%.

Furthermore, the accumulated start SoC shown in Table 3 represents the total energy in the batteries of all trucks at the beginning of each trip. This study assumes that the start SoC is restored after each trip. Therefore, the difference between the accumulated start SoC of all trips and the energy charged at public CPs represents the depot charging demand. Similarly, the share of public charging is calculated as the proportion of energy charged at public CPs relative to the accumulated start SoC. The results indicate that the share of public slow and fast charging for the chosen charging infrastructure solutions is slightly above 60%.

The subsequent sections will analyze the most relevant characteristics of the chosen charging infrastructure solutions in more detail.



(a) 5% electrification (b) 20% electrification

Figure 3: Temporal distribution of vehicles charging, waiting, and en-route throughout the simulation period

3.2 Spatial Distribution of Charging Infrastructure

This section analyzes the spatial distribution of HPC and LPC infrastructure within Germany based on the truck traffic. Figure 4 shows the locations of installed charging infrastructure differentiated by available charger types for the 1% electrification level. Most locations provide both HPC and LPC charging options, with a greater number of locations offering exclusively HPC charging compared to those offering only LPC charging. However, both charger types exhibit a comprehensive distribution, indicating that even a low electrification level necessitates a well-distributed charging network across Germany.

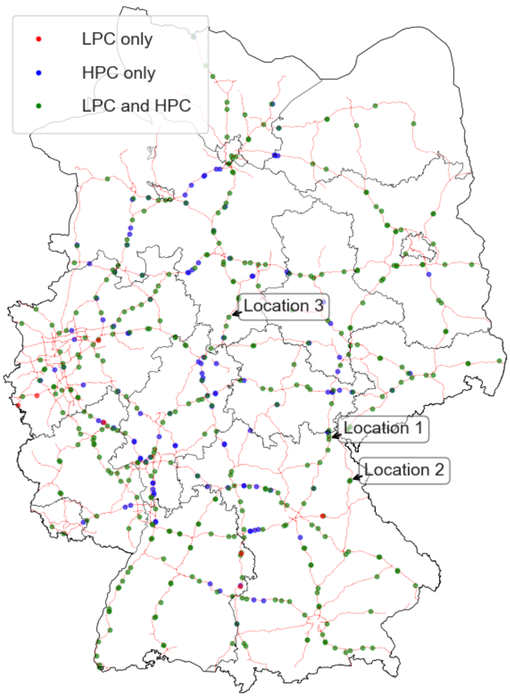
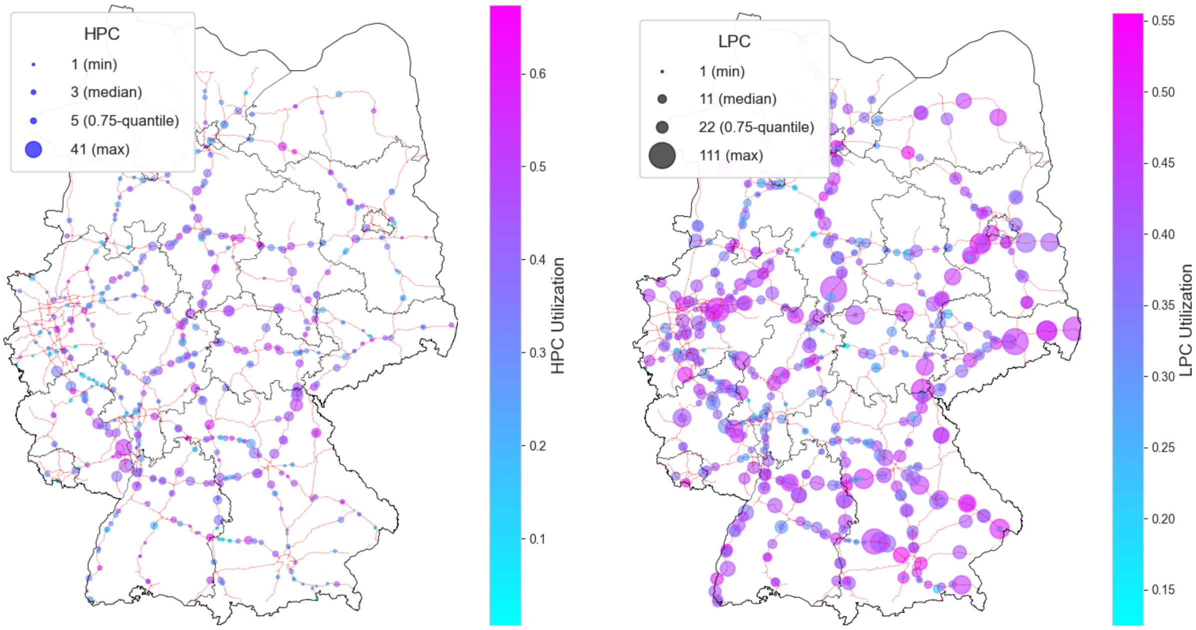


Figure 4: Locations with installed charging infrastructure per charger type at the 1% electrification level

Moreover, Figure 5 illustrates the spatial distribution and the quantity of charging points per location for HPC (5a) and LPC (5b) at an electrification level of 20%. Both HPC and LPC infrastructure show comprehensive distributions within Germany with a maximum of 41 HPC chargers and 111 LPC chargers per location. However, there are notable differences in their spatial distribution, as the HPC infrastructure is densely distributed in central parts of Germany, becoming sparser towards the borders, while the LPC infrastructure exhibits the opposite pattern.



(a) HPC infrastructure with TCU

(b) LPC infrastructure with TCU

Figure 5: Spatial distribution of charging infrastructure with TCU for 20% electrification

3.3 Temporal Charger Utilization and Waiting Times

This section evaluates the results concerning TCU and waiting times, beginning with the spatial distribution of charging points, as illustrated in Figure 5. For a 20% electrification scenario, numerous locations, particularly those with a high number of charging points, exhibit a TCU exceeding 30%. This pattern is observed across both HPC and LPC infrastructures, with LPC infrastructure generally displaying higher TCU values than HPC infrastructure. To gain deeper insights into location-specific TCU patterns, an additional analysis focusing on HPC infrastructure is conducted. Figure 6a demonstrates a consistent increase in TCU across locations with rising levels of electrification. Importantly, the median TCU per location is lower than the mean TCU values provided in Table 3, indicating that locations with high TCU disproportionately influence the mean values compared to those with low TCU. Moreover, at the 1% electrification level, approximately 75% of locations report a TCU below 10%. TCU values increase significantly for the 5%, 10%, and 15% scenarios but decelerate towards the 20% level. At this level, 50% of locations record a TCU between roughly 22% and 43%, with a median TCU of approximately 33%. Despite this upward trend, each electrification scenario includes locations with minimal TCU values, approaching 0%. This phenomenon is attributed to optimization constraints, ensuring that every location with at least one charging event is allocated a minimum of one charging point. However, in the 15% and 20% electrification scenarios, certain locations achieve TCU values up to 67%.

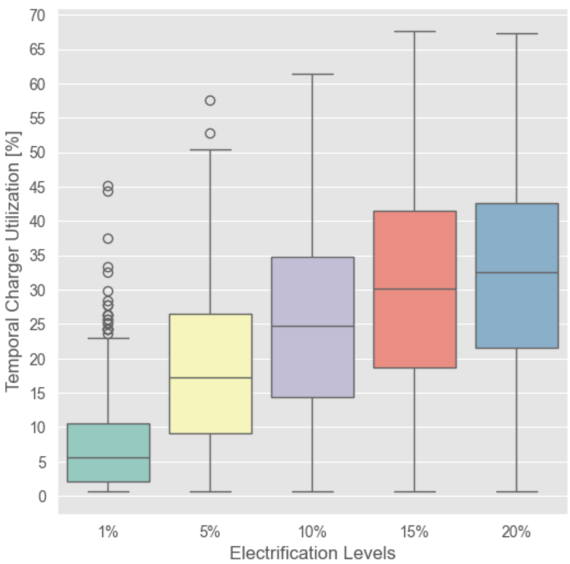
Table 4: Duration of queuing events for each electrification level

Electrification level	1%	5%	10%	15%	20%
Charging processes without queuing [%]	83.78	82.10	80.32	75.00	75.23
Mean [min]	28.90	21.48	19.28	18.14	17.92
Median [min]	26.48	16.68	14.03	12.43	11.52
75% Quantile [min]	40.62	31.56	27.42	24.50	24.06
90% Quantile [min]	57.00	45.78	43.67	42.51	44.32

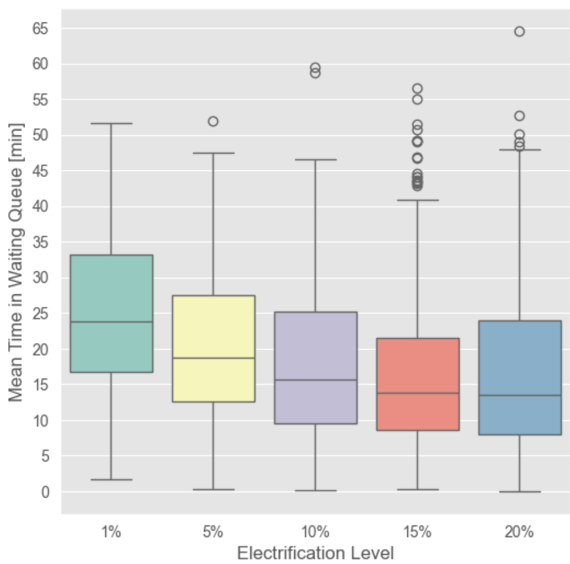
An analysis of waiting times for HPC charging processes reveals that the majority of charging events occur without any queuing delay. Table 4 provides a detailed overview of the statistical distribution of queuing durations, along with the proportion of charging processes completed without queuing. This

share declines from 84% at a 1% electrification level to 75% at 20%, indicating a gradual increase in queuing likelihood with rising electrification.
In addition, Figure 6b presents a box plot illustrating the mean waiting time per location and electrification level. The median queuing duration per location decreases as electrification increases: at 1% electrification, 50% of locations have a mean waiting time below 24 minutes, whereas this value falls below 14 minutes at 20%. Although the probability of experiencing a queue before charging increases with electrification (as shown in Table 4), the average waiting time per queuing event declines. This suggests that while queues become more frequent, the delays they cause become shorter on average.
This interpretation is further supported by the growing disparity between the mean and median queuing durations, indicating that a small number of high-duration queuing events increasingly skew the mean. Furthermore, all electrification scenarios contain locations where no queuing occurs, yet the frequency of outlier locations with exceptionally high average waiting times rises with increasing electrification.

Figures 6a and 6b both exhibit an asymptotic trend, implying that beyond a 20% electrification level, further increases in electrification are unlikely to significantly impact TCU or waiting times, provided that the charging infrastructure remains optimally distributed.



(a)
TCU of HPC infrastructure per location



(b)
Mean duration of waiting processes per location

Figure 6: Characteristics of TCU and waiting processes per location for each electrification level

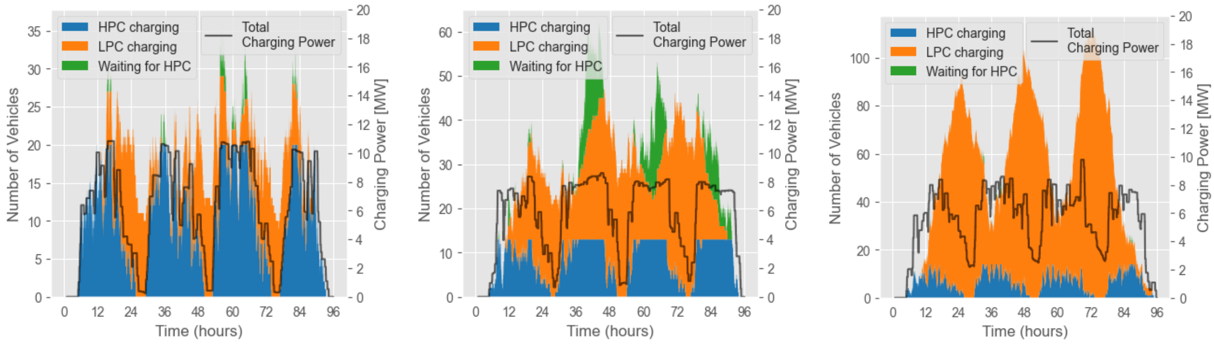
3.4 Analysis of Three Highly Frequented Charging Locations for 20% Electrification

The approach utilized in this study enables the analysis of charging demand and other characteristics at specific locations. Consequently, this chapter examines three charging locations from the 20% electrification scenario, each with distinct characteristics. Figure 4 illustrates the positions of these locations, while Table 5 presents their key characteristics. Despite their differences, all three locations rank among the most frequented in the simulation and serve a similar number of charging processes.
Location one ("Autohof Bayrisches Vogtland") on the A9 motorway is characterized by a high number of HPC plugs and a comparatively low number of LPC plugs. In contrast, location two ("Autobahnraststätte Waldnaabtal Ost") on the A93 motorway offers a more balanced charging infrastructure, with approximately three times as many LPC plugs as HPC plugs. Location three ("Autohof Northeim") on the A7 motorway contains one of the largest amounts of LPC plugs among all sites. These distinct infrastructure configurations highlight the importance of tailoring charging infrastructure designs to the specific characteristics and requirements of each location.
Figure 7 presents the number of vehicles charging per charger type, the number of vehicles waiting, and the temporal evolution of the required peak power at each of the three locations. The required peak power is calculated based on the mean power of ongoing charging processes.
At all three locations, HPC infrastructure utilization peaks during daytime hours, whereas LPC infrastructure is predominantly used at night. Consequently, the overall power demand also peaks during the day. Notably, location two exhibits the lowest peak power demand during the simulation period, despite experiencing high utilization of its HPC infrastructure during daytime hours. The elevated total charger utilization (TCU) at this site leads to increased waiting times during peak periods. Given that location

Table 5: Characteristics of selected charging locations at the 20% electrification level

	Location 1	Location 2	Location 3
HPC plugs	20	13	14
LPC plugs	18	41	110
HPC charging processes	1229	1030	787
LPC charging processes	54	151	396
Mean waiting time [min]	1.08	18.01	0.43
HPC TCU [%]	42.67	55.02	39.038
LPC TCU [%]	28.13	34.53	33.75
Mean HPC charging power per process [kW]	526.37	559.76	526.69
Mean LPC charging power per process [kW]	35.17	37.29	37.67
Total peak power [MW]	10.83	8.6	9.78

two has the fewest HPC plugs among the locations analyzed, this observation suggests that the primary determinant of a site's maximum power requirement is the number of HPC plugs, with the quantity of LPC plugs playing a comparatively minor role. In contrast, locations one and three achieve above-average HPC plug utilization while maintaining low average waiting times, indicating a more favorable balance between infrastructure capacity and demand from the user perspective.
Among the analyzed locations, location one exhibits the highest simulated power demand, suggesting the need for the most robust grid connection. However, assuming nominal charging powers of 720 kW per HPC plug and 75 kW per LPC plug, location three would theoretically require the largest grid connection, exceeding 18 MW due to the high number of LPC plugs. Nevertheless, the observed peak power demand at this site remained below 10 MW during the simulation, indicating that load management strategies could substantially reduce the actual grid connection requirements.



(a) Location 1 (b) Location 2 (c) Location 3

Figure 7: Temporal development of vehicle activity and total charging power at selected locations under 20% electrification level

4 Discussion

This study aimed to quantify the number of charging points required for varying levels of long-haul truck electrification on the German motorway network and to determine an optimal LPC-to-HPC plug ratio that ensures both infrastructure availability and efficient utilization. Using a long-haul freight traffic scenario based on 2020 traffic volume data, a set of non-dominated charging infrastructure configurations was identified for five electrification levels. Selected solutions represent balanced trade-offs between the perspectives of logistics companies and CPOs, with user waiting times reflecting logistics priorities and TCU representing CPO interests.
Some previous research papers investigate the required number of charging points for BETs, providing a basis for comparison with our study's findings. [12] employ a trip chain based approach to model long-haul truck traffic and estimate charging demand in European Countries at a 15% electrification level. They determine the necessary number of HPC and LPC ([12] calls it MCS and CCS) charging points for charging areas of 25 km^2, consisting of multiple charging locations, to maintain a waiting time of five minutes. Their findings indicate that more LPC plugs than HPC plugs are required with increasing electrification, which aligns with the results of this study. However, they estimate the need for 10,300

LPC and 1,360 HPC (ratio: 7.57) charging points in Germany, showing a significantly higher LPC to HPC plug ratio compared to our study, which requires 6,874 LPC and 1,899 HPC plugs (ratio: 3.62) at the 15% electrification level [12]. The discrepancy in HPC requirements can be partly attributed to the difference in assumed charging durations. The shorter charging duration of 30 minutes assumed by [12] results in fewer HPC charging points with higher charging powers, as also noted in their study. Additionally, a crucial difference is the use of trip chains in [12], which are not considered in the MATSim model that our study is based on. This omission in our study leads to an underestimation of long breaks, as trip chains connecting multiple trips over several days result in more long breaks and fewer short breaks due to European rest regulations. Moreover, transit traffic without a start or end in Germany is not considered in the MATSim model, potentially further reducing the LPC charging demand. Consequently, the observed differences in the results can be partly attributed to methodological differences and limitations of our methodology, which will be addressed in future research. Nevertheless, the results of this study indicate that the majority of the total energy delivered originates from HPC plugs, and that the number of HPC plugs is the primary driver of a location's peak power demand. Despite this, LPC infrastructure remains an attractive option for CPOs, particularly when synergies with the existing HPC grid connection can be leveraged. As the peak usage times for HPC and LPC infrastructure do not coincide, a substantial number of vehicles can be serviced via LPC plugs without necessitating an upgrade to the existing grid connection.
Moreover, the results indicate that both HPC and LPC infrastructure need to be well-distributed across the major German road network even at an electrification level of 1%. Notably, this is based on the underlying MATSim scenario which assumes an evenly electrification of long-haul freight traffic. The results do not apply if early stages of electrification would focus on a few origin-destination connections. At higher electrification levels, the distribution of HPC and LPC infrastructure exhibits slight differences. HPC infrastructure tends to dominate in the more central parts of Germany, whereas LPC infrastructure becomes more prevalent towards the borders, suggesting a higher number of long driving breaks at these locations. This distribution is influenced by the MATSim model used. In future research, it is important to investigate whether this reflects actual driving behavior or if it is a consequence of the model's limitations, which only consider trips that at least start or end in Germany. This could explain the observed infrastructure distribution, as long breaks typically occur after covering long distances, leading to more long breaks near the borders. However, the analysis of highly frequented charging locations in Section 3.4 reveals that the requirements for HPC and LPC charging infrastructure can vary significantly among different locations, depending on the frequency of long and short breaks at each site.
In addition, our study determined the share of public charging as the ratio between the energy charged at public LPC and HPC infrastructure and the accumulated start SoC of all trips. According to [5], multiple truck manufacturers estimate that approximately 50% of the driving energy for long-haul trucks will be charged at public charging infrastructure. our study suggests that this share could be slightly higher, around 60%, if every charging process ends with a SoC of 100%. However, in real-world applications where not every charging process will end at an SoC of 100%, this share would likely decrease towards 50%, aligning with the manufacturers' estimates. The share of public charging is highly dependent on operational schedules, trip structure, and the availability of charging infrastructure. Therefore, considering a public charging share of approximately 50% seems to be appropriate when planning public and depot charging infrastructure for long-haul freight traffic.
Furthermore, the TCU is a relevant criterion from the CPO perspective. The network-wide TCU for HPC infrastructure from Monday to Thursday increases to 38.02% at the 20% electrification level. The results also show a sharp increase in TCU from 1% to 5% electrification, reaching 21.88% which can be sufficient for profitable HPC charging infrastructure operation according to [16, p.23]. This suggests that charging infrastructure may not be economically viable at lower electrification levels, except in highly frequented areas. Given that 1% electrification already requires 519 HPC plugs distributed across the German transport network, CPOs must accept lower TCUs at this early stage to facilitate a rapid transition to battery-electric long-haul freight traffic and establish a profitable business.
From the perspective of drivers or logistics companies, the waiting time statistics presented in 3.3 indicate that the average trip delay due to fast charging stops will be between three and five minutes per stop across the entire network. While this seems to be generally acceptable to logistics operators, higher waiting times may be encountered on highly frequented routes, particularly at outlier charging locations with significantly high mean waiting times per charging process. However, the numbers provided by our study are a result of a network-wide optimization, whereas in reality charging location design is managed individually by CPOs. It is therefore likely that CPOs will expand infrastructure at these high-demand locations or set up additional charging locations where feasible. Nevertheless, the existence of those outlier locations like location 2 in Section 3.4 shows that other mechanisms are necessary to further optimize the charging infrastructure distribution. Allowing the re-routing of trips could prevent the excessive queuing of BETs at charging locations in peak hours and distribute the charging demand more evenly on potential charging locations. This will be a topic of future research.
Moreover, Figure 7 in Section 3.4 illustrates the power demand at the selected locations. The observed total peak power does not exceed 10.83 MW (Location 1). However, all charging processes in the simulation are based on a linear charging profile, meaning that variations in charging power throughout the session are not taken into account. In practice, real-world charging behavior, characterized by non-linear power curves, may significantly affect the actual peak power requirements of a charging site. This potential influence warrants further investigation.

The analyzed charging infrastructure configurations for each electrification level were selected from the final set of solutions (Figure 2) to illustrate a potential trade-off between the interests of logistics companies and charge point operators. However, the employed evaluation criteria, temporal charger utilization (TCU) and user waiting times, do not fully capture all factors influencing the operational efficiency and economic viability for both stakeholder groups. To support data-driven decisions on the most favorable trade-offs, future research should develop and incorporate comprehensive cost models tailored to the needs of each stakeholder. These models should be integrated as optimization criteria to enable a more holistic assessment of infrastructure configurations.

5 Conclusion

Using a methodology that combines multi-agent simulation with bi-objective evolutionary optimization, this study provides a detailed assessment of the public HPC and LPC charging infrastructure required to support different levels of long-haul truck electrification in Germany, while balancing the needs of logistics companies and CPOs. Results show that infrastructure requirements scale non-linearly with electrification: a 20-fold increase in BET trips (from 1% to 20%) demands only a 4.2-fold increase in HPC plugs. HPC plug requirements range from 519 to 2,155, and LPC plugs from 742 to 8,147. Network-wide HPC utilization increases from 8.26% to 38.02%, while average waiting times remain between three and five minutes. This indicates the compatibility of high charging infrastructure utilization and efficient BET operations.
Our study also shows that the ratio of LPC to HPC plugs increases with increasing electrification, reaching 3.78 at 20% electrification, although HPC remains the dominant contributor to total charged energy (over 80%). Spatial analysis highlights the necessity for a widespread and balanced infrastructure rollout from the outset, even at low electrification levels, while usage patterns underscore the complementary nature of HPC and LPC in managing daily and overnight charging demands.
The growing LPC-to-HPC ratio and complementary usage patterns emphasize the need for integrated infrastructure strategies. Location-specific analyses further underline the importance of tailoring infrastructure deployment to local conditions, enabling both economic viability for CPOs and reliable access for logistics companies.
Ultimately, these findings support the scalable and coordinated development of a robust public charging network for long-haul freight transport in Germany and lay the groundwork for further research into dynamic routing strategies, real-world charging behavior and grid integration.

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ChatGPT-4o was used to improve language. The content of our research remains unaffected by this.

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Diego Fadranski earned his B.Sc. in Mechanical Engineering and his M.Sc. in Transportation Planning and Operations from Technische Universität Berlin. He is currently working as a research associate and PhD candidate at the Chair of Product Development and Mechatronics. As a member of the project High-Performance Charging for Long-Haul Trucking (HoLa) he investigates charging infrastructure requirements for heavy-duty trucks focusing on spatial distribution of charging points as well as the configuration of potential charging sites. Additionally, as part of the Mobility2Grid (M2G) research campus, he explores how electric heavy-duty vehicles could serve as emergency power supplies through bidirectional charging.