38th International Electric Vehicle Symposium and Exhibition (EVS38) Göteborg, Sweden, June 15-18, 2025

Charging strategies for battery electric trucks in Germany

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Executive Summary

Battery electric trucks (BET) are a promising option to reduce emissions from heavy-duty vehicles. However, the transformation to BET will cause an additional demand for electricity. Future charging strategies will influence the future peak load as well as the usability of BET. We simulate 2,400 representative single-day German truck driving profiles with three different charging strategies: (1) as slow as possible, (2) as fast as possible, and (3) slowly at depots and as fast as possible at public locations. Assuming 33 % electrification in 2030 and almost full fleet conversion in 2045, we scale our results to Germany. We find that charging as fast as possible leads to additional peaks up to 6 GW in 2030 and up to 18 GW in 2045, while the other charging strategies reduce peaks to 3 GW in 2030 and 8 GW in 2045. Therefore, implementing wise charging strategies will reduce future peak load.

Keywords: Heavy Duty electric Vehicles & Buses, Smart charging, Smart grid integration and grid management, Fast and Megawatt charging infrastructure, Modelling & Simulation

1 Motivation

Heavy-duty vehicles (HDVs) (> 12 t) are 5 % of the European vehicle fleet but cause 15 - 22 % of CO_2 emissions from road transport in 2019 [1]. Climate neutrality necessitates ambitious measures in the transport sector, with electrification as the most likely option for HDVs [2]. First battery electric trucks (BETs) are available, and European manufacturers anticipate about half of all trucks sold by 2030 to be BETs [2]. Megawatt charging will enable trucks to charge within the 45 minutes driver break. By 2045, approximately 45 TWh - a quarter of the expected electricity demand in the transport sector in Germany - could be needed for HDVs [3].

Earlier publications have focused on the economic feasibility of BET or the regional demand for charging infrastructure [4, 5]. The European Commission aims to provide charging stations for BET at a maximum distance of 60 km along the main traffic routes (TEN-T Core network) and at a maximum distance of 100 km along the TEN-T Comprehensive network until the end of 2030 [6]. Assuming optimal charging strategies, analyses show that charging can be integrated into the daily logistics process. For a large share of the fleet, depot charging will be the most relevant option to recharge. Public megawatt charging as intermediate charging option will be relevant for vehicles with a high daily mileage [7, 8]. However, different charging strategies will influence the usability of BETs as well as the associated load curve and need to be evaluated. Based on a hypothetical fleet of 100 vehicles in California, exemplarily analyses show that managed charging can avoid charging peaks and lower costs for logistics companies [9]. However, the authors are not aware of any study that looks at the effects of different truck charging strategies on a country's temporally resolved energy demand.

Therefore, this analysis aims to provide representative load profiles for a future German BET-fleet in 2030 and 2045, given three different charging strategies. The charging strategies are differentiated by charging power, charging duration and the location of the charging points.

2 Scenario Description

In the following, we briefly describe the assumed charging behavior (section 2.1) and the truck fleet development (section 2.2).

2.1 Charging behavior

Our model distinguishes public and private charging locations. Private charging locations are located on the premises of forwarding agencies or customers and on private properties. Public charging locations include service stations on highways or other public parling locations for trucks. As our dataset allows for differentiation between public and private locations, but not for georeferencing, a more detailed description of potential charging locations is not possible.

Regarding the charging power, we distinguish between three categories: The first category covers charging power levels up to 44 kW, which is the maximum achievable using an alternating current (AC) plug. We refer to this category as “slow charging”. The second category covers a charging power of up to 350 kW, currently known from the passenger car sector as “Combined Charging System” (CCS). As a third category, the newly developed “Megawatt Charging System” (MCS) will provide power levels significantly higher than 350 kW [10]. Approximately 1 MW will be a satisfying level for BET [7]. For the sake of simplicity, we use “MCS charging” as nameplate for an average charging power between 350 kW and 1 MW, although charging with lower could be technically also realized with MCS. It should be noted that we do not distinguish between charging power of up to 350 kW (referred to as “CCS charging) and more than 350 kW (referred to as “MCS charging”) in terms of modeling but evaluate them separately.

This analysis aims to provide representative load profiles for a future German BET fleet in 2030 and 2045, given three different charging strategies: (1) As slow as possible (*ASAP*). The entire time available for a charging process is used to charge the vehicle battery. The strategy aims to minimize the additional load on the electricity grid. (2) As fast as possible (*AFAP*). The charging process starts immediately after a trip is completed and ends when the battery is fully charged. This is the most challenging strategy for the electricity grid. (3) *Combination*. Charging at the depot is limited to 44 kW and follows the *ASAP* strategy. Public charging follows the *AFAP* strategy. This strategy provides a real-world oriented approach. In each strategy, it is tried to fully recharge the vehicle, if possible, within the boundary conditions. Table 1 sums up the most important aspects.

Table 1: Overview of the charging strategies and their characteristics

		ASAP	***AFAP***	***Combination***
Available charging power per vehicle	Private	≤ 44 kW ≤ 350 kW > 350 kW	> 350 kW	≤ 44 kW
	Public	≤ 44 kW ≤ 350 kW > 350 kW	> 350 kW	> 350 kW
Charging strategy	Private	As slow as possible	As fast as possible	As slow as possible
	Public	As slow as possible	As fast as possible	As fast as possible

To schedule a charging event, a minimum charging period of 30 minutes is assumed. The minimum charging period reflects the additional effort that comes with each additional charging event. In addition, the vehicle is only charged if the current battery level is not sufficient to cope with the next trip (c.f. section 3.2) or if the last trip was the last trip of the day. We assume that the vehicle starts the first trip of the day fully charged. As a simplification, we assume a continuous charging process at constant power, regardless of the current state of charge (SOC). The charging events are based on the assumption that there is no competition for charging points and therefore no waiting times.

2.2 Fleet development

For simplification, we assume a constant HDVs stock of 470.000 vehicles. By 2030, we assume 33% of HDVs will be electrified [2, 3]. By 2045, all vehicles that are technically eligible for electrification will be included, meaning that only driving profiles feasible for BET models will be transitioned accordingly. Routes that are not feasible for BETs under the assumed parameters will continue to be served by conventional HDVs. The feasibility of this transition depends on the charging strategy applied.

Additionally, we assume that charging infrastructure is built as needed. This means that there is no competition for charging points; charging events can start immediately after arrival.

3 Data

The following subchapters contain information on the underlying driving data (section 3.1) and technical assumptions (section 3.2).

3.1 Driving data

To model charging and driving behavior of battery electric trucks (BETs), we use real driving data from diesel vehicles, specifically the "Motor Vehicle Traffic in Germany 2010" (KiD) survey [11]. The analyzed vehicles were randomly selected from the central vehicle register of the Federal Motor Transport Authority (Kraftfahrt-Bundesamt) between October 2009 and November 2010 and the data was collected by using questionnaires. The dataset contains 2,810 single day driving profiles from rigid trucks and tractor-trailers (> 12 t GVW), representative for Germany. 400 of these are excluded from the analysis in this paper, because they contain incomplete information on individual trips. We therefore use 2,410 datasets for our analysis, consisting of 1,350 rigid and 1,060 tractor-trailers.

The KiD data include all trips of the sampled vehicles over a single day. The dataset contains, among other details, the following information for each vehicle: vehicle ID, size (“rigid” or “tractor-trailer”), gross vehicle weight (in kg), daily mileage (in km), the number of trips, and information on individual trips. A single trip includes the departure and the arriving time, the distance travelled during the trip (in km), and the type of parking location. We define company premises, private properties, and parking lots as private. Public parking spaces as well as unknown locations are defined as public.

Figure 1 illustrates the distribution of the daily mileage in the sample. It is evident that driving profiles for all types of use are included in the calculations. We consider trucks used for long-, medium- and short-distance transportation.

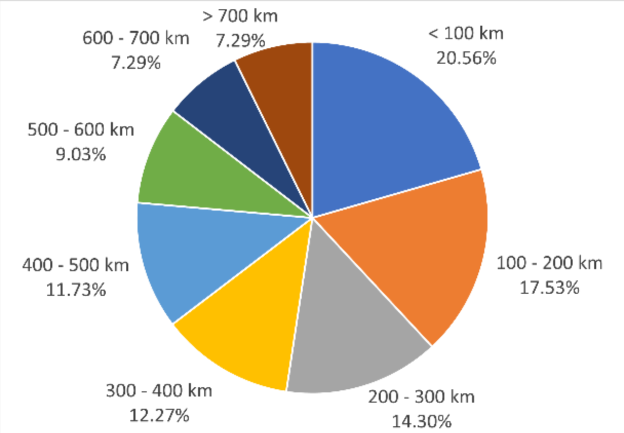

Figure 1: Cumulative total distance of the journey profiles per day [11]

3.2 **Technical assumptions**

In the following, technical assumptions as well as assumptions on the expected development of the truck fleet are presented.

We define a minimum range a fully charged BET travels without scheduling an additional charging event. The minimum range is defined as 80% of the maximum range. In 2030, a minimum range of 280 km is assumed. In 2045, we assume 470 km. Therefore, the maximum achievable distance for BET in 2030 is assumed to be 350 km. In 2045, we assume 590 km maximum range. Please note that the maximum range does not refer to highest range available for a newly registered vehicle, but rather for an average stock vehicle in the corresponding year, based on announcements from truck manufacturers [12, 13]. Furthermore, the range in 2030 covers the legally binding maximum driving time of 4.5 hours [14].

We estimate the maximum average charging capacities to be 430 kW in 2030 and 810 kW in 2045 (own assumptions, based on [2]). Maximum average charging capacity means the highest possible average charging power during a whole charging event. Peak power may be higher. Moreover, we estimate an energy consumption of 1.12 kWh/km for rigids and 1.24 kWh/km for tractor-trailers in 2030. That will improve in 2045 to 0.95 kWh/km for rigids and 1.06 kWh/km for tractor-trailers. For simplicity, we assume constant energy consumption, though practical implementation must consider factors like weather conditions, driving behavior, road topography, loading and design. Table 2 summarizes the most important technical vehicle assumptions.

Table 2: Technical vehicle data

Year	Minimum range [km]	Maximum range [km]	Maximum charging power [kW]	Energy consumption rigid truck [kWh/km]	Energy consumption tractor-trailer truck [kWh/km]
2030	280	350	430	1.12	1.24
2045	470	590	810	0.95	1.06

4 Methodology

The goal of the model is to determine the charging and driving patterns of the individual vehicles in five-minute intervals throughout the day (1,440 Minutes). We use an agent-based simulation and simulate each driving profile separately, allowing for a highly realistic representation of fleet electrification.

First, the driving and parking behavior of each vehicle is simulated. Departure and arrival timestamps for each trip and vehicle are converted into a discrete-time simulation. Using the start and arrival times along with the traveled distance data from the KiD dataset for each vehicle and trip, the vehicle's status (private parking, public parking, or driving) and the distance travelled at specific timestamps are recorded in five-minute intervals.

Truck drivers need to take a 45-minutes break after 4.5 hours of driving [14]. Some single trips of the KiD-dataset do not comply with this regulation. If a trip exceeds legal limits, a mandatory, synthetic 45-minutes break is inserted 270 minutes after the departure time. We assume the reported arrival time to be right, so that the vehicle covers the distance in a shorter time span. Therefore, we recalculate the average speed of the vehicle. For trips where the end of the mandatory break would extend beyond the end of the original journey, the break is set halfway through the trip.

Based on these previous calculations, we simulate the driving behavior for each rigid-truck and each tractor-trailer over the course of a day and save the information every five minutes from minute 0 (00:00) to minute 1435 (23:55). We know at any point in time whether the vehicle is driving or whether and where it is parked, as well as the distance traveled. Figure 2 provides an overview of the available information.

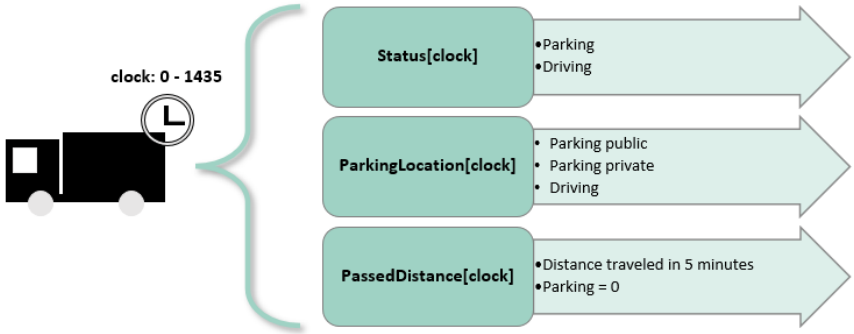

Figure 2: overview of the driving and parking behavior of a single vehicle

Afterwards, we simulate the single day driving profiles as BET profiles. The charging demand of the vehicles is determined at each timestamp. The demand is based on the distance traveled in kilometers. At each timestamp, we know the distance travelled (in km) since the last charging event and we know the SOC after the last charging event. Therefore, we can determine the kilometers that need to be recharged at every timestamp. In summary, we simulate the SOC at 5-minute intervals, assuming a constant energy requirement per kilometer.

Charging events occur during breaks that are also taken by conventional trucks. For a charging event to take place, two conditions must be met: (1) The break must last at least 30 minutes and (2) the SOC is below the minimum or will be below the minimum range after the next trip. Additionally, charging events are scheduled after the last trip of the day.

The charging process is guided by the specific strategy in use. As described in section 2.1, we define three different charging strategies: (1) As slow as possible (*ASAP*), (2) As fast as possible (*AFAP*), and (3) *Combination*.

The procedure for *ASAP* charging is summarized in the following program description.

Program description ASAP

timestamp t = departure first trip / 5; each timestamp reflects 5 minutes with t_0 = 00:00 and t_{287} = 23:55

SOC = 1

1. Check for charging occasion:
   IF t = departure first trip / 5 + 287:
      FINISH EXECUTION; simulation for 24 hours has finished
   ELSEIF (status[t] = parking) AND (status[t-1] = driving):
      Examine necessity of charging event
   ELSE:
   $$SOC = SOC - \frac{travelled\ distance\ in\ t\ [km]*energy\ consumption[\frac{kWh}{km}]}{Maximum\ range\ [km]*energy\ consumption[\frac{kWh}{km}]}$$
      t = t +1
      Check for charging occasion

2. Examine necessity of charging event:
   IF ((duration of stop ≥ 30 minutes) AND (SOC after next trip < minimum range)) OR (final stop):
      Calculate charging power
   ELSE:
      t = t +1
      Check for charging occasion

3. Calculate charging power:

$$charging\ per\ timestamp = \min(maximum\ charging\ power, \frac{1-SOC}{duration\ of\ stop})\ [kW] * \frac{1}{12}\ [h]$$
t = t + 1
Execute charging

4. Execute charging:
IF (SOC < 1) AND (status[t] = parking):
$$SOC = SOC + \frac{charging\ per\ timestamp\ [kWh]}{Maximum\ range\ [km] * energy\ consumption[\frac{kWh}{km}]}$$
t = t + 1
Execute charging
ELSEIF ((SOC = 1) AND (status[t] = parking):)
t = t +1
Execute charging
ELSEIF (status[t] = driving):
Check for charging occasion

The procedure for *AFAP* works similar to the *ASAP* procedure apart from the determination of the charging speed (step 3 in the program description). While *ASAP* calculates the minimum charging power necessary, *AFAP* uses the maximum power available. The modified program description (step 3) is given below:

Program description AFAP, step 3

3. Calculate charging power:
$$charging\ per\ timestamp = maximum\ charging\ power[kW] * \frac{1}{12}[h]$$
t = t + 1
Execute charging

The procedure for the *Combination* strategy combines slow depot charging, following the *ASAP* strategy with fast public charging, following the *AFAP* strategy. Again, the modified program description (step 3) is given below:

The procedure for *AFAP* works similar to the *ASAP* procedure apart from the determination of the charging speed (step 3 in the program description). While *ASAP* calculates the minimum charging power necessary, *AFAP* uses the maximum power available. The modified program description (step 3) is given below:

Program description COMBINATION, step 3

3. Calculate charging power:
IF parking location (t) = public:
$$charging\ per\ timestamp = maximum\ charging\ power_{public}[kW] * \frac{1}{12}\ [h]$$
ELSEIF parking location (t) = private:
$$charging\ per\ timestamp = \min(maximum\ charging\ power_{private}, \frac{1-SOC}{duration\ of\ stop})\ [kW] * \frac{1}{12}\ [h]$$
t = t + 1
Execute charging

Simulations are conducted for each strategy-year scenario using the specific technical parameters. Figure 3 shows an exemplary driving profile for 2030. The vehicle starts driving at 7:00. After six trips and 321 km, the vehicle recharges at a public location. In 45 minutes, 280 km are recharged, which equals the maximum average charging power of 2030. After another trip, the vehicle arrives at its depot. Depending on the charging strategy, the vehicle is either charged slowly overnight or fast on arrival. As the vehicle cannot fully charge during the first charging stop and therefore charges at the maximum possible charging power, the *ASAP* and *Combination* strategies are identical in this case.

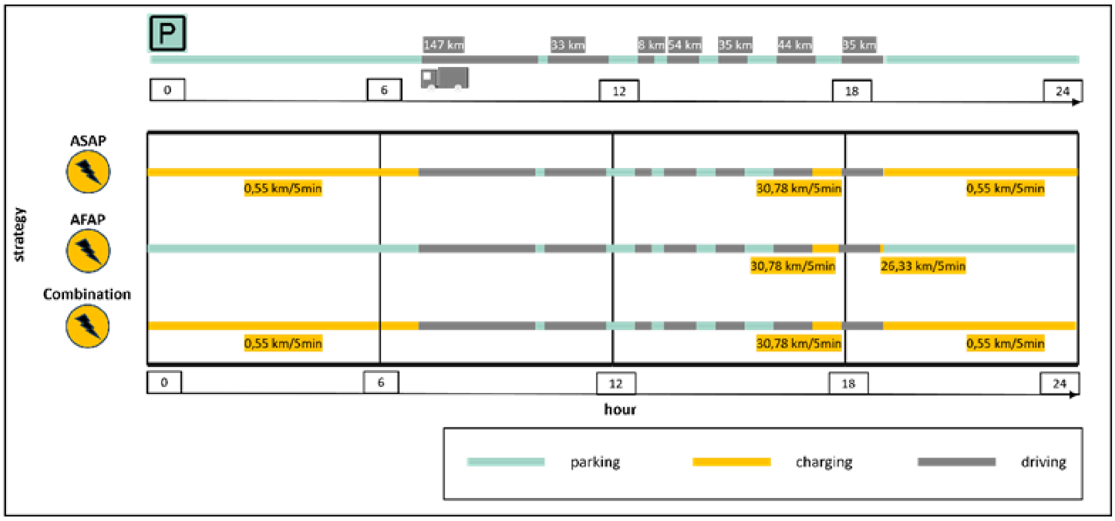

Figure 3: Overview of the charging, driving and parking behavior of a single HDV based on the KiD data

A driving profile is deemed to be feasible if the required range is not higher than the maximum possible range of the battery electric model in the corresponding year and if the vehicle can be recharged after the last trip until the first trip on the next day starts. In other words, a conventional HDV cannot be replaced by a BET if a single trip exceeds the maximum range for a specific year, or if the combined distance of multiple trips exceeds the maximum range and the vehicle can't be sufficiently recharged during the stops.

Finally, the profiles are scaled for the total electrified truck fleet, considered in the corresponding year. By 2030, one third of all vehicles are assumed to be electric vehicles. Depending on the charging strategy, the scaling factor varies, as a different number of driving profiles are feasible under different charging strategies. However, the total number of electrified trucks remains constant. By 2045, the number of electric trucks varies between the different strategies, depending on the share of the fleet that can be electrified.

5 Results

In the following, we give an overview of the parking and driving behavior of the vehicles (section 5.1). Afterwards, we present the technical feasibility of electrification in the different scenarios (section 5.2). Finally, the resulting load profiles are presented (section 5.3).

5.1 Overview

Figure 4 gives an overview of the activities of the fleet during the day. The shape of the curve for driving profiles remains quite consistent across all strategies and years. In the morning, the proportion of vehicles on the road increases, peaking between 7:00 and 13:00, before gradually declining.

Using the *ASAP* strategy, charging up to 44 kW – mainly at private locations – dominates, accompanied by a smaller share of charging with higher power. Looking at the *AFAP* strategy, most charging events take place at private locations with MCS charging. Afterwards, the vehicles remain parked throughout the night without charging. In the *Combination* strategy, private charging events with power levels up to 44 kW play the most significant role. Due to the assumption that vehicles use MCS at public charging stations, a substantial share of vehicles remains parked in public without charging– reaching up to 30% of vehicles at the same time by 2045. However, the lack of private charging infrastructure with a higher power than 44 kW leads to a higher share of vehicles that cannot be electrified.

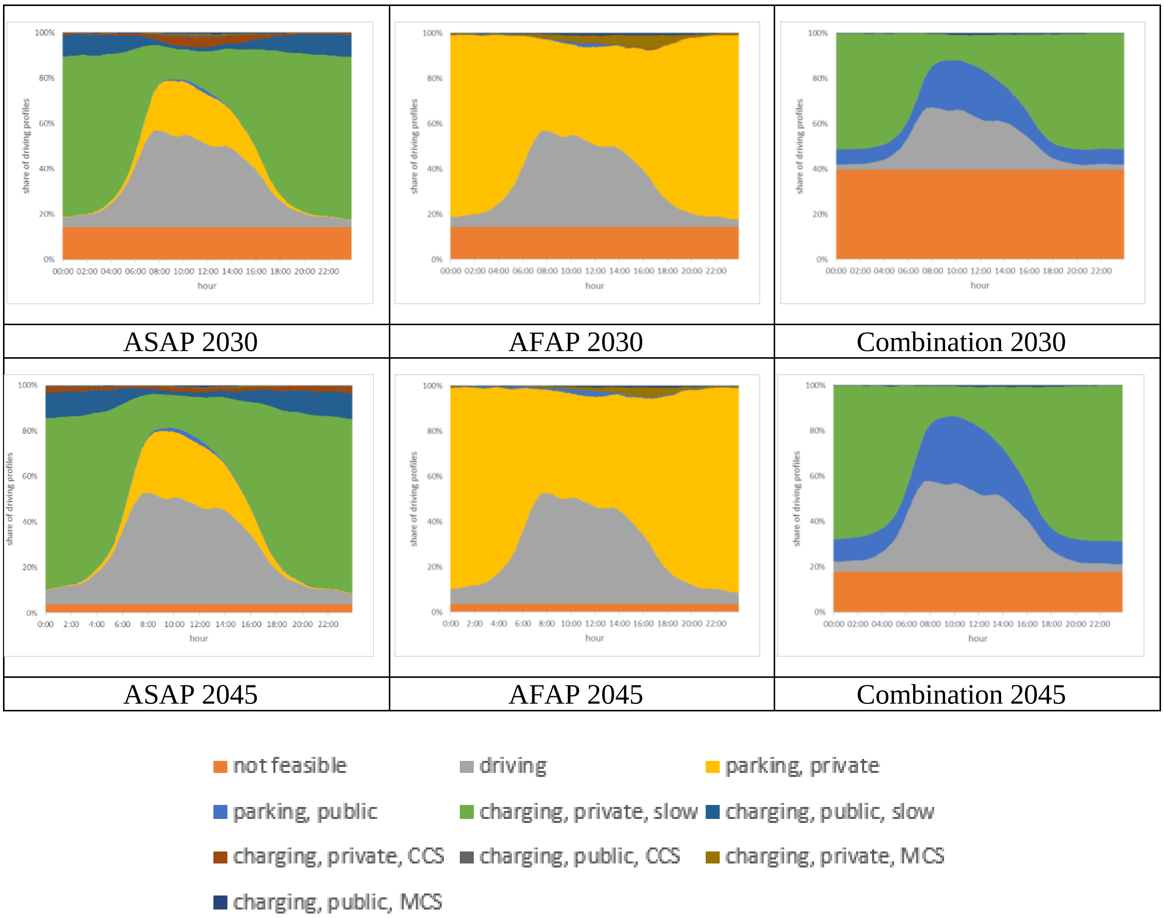

Figure 4: Activities of the fleet during the day

5.2 Technical feasibility and number of charging events

Given the limited charging power and charging time, some charging profiles cannot be electrified. While their share is comparatively low in the *ASAP* and *AFAP* strategies (14% in 2030, 4% in 2045), the *Combination* strategy counts 40% not electrifiable driving profiles in 2030 (18% in 2045). A limited charging power at the depot (max. 44 kW) is the main reason, which prevents the vehicles from being fully charged.

As shown in Figure 5, one (overnight) charging event per day is enough to electrify half of the fleet in 2030. By 2045, the share increases to almost three quarters of the fleet. In the *ASAP* and *AFAP* strategies, the number of required charging stops decreases significantly between 2030 and 2045. While 36% of battery-electric driving profiles require at least two charging stops in 2030, this proportion falls to 23% in 2045. In the *Combination* strategy, the number of driving profiles requiring more than one charging stop per day remains at roughly the same level over the years (10%), mainly due to the inability to electrify a large share of long-haul profiles.

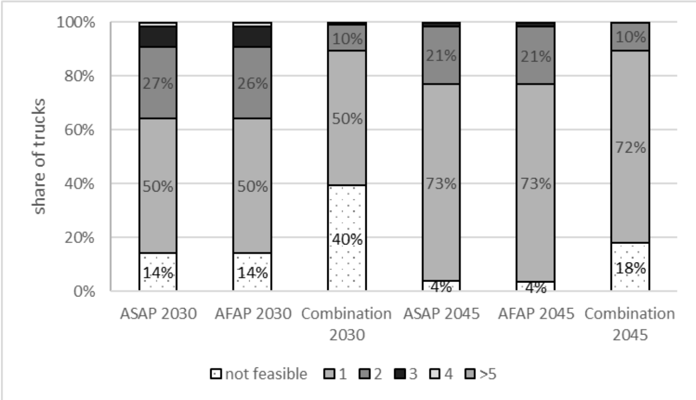

Figure 5: Overview of the feasibility and the required charging stops of the fleet

Additionally, we examined the share of driving profiles that rely on public MCS charging. The specific shares in 2030 and 2045 vary only slightly across all strategies. In the *ASAP* strategy, the shares are in the range of 10%, while for the two other strategies they are in the range of 20 to 25%. This difference arises from the assumption that vehicles charge as slow as possible in the *ASAP* strategy. Fast charging, particularly MCS charging, is only needed in rare cases. It should be noted that public MCS charging involves only a minority of all charging events, however, to enable long-haul trucking the MCS charging events are highly relevant.

5.3 Load profiles

To get an overview of the potential impact of the electrification of the German HDV fleet on the energy system, we carry out an extrapolation of our driving profiles to a possible future BET fleet size. We estimate the additional energy required and discuss the power demand throughout the day.

Figure 6 shows the load profiles in 2030 and 2045. The *AFAP* strategy leads to peaks in midday and evening hours. The midday peak is due to intermediate charging, while the evening peak results from charging for the next day. At 6 GW in 2030, the peak reaches almost 10 % of today's usual power demand in Germany. In 2045, the peak reaches 18 GW. The *ASAP* and *Combination* strategies have a much lower power demand. *ASAP* is always higher than *Combination*. As we assume that one third of the fleet is electrified in 2030, the fleets are not identical in the scenarios. In the *Combination* strategy, mainly vehicles with below-average mileage are electrified, resulting in lower energy demand (36 GWh/day vs. 52 GWh/day). In 2045, the share of electrified vehicles and their energy demand in the *Combination* strategy is lower than in the other strategies (82 % vs. 96 %, 145 GWh/day vs. 103 GWh/day).

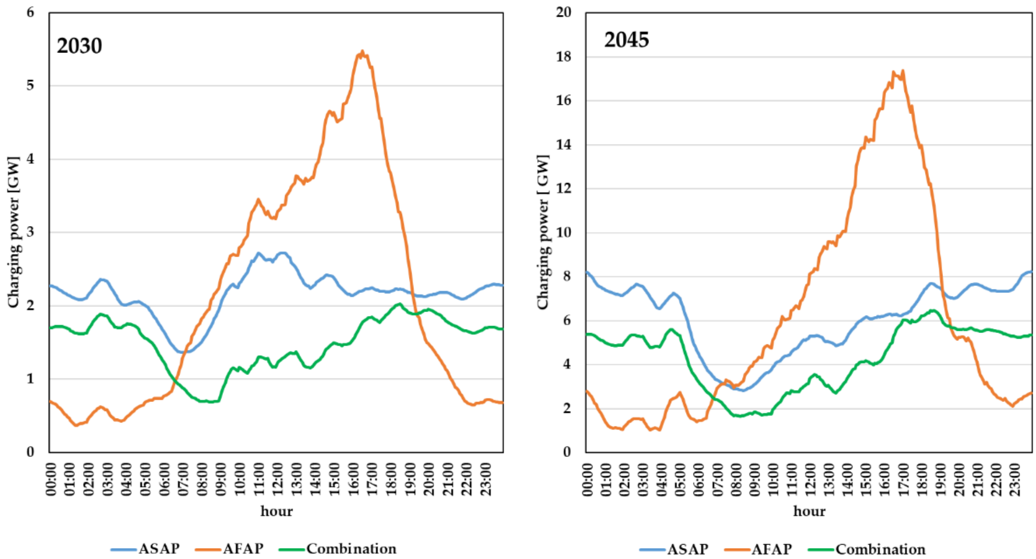

Figure 6: load profiles for the defined charging strategies in 2030 and 2045

For comparison, Figure 7 shows the additional load for the defined charging strategies and the average electricity load curve in 2022. Even though electricity demand will increase in the future, BETs will generate relevant demand and need to be considered in energy system modeling.

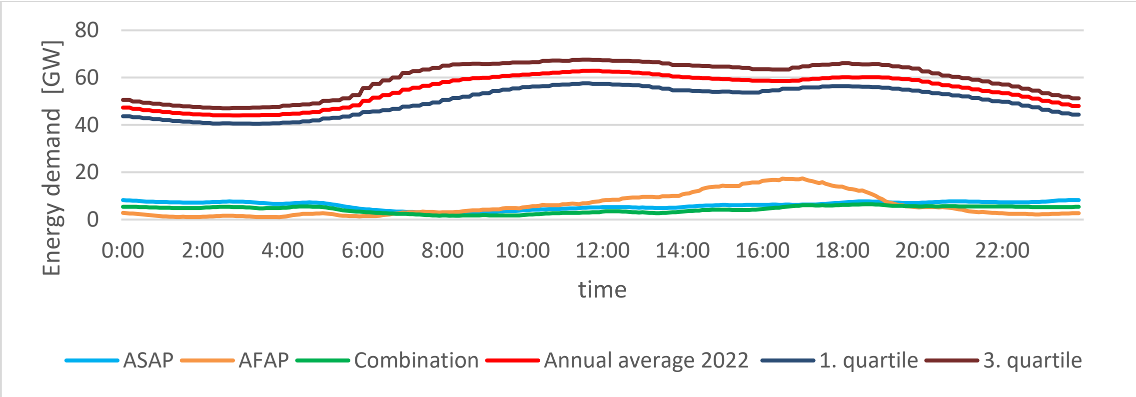

Figure 7: Load profiles for the defined charging strategies in 2045 compared to the average electricity load curve in 2022, based on [15].

6 Discussion

In the following relevant assumptions, our model itself, and the results are briefly discussed.

The energy consumption of the vehicles is a relevant input parameter. It depends on the weather conditions, the nature of the road, the individual driving behavior, the design, and the weight of the vehicle. Higher or lower consumption can also change the range of the vehicles. A higher range would reduce the demand for intermediate charging, and therefore the midday charging demand. Conversely, a lower range would increase the intermediate charging demand. However, as our range assumptions are rather conservative, higher demand would potentially lead to higher ranges (and bigger batteries). Therefore, the charging behavior would remain similar, while the energy demand would increase linearly to the additional energy consumption.

Another limitation is given by our driving profile data. There is only a limited number of driving profiles and trip data is recorded by hand. Even though the dataset has a high consistency with German traffic count data and is therefore deemed to be representative [7], future analysis should include additional driving profiles. Additional geographic information (GPS coordinates) could improve the identification of suitable charging locations, compared to the pure differentiation between public and private locations.

Our assumptions of the future BET fleet are based on literature and the technical feasibility calculated in our analysis. A smaller or higher penetration of BETs would linearly influence the load profiles.

The implemented charging strategies simplify the scheduling of charging events by triggering charging events based on the SOC. As most of the truck traffic is scheduled, one might assume that charging events will be integrated into the trip planning process. This may slightly change the results. For example, there are stops shortly before arriving at a depot. In such cases, a logistics company will likely reschedule the trip or select a vehicle with a slightly higher range. This means that our analysis potentially overestimates the need for public and intermediate charging.

The load curves of potential strategies we generated in this paper offer an overview of their impact under simplified assumptions. To assess their practical applicability, we evaluate these strategies with a focus on meeting the diverse requirements and needs of different stakeholder groups: (1) Logistics companies and fleet operators prioritize minimizing the likelihood of waiting times. To achieve this, the *AFAP* strategy is highly suitable, as it charges vehicles as fast as possible, keeping charging stations available for subsequent charging processes. Additionally, these stakeholders aim to reduce the number of charging events on a trip, enhancing route plannability [16] and avoiding detours to reach charging points. (2) For grid operators, however, it is very crucial to understand the vehicles' energy requirements and to prepare the grid accordingly. A strategy that provides a relatively even distribution of load and limits demand during national peak electricity times is ideal. Both the *ASAP* and *Combination* strategies meet these requirements. *AFAP*, in contrast, causes additional load peaks and is therefore rather unsuitable for widespread application. When it comes to implementation, strategy *Combination* is the most feasible, as it combines both objectives: flattening the load curve and minimizing waiting and charging times during trips. (3) Another stakeholder group consists of policy makers. Funding is needed to set up a charging infrastructure. To make well-informed, long-term decisions it is important to understand where and when which load capacities are required. Our results indicate that a well-developed private slow charging infrastructure will be the backbone of a future electrified truck traffic. However, especially long-distance traffic will rely on public and private high-power charging infrastructure.

One aspect that has not yet been considered in this work, but which holds great promise for future research, concerns the application of intelligent charging methods and bidirectional charging, also known as “Vehicle-to-X” (V2X). This involves the integration of electric vehicles into the power grid. In smart charging scenarios, different targets can result in different operational and charging decisions, leading to different patterns of charging loads [17]. However, the integration of V2X requires extensive further data collection and assumptions that would exceed the scope of this study.

7 Conclusions

We simulate all daily trips of 2,410 trucks in Germany as BETs and apply three different charging strategies. Aiming to give initial insights into upcoming effects of trucks electrification on the energy system, we find that a full fleet conversion can lead to additional load peaks. By 2030, BETs may lead to an additional load of up to 6 GW (10 % of the average load in Germany), if not properly managed. However, if slow charging is applied, peaks will be approximately halved. Compared to immediate fast charging, slow charging shifts energy demand from early evening hours to night hours. By 2045, the additional demand may increase to 18 GW in the fast charging strategy and 8 GW in the slow charging strategy. Our results provide first insights for (1) logistics companies to plan their private charging infrastructure, (2) grid operators and energy providers to prepare their infrastructure, and (3) politicians to support a suitable infrastructure ramp-up.

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Acknowledgments

The Federal Ministry for Digital and Transport (BMDV) in Germany funded this research within the project HoLa under grant agreement No 03EMF0404A. DS acknowledges funding from the German Federal Ministry of Education and Research (Ariadne project FKZ 03SFK5D0-2).

Presenter Biography

Daniel Speth studied Industrial Engineering and Management at the Karlsruhe Institute of Technology (KIT). His master thesis dealt with European CO_2-legislation for passenger cars and its implications on market diffusion of alternative fuel vehicles. Since 2019, he is a researcher at the Fraunhofer Institute for Systems and Innovation Research ISI in Karlsruhe, Germany. In 2024, he completed his doctoral degree at KIT on electrification of road freight transport and the necessary public charging infrastructure for trucks. Areas of work are the modelling of market diffusion of electric vehicles with a special focus on heavy-duty vehicles, their infrastructure, and the implications on the energy system.