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Notes

Abstract

Heavy-duty vehicles (HDV) account for less than 2-5% of the vehicles on the road in Europe but contribute to 15-22% of CO2 emissions from road transport. Battery electric trucks (BETs) could be deployed on a large scale to reduce greenhouse gas emissions but they require charging infrastructure that supports long-haul operations. Therefore, assessing the required charging locations, energy, and power requirements is critical. We use a trip-chain-based model to derive charging requirements for BETs in long-haul operation (defined as travel times over 4.5 hours or distances over 360 km) for Europe in 2030. We convert an origin-destination (OD) matrix into trip chains combined with European truck driving regulations to derive break and rest stops. We show that an average charging area (defined as a 25 × 25 km square, where each square can include multiple charging stations and parking lots with multiple charging points) needs to have four to five times more overnight than megawatt (MW) charging points: We estimate that about 40,000 overnight charging points (50-100 kW, combined charging system, CCS) and about 9,000 megawatt charging system (MCS, 0.7- 1.2 MW) points are required to support a BET share of long-haul operations at 15%. On average, 8 and 2 CCS and MCS chargers are required per charging area, and each CCS and MCS serves, on average, 2 and 11 BETs daily, respectively. The daily electricity demand for public charging of BET in each charging area would be around 110 GWh. The model can be applied to any region with similar data. Future work can consider improving the queuing model, assumptions regarding regional differences of BET penetration and heterogeneity of truck sizes and utilization.

Key words: Electrification; Heavy duty truck; Charging Station; Battery Electric Truck.

Contents

1 Introduction

Road transportation is a key enabler of global economic activity and a major consumer of fossil fuels, which presents a challenge in reaching a low-carbon future (Mulholland et al., 2018). Road transport alone accounts for 20% of global total greenhouse gas (GHG) emissions (Santos, 2017); 30% from road freight transport (Ge and Friedrich, 2020). Heavy-duty vehicles (HDVs), defined as vehicles with more than 12 tonnes gross vehicle weight, account for less than 2-5% of the vehicles on the road in Europe, but contributed to 15-22% of CO_2 emissions from road transport in 2019, and their emissions are growing fast (+ 9% between 2014 and 2019) (Danese et al., 2021; Suzan and Mathieu, 2021). To substantially reduce GHG emissions from road freight transport by electrification, battery-powered electric trucks (BETs) would need to be deployed on a large scale (Hurtado-Beltran et al., 2021; Osieczko et al., 2021). BETs have numerous advantages, including zero tailpipe emissions, fuel cost savings, and lower maintenance costs. Several truck makers have already manufactured models up to about 350 kWh, with an estimated range of up to 400 km with full payloads (Al-Hanahi et al., 2021).

The deployment of BETs to replace fossil-fuel-based HDVs in long-haul operations depends on the development of a network of charging stations that can provide sufficient driving coverage and suit the charging requirements of these vehicles along their travel routes (Al-Hanahi et al., 2021; Hurtado-Beltran et al., 2021; Osieczko et al., 2021; Speth et al., 2022a). Existing fast-charging stations target personal cars and are thus inadequate for BETs (Hurtado-Beltran et al., 2021). Currently installed charging stations supply some BETs for short outings that return to a base location (ICCT, 2019). A large share of HDVs are in long-haul operation; some define it as more than 400 or 500 km of daily driving distance, including multi-day intercity travel without daily return to the truck's home base. Thus, the electrification of HDVs presents distinct challenges from those for passenger vehicles due to high-power demand and longer travel distances (Danese et al., 2021). Vehicle users, manufacturers, and authorities are interested in better estimating these needs for planning charging infrastructure.

The main objective of this study is to identify the public charging requirements according to possible projections for the BET fleet in 2030 for Europe. Many recent studies examining BETs charging needs are limited to a small geographical scale, e.g., nationally (Çabukoglu et al., 2018; Mareev et al., 2018; Mishra et al., 2022), due to a lack of detailed travel data from HDVs (Hurtado-Beltran et al., 2021; Jochem et al., 2019). Further, studies do not identify charging-station requirements, i.e., locations of charging stations, characteristics, and number of installed charging points, and daily energy requirements. The detailed charging requirements also affect (or are constrained by) other significant connected systems to the charging stations, such as the power grid. Other studies, such as Çabukoglu et al., (2018) and Mishra et al. (2022), utilizing detailed datasets from original equipment manufacturers (OEM)s have the downside of not being representative of the whole region and fail to consider the impact of passing trucks from other neighboring countries. A recent study by Speth et al. (2022a) utilizes representative data for traffic counts of all long-haul trucks to identify the charging needs. However, its methodology does not distinguish by truck travel-pattern heterogeneity and thus fails to capture the charging-point differences, such as the charging point's power rate.

We propose a model that captures the charging station's characteristics according to the HDV movements and charging requirements of BETs in long-haul operations that travel across European regions. This study models complete trip chains for all HDVs in Europe by disaggregating the flows in the origin-destination (OD) matrix into vehicle-based tours in order to identify the location of required charging stations, the characteristics, and number of charging points, and the daily energy requirements. An OD matrix contains aggregated information about traffic flows between zones or regions, typically in tons. A trip chain denotes a set of connected trips between a journey's 'significant' locations (e.g., depos and shops). It captures the behavior of HDVs, including locations and durations of vehicle activities, frequency of visiting these locations, and the sequence in which they are visited (Joubert and Meintjes, 2015; Peterson and Michalek, 2013). Our trip chains method provides new perspectives for analyzing the charging demand from long distance freight transportation (Duan et al., 2020).

In this research, we develop a geographic information system (GIS)-based trip chains methodology to allocate charging facilities for BETs in the year 2030 for Europe, considering the movement patterns between all regions and charging needs for individual trucks. The study does not consider regional deliveries due to differences in travel patterns. The model is based on a publicly available European Union (EU) OD matrix for HDVs (Iww et al., 2012) and considers EU truck driving regulations (Ahlström et al., 2022). The detailed trip chain identifies the multiple stop locations and durations, energy consumption, and required energy charging at each stop for each BET. The study thus provides insights into charging infrastructure requirements (i.e., charging types, station capacity, and energy supply) of all BETs in EU member states. We estimate the daily energy requirements of charging areas aggregated to larger regions and nationally.

The paper is organized as follows. The following section provides a short literature review of different methodologies for allocating public charging stations for BETs in long-haul operations. Section 3 describes our methodology and data for allocating charging requirements. Section 4 and section 5 present the results and discuss our findings and the impact of the assumptions on the results. Finally, we conclude in section 6.

2 Literature review

Recent research has studied charging station needs for BETs and the impact of these on the power grid. Mareev et al. (2018) develop a vehicle simulation model for BETs to simulate the energy consumption for a transportation scenario. The model calculates the BET fleet's required battery capacity and charging infrastructure. Their simulation relies on real-world data of long-haul transportation in Germany but from limited road segments. Çabukoglu et al. (2018) investigate the electrification potential of the Swiss heavy-duty fleet. They use a multi-agent discrete event simulation for each vehicle's day, simulating the required battery swapping stations and stationary charging infrastructure. Jochem et al. (2019) estimates the minimum number of fast-charging stations along the European highway network of eight EU countries, including France and Germany. Besides the minimum number of required fast-charging stations, they also estimate the profitability of these stations. Hurtado-Beltran et al. (2021) develop a methodology for identifying the driving coverage if fast-charging stations were located at truck stop facilities along the United States interstate highway system. The study is based on a GIS network analysis focusing on the service area. Mishra et al. (2022) propose a framework that integrates an agent-based charging station model with vehicle schedules obtained through real-world hourly vehicle telemetry data in five states in the United States. The framework elucidates the dependencies of fast charging stations operation on vehicle traffic data and station design parameters and how that affects vehicle electrification. Al-Hanahi et al. (2021) study two major charging strategies for commercial vehicles: the return-to-base and on-route charging models. They analyze the challenging issues related to charging commercial vehicles at public charging stations, including HDV. Danese et al. (2021) develop a methodology to allocate charging infrastructure that supplies static and dynamic charging for HDVs. Speth et al. (2022a) recently developed a public long-haul BETs high-power fast-charging model for Germany that combines open-source traffic count data with queueing models.

So far, there are two main approaches for modeling the nationwide or international rollout of charging infrastructure along motorways (Speth et al., 2022a). One approach is distributing infrastructure as evenly as possible to guarantee maximum geographical coverage. Examples of this are an "ad-hoc" model, as suggested by Jochem et al. (2019), and the coverage-oriented approach by Speth et al. (2022a). The other approach, referred to as the demand-oriented approach by Speth et al., (2022a), is to position infrastructure at locations with high charging demand that enables high utilization of charging sites. The coverage-oriented approach works with widely available local traffic volume data, but the results lack important details such as a station's capacity and energy requirement. The demand-oriented approach computes the minimum number of charging stations but requires high-resolution traffic flow data and considerable computational power (Speth et al., 2022a). The demand-oriented approach can be further extended by considering queuing effects at the charging stations (Jochem et al., 2019). The demand-oriented approach could yield better insights into charging requirements and the limitations of selected locations, such as charging station capacity. Neither coverage nor demand-oriented approaches provide details on the heterogeneity of chargers due to a lack of detailed vehicle-related information. For instance, using traffic counts as inputs is inadequate to distinguish the parking duration of the vehicle, e.g., short or long parking periods (Speth et al., 2022a). With either approach, insufficiently detailed data limit us in understanding a station's energy and power requirements and the impact of these on the power grid.

Some studies introduce data-driven, bottom-up approaches, e.g., assessing each vehicle's impact individually and then aggregating. Çabukoglu et al. (2018) use OEM data for the Swiss truck fleet. However, while this type of data-driven approach gains significant insights into detailed individual vehicle operations and routes, the representativeness of the dataset is usually limited, as the findings are often limited to restrictive sampling periods, the number of participating trucks/companies, etc. A model that covers the whole or most of the HDV movements within the geographical area with representative activity details is essential to better reflect the fleet's needs regarding charging types, station capacity, and energy supply.

3 Methods and Data

We develop a method for placement of charger locations in Europe that meets the demand of goods movements between regions and the EU driving regulations (Ahlström et al., 2022). The spatial resolution of regions is based on the Nomenclature of Territorial Units for Statistics (NUTS)-3 regions. The annual flow of goods transported by HDV is identified using the ETISplus dataset, see section 3.1. The HDV travel pattern assumptions and our approach to converting flows into trip chains with the number of HDV travelling are explained in section 3.2. Traveled routes between the regions are mapped. Locations of short-period stops (i.e., breaks) and long-period stops (i.e., rests) are allocated along the traveled routes to construct a trip chain for each traveling HDV. Break and rest locations for all traveling HDVs are aggregated to estimate energy requirements when assuming these HDVs are BETs. The aggregated energy to charge stopped BETs is used to identify the number and type of chargers within each suggested charging area, as explained in section 3.3 and section 3.4.

3.1 Movement data for goods

The ETISplus dataset contains an OD demand matrix for the EU member states plus Russia, Norway, Switzerland, Turkey, Morocco, and the UK at the level of the NUTS-3 region for 2010 (Iww et al., 2012). The OD matrix comprises about 1,630 regions and 2.5 million origin-destination (OD) pairs. Our study considers connected trips between all regions. The analysis does not include Russia, Turkey, and Morocco due to limited flow data and sparse locations in these countries.

The methodology for generating the transport OD matrix follows the classical "four-step" approach of transport demand modeling (Jochem et al., 2019). The ETISplus includes a road network model for freight vehicles. Speth et al. (2022b) project the change in road freight flow in tons and the truck traffic flow in the number of vehicles for 2019 and 2030 using a country-specific export growth factor. The projection for transported goods between regions for 2030 is from Speth et al. (2022b).

3.2 Battery electric truck movements

3.2.1 Identifying long-haul truck trips

In this study, we focus on BETs that use public chargers to reach their destination, not including routes where charging will exclusively occur at destinations, e.g., depots. Plötz and Speth (2021) define truck operation as "regional" if at least 90% of the stops are within a 200 km radius of the truck's home base. Speth et al. (2022a) consider HDVs long-haul if they have a travel period corresponding to 333 km using average travel speed on German roads and a buffer distance, resulting in 4.5 hours. Likewise, Mareev et al. (2018) use 350 km as a distance threshold, and Suzan & Mathieu (2021) define HDV long-haul trips as those with distances over 400 km. Here, we follow the frequently used distance-based definition of "long-haul operation" that considers ODs with travel times over 4.5 hours or 360 km distance traveled using the typical average speed of trucks of about 80 km/h. This assumption leads to 275,000 OD pairs in our analysis.

3.2.2 Break and rest assumptions

We assume that fleet operators charge their vehicles at locations where vehicles are parked during breaks between two shifts or during long rest periods to avoid disrupting their operational schedules. Thus, the deployment of public charging infrastructure is aligned with duties and routes required by transport missions of commercial vehicles and is located in areas around their destination and parking places during the day (Al-Hanahi et al., 2021). Regulation (EC) No. 561/2006 of the European Union states that the daily driving period shall not exceed nine hours, and drivers should take breaks of at least 45 minutes after 4.5 h at the latest. Nine hours of driving is followed by a mandatory rest of at least nine hours. In the case of two drivers, drivers may use two more breaks before having a nine-hour mandatory rest (Ahlström et al., 2022). For comparison, in the US, truck drivers may travel more with fewer pause periods: up to 11 hours of driving or 14 hours of total active time per day (ICCT, 2019).

This study utilizes the EU travel regulations to convert OD pairs into HDV connected trips. Stop locations and durations are identified according to the travel time on the road, and the number of drivers, as further explained in the following subsection.

3.2.3 Trip chains

The study assigns trip chains for each HDV according to the fastest route between origin and destination while respecting constraints based on regulations for travel and rest time. We use the Dijkstra algorithm to assign the shortest route between each OD pair (Speth et al., 2022a). We then implement a GIS model to identify stop locations along the route described above. Each trip is a connection between two consecutive stops, i.e., rests or breaks. A trip chain is a sequence of such trips.

For simplicity, we assume a uniform share of BET (BET_{share}) adoption across all regions. The total number of BETs (N_{BET_r}) on route r is calculated by converting the annual transported flow of goods (AF_{OD}) between ODs multiplied by the share of the electrified trucks (BET_{share}) (see Equation(1)). We assume a truck operates 300 working days a year (YWD) (Speth et al., 2022a), which is higher compared to other studies, for instance 250 working days for trucks in Sweden (Bischoff et al., 2019) and 235 working days per year for US trucks (ICCT, 2019).

The flow of transported goods (in tonne-km) is converted into a representative number of HDV transporting the goods by an assumed increase in average payload capacity. We use an average loading factor (γ) of 13.6 tons, as in Speth et al. (2022a) and slightly higher than the current 12.5 tons (Suzan & Mathieu, 2021), to convert the goods volume in 2030 into the number of electrified trucks moving on roads, N_{BET}:

$$N_{BET_{r,OD}} = \frac{AF_{OD} \times BET_{share}}{YWD \times \gamma} \tag{1}$$

According to the assumed travel pattern, we distinguish between breaks (B), which are 45-minute stops, and rests (R), which are nine-hour stops, to identify possible fast and slow charging events, respectively, explained further in the next subsection. Trip duration TD_i is the travel time between the stops for trip i. Total travel duration of the tour (the travel between an OD pair), $TTD_{o,d}$, is $\sum_{i=0}^{n} TD_i$ for n trips. The study assigns rests and breaks as follows. If the total travel time of the tour, i.e., trip chain, between a pair of OD $ttt_{o,d}$ is $\leq 6\ (days) \times\ 9\ (hours\ of\ daily\ driving)$ hours in one direction, then one driver is assigned. Otherwise, two drivers are assigned. The locations of B and R are assigned according to the following algorithm (Figure 1).

Figure 1: Algorithm for assigning break and rest locations.

$TTD_{o,d}=\sum_{i=0}^{n} TD_i$

$ttt_{o,d} \leq 54$ → One driver

Pause = 0
For i in n:
 If TD_i > 4.5 and Pause = 0:
  Assign B
  Pause = 1
 Elif TD_i ≥ 4.5 and Pause = 1:
  Assign R
  Pause = 0

$ttt_{o,d} > 54$ → Two drivers

Pause = 0
For *i* in n:
 If TD_i > 4.5 and Pause ≤ 2:
  Assign B
  Pause = Pause + 1
 Elif TD_i ≥ 4.5 and Pause > 2:
  Assign R
  Pause = 0

The result is a collection of spatial locations on travel routes, travel goods in tons, and the number of BETs. The study simplifies the result by aggregating the rest and break locations within 25 × 25 km^2 polygons. Each square presents a charging area that could include multiple charging stations and parking lots of multiple charging points, as further explained in the next subsection.

3.3 Charging infrastructure

Two types of chargers are assumed according to stop duration: a megawatt charging system (MCS, 0.7-1.2 MW) and a combined charging system (CCS, 50-100 kW), with 30 minutes and nine hours charging duration, respectively. The number of MCS charging points must meet the peak traffic arriving at charging areas. The remaining 15 minutes during the break are for queuing, preparing for charging, and leaving the charging point. The number of charging points per charging area is based on the queuing theory (Speth et al., 2022a), which indicates how many counters are necessary to maintain an average waiting time for a given arrival rate and service time. A queuing system has three components: The arrival process, the service process, and the waiting (Salazar 2020). We assume that an average waiting time of five minutes is to be maintained; the number of counters corresponds to the number of charging points per location. The arrival rate is derived from the daily flow of BEV traffic and the service time from the charging time. The number of counters and queues determines the service mechanism. The distribution of service times is also part of the service process. Waiting refers to a counter's rule to select the next customer from the queue when the counter finishes serving the current customer. In the following, we assume that customers are served in the order of arrival ("first-in, first-out"). For more details about the model and assumption, check Annex A.1.

In this research, the CCS charging points are assumed to serve a maximum of two daily BETs due to long stop durations. This assumption considers that BETs are connected to the charging point during their long parking time, i.e., for at least nine hours.

3.4 BET energy consumption

The average energy consumption rate for BETs varies significantly among studies. ICCT (2019) and Suzan & Mathieu (2021) consider that the energy efficiency of new trucks entering the fleet will reach 1.2-1.23 kWh/km in 2030. Speth et al. (2022) also assume an energy consumption of 1.23 kWh/km. Lin and Zhou (2021) use real-world driving data of E Force One's energy consumption from 18 electric trucks and found energy consumption of 0.80–1.20 kWh/km on urban roads and 1.30–1.80 kWh/km on highways. Mareev et al. (2018) also find that real-world BET energy consumption rates are between 1.23 kWh/km and 1.94 kWh/km, depending on speed limits and road type. Al-Hanahi et al. (2021) review several current BETs in the market and point out that the energy consumption of the BETs is between 1-1.75 kWh/km, but the payload of the truck impacts the consumption rate significantly.

The average kWh/km for the fleet has been estimated based on the energy efficiency of new trucks expected in the coming years and considering the difference in travel patterns and conditions between urban and highway travel (Lin and Zhou, 2021). We set the average energy consumption based on road segments: 1.2 kWh/km in urban areas and 1.8 kWh/km on highways.

3.5 Electrification share

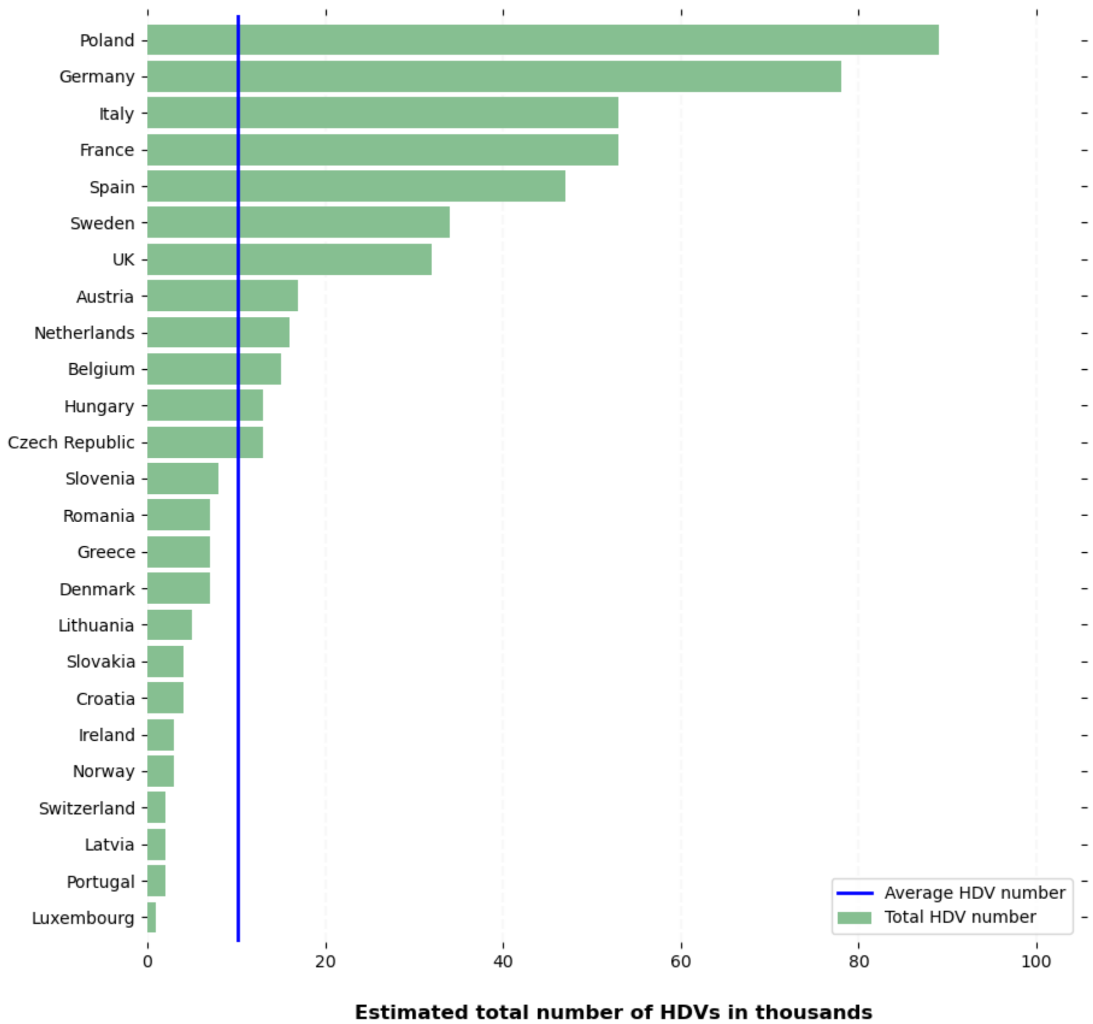
Our main scenario considers a 15% BET stock share of HDVs in Europe by 2030. We also use a scenario with a 100% stock share. The percentage of long-haul electrification in 2030 is highly uncertain. In 2030, companies expect a stock share of 15% battery electric trucks in Germany, (Speth et al. 2022a). Suzan and Mathieu (2021) follow the plans of several major OEMs, e.g., Renault, Iveco, Daimler, Iveco, Scania, Volvo Group DAF, and MAN, to predict a similar average of battery electric truck share in the EU. The BET stock share is motivated by forecasted average of new vehicle sales from OEMs of 30% in 2030. The BET stock share also aligns with the Paris Agreement objectives and the European Green Deal commitments for a zero-emission road transport sector by 2050 (Suzan and Mathieu, 2021).

4 Results

4.1 Long haul trucks originating from EU countries

The estimated number of HDVs in long-haul operations starting from the 25 European countries with the most HDVs in 2030 using Equation (1), is shown in Figure 2. Our calculated number of long-haul trucks for all OD pairs with over 4.5 hours of travel time is 519,000 HDV in long-haul operation in 2030. The result is comparable to about one-quarter of a total of 2.2 million heavy trucks (over 12 tons – long-haul, regional and urban) on the roads in Europe (Eurostat, 2022). Western Europe has a high concentration of most of the originating trucks, see Figure 2. Poland and Germany have the highest number of originating trucks of 89,000 and 78,000, respectively; together, they constitute about a third of the trucks in Europe.

Figure 2: The estimated total number of HDVs in thousands (including both BET and non-electrified HDV) in long-haul operations originating from the 25 European countries with the most HDVs in 2030



4.2 Required battery range and capacity

The total travel time, including rests and breaks, and the total distance for all BET trip chains between the NTUS-3 OD pairs vary significantly. The average travel time and distance for trip chains are 30 hours and 1,449 km, respectively, see Table 1. The medians are 27 hours and 1,227 km, respectively. The sum of travel time could reach up to 300 hours for some trip chains, such as travel between the regions of Kamchatka, Russia, and Pohjois-Karjala, Finland. However, 99.9% of all trip chains take less than 106 hours, ~ 4 days. Most trip chains include multiple rests and/or breaks. Note that travel times may be underestimated, as we consider two drivers for all trip chains exceeding 54 hours of total driving. Only 3% of the trip chains in our data have more than 54 hours of total driving time; these are allocated as two-driver trip chains.

The distance between stops (i.e., origin, rest, break, and destination) varies according to speed on the road and traversed segment type (e.g., tunnels and ferry lines). The average (99th percentile) travel distance between stops is about 350 (435) km, which corresponds to an average (99th percentile) battery capacity of 556 (749) kWh, see Table 1, according to our vehicle energy consumption rates.

Table 1: Statistics summarizing the trip chains and trips between stops for all BETs

				Percentile			
Level	Variables	Mean	Standard deviation	25%	50%	75%	99%
Trip	Distance between stops (km)	350	98	326	343	370	435
	Required energy between stops (kWh)	556	155	485	549	636	750
Trip chains	Total travel time (hour)	30	19	20	27	38	106
	Total travel distance (km)	1450	927	826	1230	1785	5130

4.3 Charging region distribution and capacity requirements

The analysis of the electrified trucks in our main electrification scenario (i.e., 15% BET penetration) yields about 78,000 daily BETs in operation. The break or rest locations are identified along the route but can vary across trucks using the same road segments. These locations are aggregated in 25 km × 25 km squares of charging areas, implying that each charging area could have multiple charging locations within this area and each location multiple charging points. The number of daily BETs stopping at each aggregated charging area is illustrated in Annex A.2.

The analysis yields 4,160 aggregated charging areas in our study regions. 45% of all charging areas are located in 5 countries (i.e., France, Germany, Spain, Italy, and Sweden). France requires the most charging areas in Europe (496 areas), followed by Germany and Spain with 364 and 353 areas, respectively. The stations are approximately 25-35 km apart, covering most of the European highways. For comparison, Speth et al. (2022) suggest 267 charging regions (i.e., areas) in Germany by assuming one charging area every 50 km.

The capacity of each suggested charging area is impacted by stopped trucks and the type of charging points deployed. The charging area serve an average of 47 BETs daily. Countries in the middle of Europe, such as Belgium, Germany, and Luxembourg, have the highest utilization of their charging areas, with over 100 BETs stopping daily. Other peripheral EU countries have low charging-area utilization. Bulgaria, Greece, Romania, Norway, Ukraine, Moldova, Albania, Montengero, and Finland have an average of less than ten parked BETs per charging area per day. There are four charging areas with daily use (i.e., BETs parking for rest or break) by 1,000 BETs or more. The highest number of BETs stopping at a charging area is found within Ireland, with 1,410 BETs per day. In real life, this could encompass many smaller truck parking lots, with 20-100 parking spots each. There are dense charging areas near Dublin, Liverpool, Milton Keynes and at either end of the English Channel. The remaining dense areas are concentrated mainly in the middle or Western Europe. For more insights about charging areas per country, check Annex A.2.

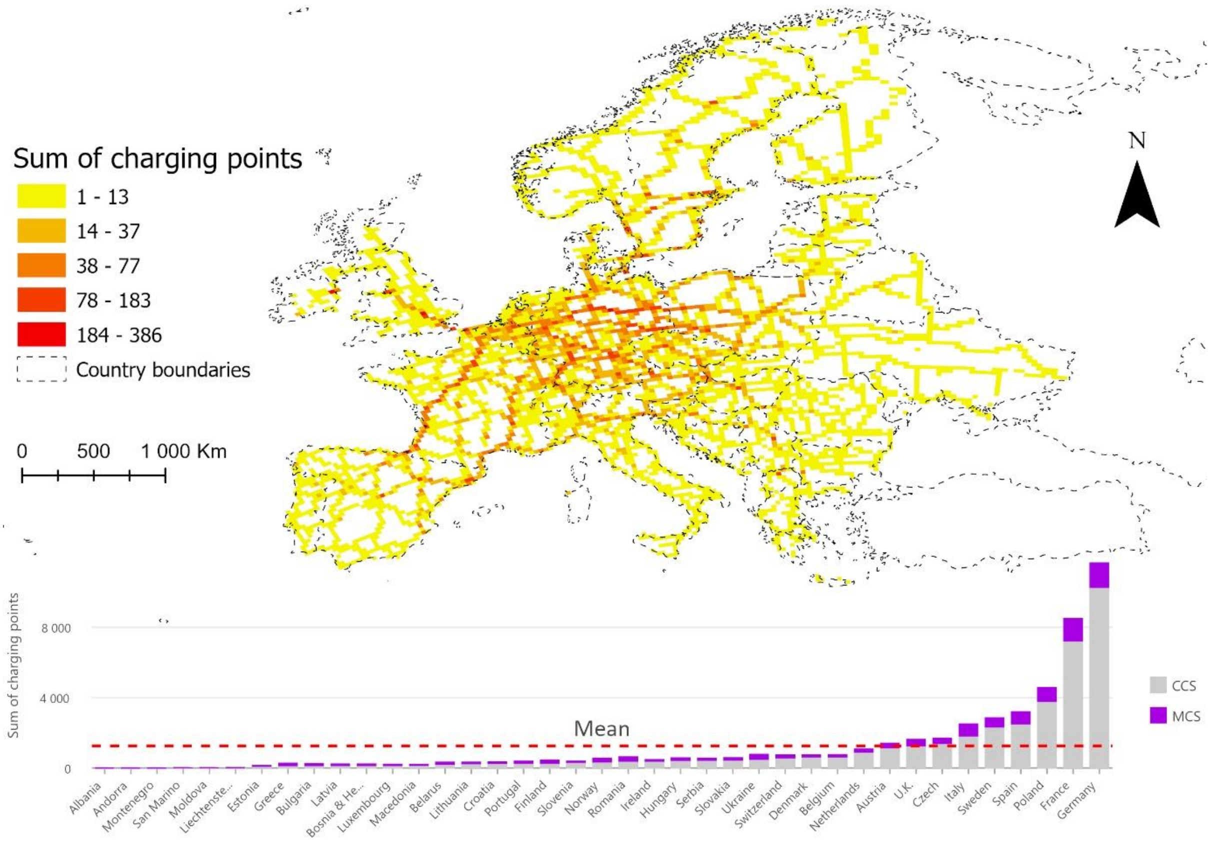
4.4 Charging point type requirement

Overall, more CCSs than MCSs are required. Meeting the charging demand of the parked BETs requires 40,400 and 8,900 CCS and MCS charging points, respectively. See Annex A.3 for more details about CCS and MCS charging point distribution and daily use. On average, 8 and 2 CCS and MCS chargers are required per charging area for the specified 15% BET share of long-haul operation. Electrifying 100% of the BET fleet requires 264,300 and 32,600 CCS and MCS chargers, respectively, representing a shift in the ratio between CCS and MCS towards 90% CCS and 10% MCS.

The required number of chargers is sensitive to the assumed actual charging duration. On average, the required charging power rates for MCS and CCS chargers are 1,100 and 60 kW, respectively, assuming that chargers deliver power at a fixed hourly rate within the corresponding charging durations, i.e., 30 minutes and nine hours, respectively. Increasing the MCS's charging duration to one hour would require more chargers, from 8,900 to 14,200 MCS chargers (a 60% increase) at an average lower power rate of 550 kW.

The average CCS to MCS charging point ratio is 4.5 to 1, equivalent to 80% CCS charging points and 20% MCS charging points. The CCS to MCS ratio is higher in countries in the middle of the EU with trade routes from all directions, requiring drivers to rest more when passing these countries to their destinations (Figure 3). For instance, Germany requires 10,300 and 1,360 CCS and MCS chargers, respectively. In contrast, countries on the margins with trade flow centres close to the border require a similar number of MCS and CCS chargers, for instance, Greece requires 146 CCS and 128 MCS chargers. On average, MCS chargers serve 11 BETs daily. Belgium and Germany have the highest utilization for both charger types. Even though the U.K. and Ireland have some high-demand charging stations, the overall number of chargers in both countries is relatively low compared to other neighbouring countries such as France and Spain. Speth et al. (2022) suggest a total of 950 MCS charging points in Germany, whereas our results identify 1360 MCS chargers. For more details and statistics about each country's CCS and MCS charger requirements, see Annex A.2.

Figure 3: Total number of CCS and MCS chargers by charging area and country in Europe

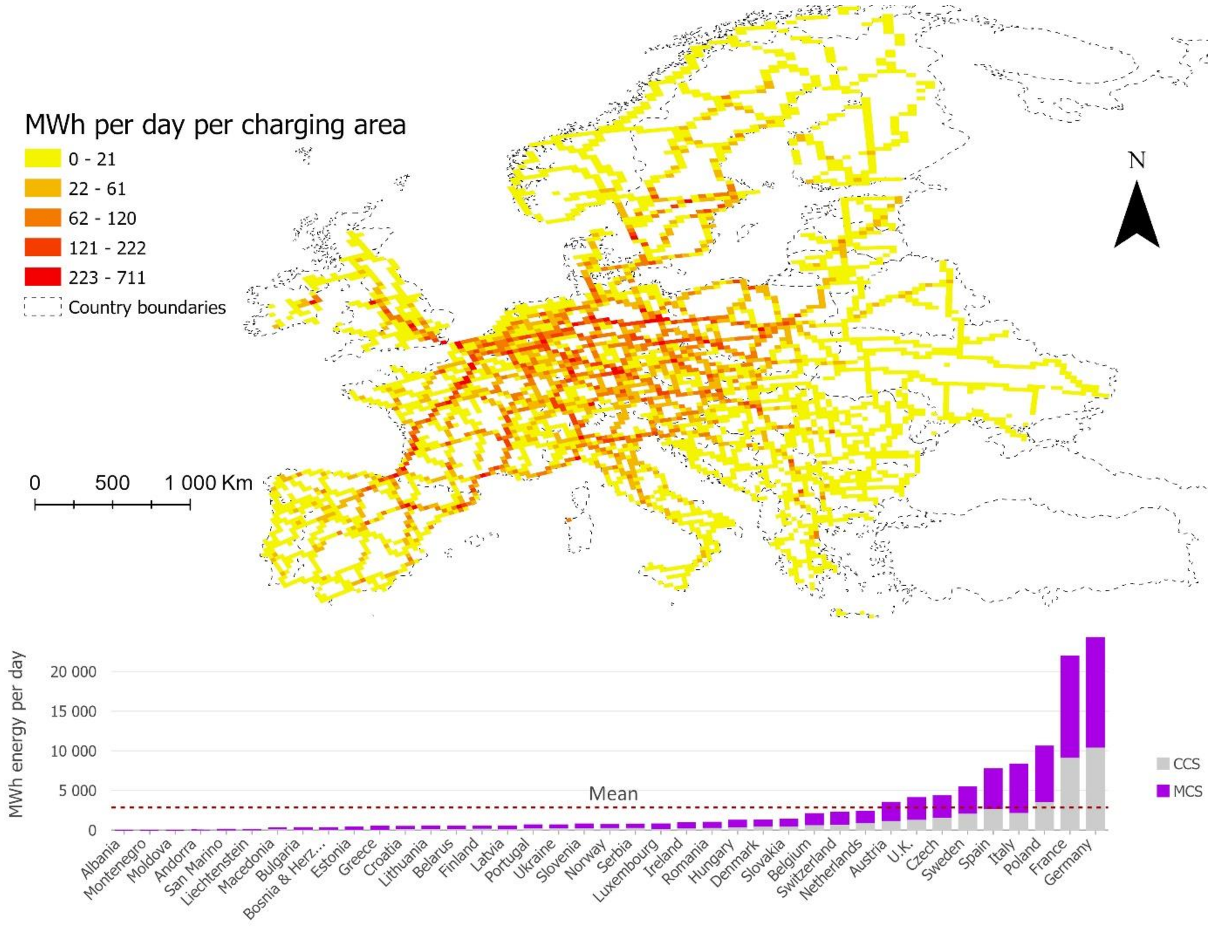


4.5 The energy requirements at charging stations

The energy required to charge all trucks at public stops could reach 110 GWh per day, or 1 MWh for each truck. Certain charging areas (Ireland and the UK) would require up to 544 MWh for all BET daily charging, see Figure 4. On average, a charging area requires 23 MWh per day. 65% of the energy is charged in five countries, i.e., Germany, France, Poland, Spain, and Italy. With a 100% electric share of the HDV BET fleet about 540 GWh per day will be needed for public charging.

The majority of the energy requirement, i.e., 62%, arises from the MCS chargers at break locations. On a daily basis, this sums up to 68 GWh. While these stops only represent 8% of the total parking time for the BETs, the higher charging power also implies a greater energy need. In contrast, the rest stops comprise only 27% of the stops but 92% of the stopping time.

Figure 4: Daily energy requirement for each charging area and country (MWh per day) from both CCS and MCS charging



5 Discussion

5.1 Methodology and assumptions

This article develops an innovative trip chain approach to estimate the charging infrastructure demand for long-haul electric trucks in Europe. Our methodology has several advantages compared with the literature, including coverage-oriented, demand-oriented, traffic counts, GPS measurements of selected vehicles, and agent-based simulations. The trip-chain methodology simulates truck travel distances, stop locations, durations, and energy requirements using publicly available OD data representative of European freight demand. The methodology quantifies the daily BET stops at each charging area to identify the required charging facilities that meet the energy demand from the BETs. The methodology provides insights into heterogeneous station specifications and requirements in European countries. However, the lack of detailed HDV travel schedules limits our ability to provide a more precise temporal distribution of traffic/energy demand. Thus, the methodology is uncertain about each suggested charging area's exact charging point numbers. We followed a detailed minimum estimate of energy and charging type requirements at each area and used a queuing model to overcome the data limitation issue.

The research predicts charging area locations, daily capacity, charger point types, and daily energy requirements that might occur in 2030 under certain assumptions that affect BET energy consumption, travel patterns, and charging durations. The research could overestimate BET energy consumption due to our assumptions for consumption on highway roads. By 2030, energy efficiency is predicted to improve, and energy consumption rates might drop. We illustrate the average travel distance between stops as an alternative metric to inspect the battery capacity requirements between stops. Such metrics help OEMs and other researchers check our calculations by comparing their results with our battery requirements in terms of distance and capacity.

EU regulations allow HDV drivers to divide their break period into two shorter periods (i.e., two separate stops of 15 and 30 minutes). Such flexibility might impact the results in two ways. First, this might force planners to double the required power rates at MCS chargers to allow for a full battery charge in 15 minutes, plus the additional 15 minutes for queuing and service. Second, the locations of the second short break might differ from the earlier break locations. We account for the latter by aggregating stop locations within a 25 x 25 km^2 area. The actual site selection could be allocated anywhere within this area depending on other factors, such as the available parking area or the possible electricity grid connection. These must be assessed individually for each area (Speth et al., 2022a). A charging area should serve at least one of the stops with 15 minutes of driving (~ 20 km, assuming an average speed of 80km/hour) between stops, assuming a break period is divided into two shorter periods.

The assumed charging durations to fulfil the charging requirement influence the required number and power rates of the charging points. We assume an optimistic CCS utilization of two trucks per day. CCS charging at rest stops is expected to occur at night while the drivers rest. Without information regarding actual HDVs/BETs driving schedules, a CCS charger's utilization might drop to one per day, requiring more CCS chargers at each assumed charging area. BETs are assumed to charge while plugged in during the stop period. Thus, the charger's power rate is independent of the number of available CCS charging points and truck traffic. For the MCS chargers, we consider a queuing model that accounts for the expected BET peak traffic during the day. The power rates and allowed charging durations would impact the required number of charging points. Additionally, our assumption of two drivers for trip chains with a travel distance over 9x6 hours of total driving time in one direction requires more chargers for MCS charging stops than for only one driver. Our motivation is to reduce travel time, thus saving on cost for the freight company. More CCS chargers with lower daily charged energy could facilitate the charging energy requirements for more BETs with only one driver.

Overall, our energy requirements and charging points estimates might be on the lower end. The identified trucks transport full loads of goods between only one pair of ODs. Thus, a truck does not transport goods to other destinations within a trip chain. This method underestimates the BET number if more than one truck is involved in transporting the goods between a pair of ODs, e.g., trucks meeting at a depot in between the origin and the destination to swap goods. We disregard the energy requirements for BETs that might return empty from a delivery.

We assume a uniform 15% BET share in all European countries in 2030. In reality, some countries, e.g., Germany and Sweden, might have higher BET rates, requiring more charging points. This might shift the geographical distribution of the needed chargers. We might also underestimate the number of operational trucks on the roads due to our assumption of 300 working days for a truck.

5.2 Results and implications

Our model places charging areas every 25-35 km on highways where demand for charging is required. Charging area placement could be adjusted by controlling the aggregate area to modify the placement distance between areas. As a result, the number of charging points per area would change. However, the total number of charging points would remain the same for the same estimated total energy demand from BETs.

The required battery capacity, range, and charging power rates to cover most trips are within OEM expectations and plans. Our results show that to cover most of the trips (i.e., 99%), BETs should be equipped with a 435 km range, equivalent to a 750 kWh battery, based on our energy consumption rate assumptions, and the average charging power rates of 60 kW and 1100 kW for CCS and MCS chargers. The expected battery capacity to cover most trip chains is within the expected plans for major OEMs to cover the same distances, i.e., 300-1000 kWh to cover 300-800 km of range, as reported by (Al-Hanahi et al., 2021). Announcements from manufacturers, pilot projects, and other studies show that it is reasonable to assume MCS chargers with power rates between 720 kW and 1 MW by 2030 (Speth et al., 2022a). Tesla Inc. has announced a plan to add a mega-charger network of 1 MW power capacity that can provide 640 km range in no more than 30 minutes of charging (Al-Hanahi et al., 2021). Mohamed et al., (2022) consider megawatt-scale charging facilities that can quickly charge large-capacity battery packs (i.e., ~ 800 kWh) in less than 30 minutes for HDV deployment.

Countries in central Europe, such as Germany and Belgium, have many trucks passing through (about 50% of trucks on German highways are just traversing the country) and are thus more important for inter-European long-haul transport. These countries have the highest utilization rate for their charging areas, with over 100 BETs stopping at their areas daily, demanding over 53 MWh on average. Large investments are required to allocate and install chargers and develop the power grid and electricity supply to meet demand from charging areas. Developing charging infrastructure in these countries as soon as possible is essential to allow for BETs with long travel (i.e., long trip chains).

The power supply and the grid are major limitations when planning for charging regions, which might impact our charging region allocations. Certain charging areas have a daily energy demand of up to 544 MWh, as shown in Figure 4 This high daily energy requirement also implies significant power grid investments. The required energy to supply 100% BET share could reach up to 3.6 GWh for the charging areas with the highest demand.

6 Conclusion

We used an algorithm based on trip chains to identify the locations of required charging areas in a scenario where 15% of HDVs in Europe are battery electric trucks (BET) in 2030. We also estimate the minimum power rate, the number of charging points, and the daily energy requirements. The algorithm identifies BET travel patterns to distinguish each charging area's needs. The algorithm could be further enhanced with hourly traffic details of the HDV fleet to further estimate the charging area's hourly energy distribution and each charging point's number and power rate.

We show that in 2030, about 78,000 BETs, representing a 15% share of HDVs, require a minimum of 110 GWh of charging per day. This charging will occur at 40,400 combined charging station (CCS) points and 8,900 megawatt charging station (MCS) points distributed across Europe. However, this distribution is not equal: Central and Western European countries such as Germany and Belgium will have a denser concentration of chargers compared to more peripheral countries such as Portugal. While much attention is given to the deployment of MCS chargers, our results show that the required number of CCS charging points is four and a half times the number of MCS charging points.

Our results also show that certain charging areas will require about 550 MWh daily. More research is needed to consider power grid limitations. Given the lengthy process of infrastructure development, it is essential to begin planning for these investments as soon as possible. Our results and methodology can serve as a starting point for understanding these investment needs.

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7 List of figures

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A.1 Queueing model: The number of MCS charging points per charging area

The total number of MCS charging events per charging area and day is calculated by distributing the charging events to the individual charging area. We determine the number of charging points per location in a queueing model. The following presentation is based on Speth et al. (2022).

The design of the charging location, i.e. the number of charging points per charging location, is based on the mathematical queueing theory (see Adan and Resing (2017)). Queueing theory is an established field of mathematics, which indicates how many counters are necessary in a system to maintain a given average waiting time for a given arrival rate and service time. In the application presented here, we assume an average waiting time of five minutes is to be maintained; the number of "counters" corresponds to the number of charging points per charging area. The arrival rate results from the daily flow of BEV traffic and the service time from the charging time.

A queueing system is characterized by three components: Arrival process, service process, and waiting (Salazar 2020). The arrival process describes how the customers arrive in the system and the distribution of the arrival of the customers. Second, the service mechanism is determined by the number of counters and by the number of queues. The distribution of service times is also part of the service process. Third, waiting refers to the rule that a counter uses to select the next customer from the queue when the counter finishes serving the current customer. In the following, we assume that customers are served in the order of their arrival ("first-in, first-out").

We follow the standard Kendall notation for queueing models. The average number of arrivals per period is denoted by λ and the average number of customers served per period (i.e. average service rate) is μ. The standard notation system for classifying a queue system is A/B/*c*/*k*/*m* with the probability distribution for the arrival process A, the probability distribution for the service process B, the number of counters *c*, the maximum number of customers *k* allowed in the queueing system and stands for the maximum number of customers *m* in total. In our case, *k* and *m* can be assumed infinite.

For the present case of rapid charging of trucks, it is plausible to assume Poisson-distributed arrivals, with the average arrival rate being directly derived from the number of battery trucks (Gnann et al. 2018). A Poisson distribution describes the number of events that occur at a constant rate in a fixed time interval (Johnson et al. 2005). For example, an average arrival rate of $\lambda = 4$ trucks/hour means that on average four trucks arrive per hour, but sometimes a little less and sometimes more. In the case of charging heavy trucks, the service times are approximately normally distributed, i.e. there is a typical charging time with variations around it. We thus use an M/G/c queueing model. In the literature, M/M/c queues are sometimes used for fast (MCS) charging, but Funke (2018) and Gnann et al. (2018) show that M/G/c systems correspond better to the real distribution of service times.

Exact solutions for the mean waiting time of M/G/c systems are not known, but an approximate formula is available, an extension of the Pollaczek Khinchine formula (cf. Funke, 2018). The mean waiting time $W_q^{M|G|c}$ of an M/G/c system can be approximated by the mean waiting time $W_q^{M|M|c}$ of a comparable M/M/c system (Funke, 2018)

$$W_q^{M|G|c} = \frac{C^2+1}{2} W_q^{M|M|c}. \qquad (2)$$

Here C is the variation coefficient of the distribution of service times, i.e. the quotient of the standard deviation and the mean value of the service time distribution. Since we use normally distributed service times with a pronounced peak, $C < 1$ and the mean waiting time in the M/G/c system is shorter than in the M/M/c system. We assume $C = 1/6$ in the following. This approximation formula is used together with the exact results for the mean waiting time of M/M/c systems for the design of charging stations, i.e. $W_q^{M|M|c} = \frac{1}{1-\rho}\frac{1}{c\mu}\frac{(c\,\rho)^c}{c!}\left((1-\rho)\sum_{n=0}^{c-1}\frac{(c\rho)^n}{n!} + \frac{(c\rho)^c}{c!}\right)^{-1}$ according to (Adan & Resing, 2017).

The average waiting time of 5 minutes does not mean that all users wait exactly 5 minutes. In fact, there is a distribution of waiting times. For the example of an average arrival rate of $\lambda = 4$ trucks/hour and a charging time of 30 min, i.e. an average operating rate of $\mu = 2$ trucks/hour, $c = 4$ charging points are needed to get below 5 min average waiting time. With $c = 4$, it is 1.3 min and with $c = 3$ it is 6.6 min. The average waiting time of less than 5 min is achieved in this example by the fact that the vast majority of trucks (approx. 83%) do not have to wait at all, a few (8%) wait up to 5 min or 5-15 min (7%) and very few (2%) wait longer than 15 min.

The procedure for designing the individual location is as follows: The number of BEV trucks per day determines the average hourly arrival rate λ in trucks/hour for the peak hour or the daily average. The arrival rate is derived from hourly traffic count data (see appendix) as 6.0% of daily BEV trucks for the peak hour or 4.2% of daily BEV trucks for mean hour. This percentage is multiplied with the total number of BEV trucks on the specific highway segment per day, obtained from the traffic count data and the assumption of 15% BEV trucks in stock. The average service rate is μ = 2 trucks/hour at 30 min average charging time, i.e. approx. 720 kW average charging power. For each charging location, we calculate λ from the traffic data and choose the smallest *c* fulfilling the five minutes waiting time condition. That is, the smallest number of charging points *c* at the given charging location, such that the average waiting time is less than 5 min. Due to the large space requirements of charging locations with many charging points, it is also assumed in the design that a maximum of eight charging points can have a common waiting area. If more than eight charging points are required at one location to maintain the average waiting time of five minutes, it is assumed that several separate charging parks with up to eight charging points are created at one location.

A.2 Country based details of BET charging requirement

The truck stopping points are aggregated to 25 x 25 km^2 squares of charging areas, implying each charging area could have multiple charging locations within this area and each location with multiple charging points. The number of daily BETs stopping at each 25 x 25 km^2 charging area is illustrated below in Figure A.1. The required charging areas, daily parked truck number, and daily charging requirements are aggregated to each country and summarized in Table A.1.

Figure A.1: Number of daily BETs utilizing charging areas. Points are placed in the middle of the 25x25 km^2 (charging areas)

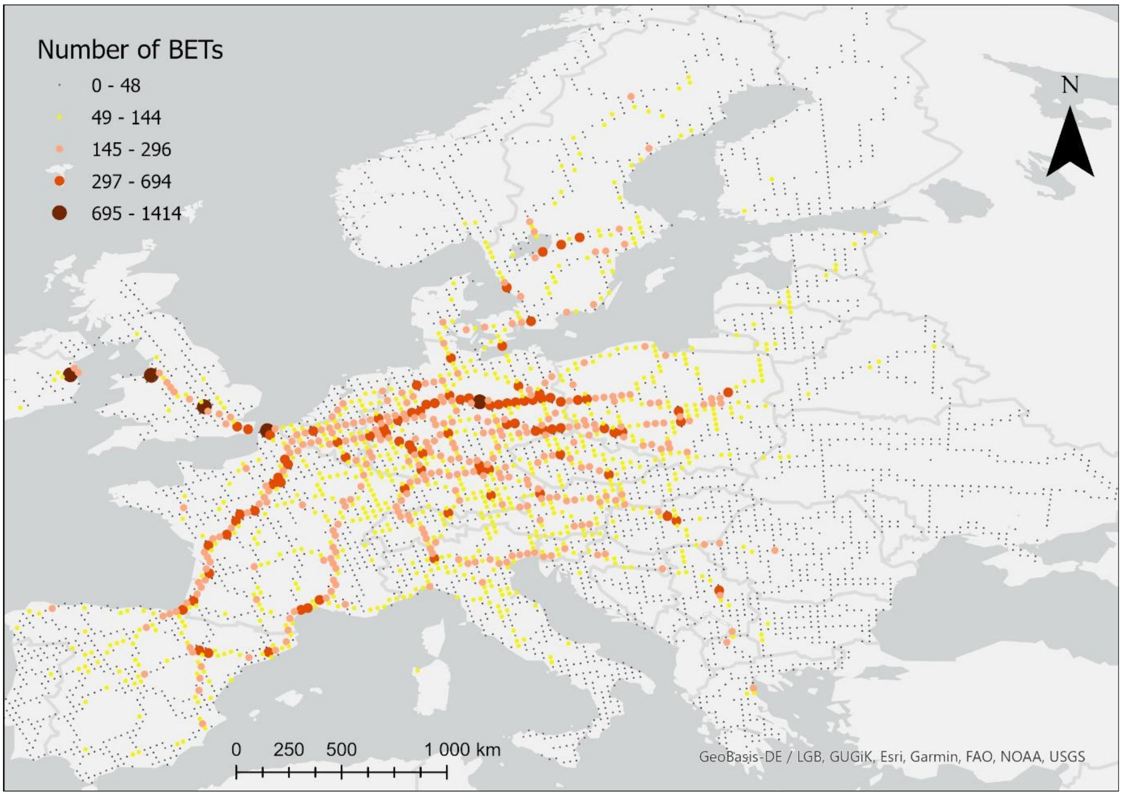

Table A.1: Country based charging specifications for main case electrification scenario of 15% BET

Country	Number of suggested charging areas	Sum of daily parked BETs	Sum of charged energy (MWh)*	Charged energy with CCS chargers (MWh)	Number of CCS charging points	Charged energy with MCS chargers (MWh)**	Number of MCS charging points	Ratio of CCS to MCS charging points
France	496	33,342	21,957	9,194	7,228	12,763	1,257	5.75
Germany	364	46,822	24,314	10,498	10,283	13,817	1,365	7.53
Spain	353	13,048	7,741	2,715	2,518	5,026	682	3.69
Italy	312	12,188	8,329	2,218	1,829	6,111	674	2.71
Sweden	249	11,324	5,467	2,141	2,344	3,327	505	4.64
Ukraine	240	1,690	666	290	506	375	275	1.84
Poland	225	21,795	10,616	3,630	3,790	6,986	778	4.87
Romania	192	1,595	989	343	395	646	233	1.70
U.K.***	168	6,961	4,095	1,355	1,262	2,740	347	3.64
Norway	165	1,204	705	312	360	392	195	1.85
Finland	142	878	518	225	277	293	162	1.71
Greece	105	829	501	102	146	399	128	1.14
Czech Republic	100	7,308	4,323	1,593	1,399	2,730	288	4.86
Portugal	91	1,067	664	286	276	378	116	2.38
Bulgaria	76	501	320	132	147	187	87	1.69
Belarus	74	951	490	207	232	283	99	2.34
Austria	71	6,617	3,510	1,221	1,169	2,289	240	4.87
Hungary	70	2,404	1,236	426	442	811	132	3.35
Netherlands	70	4,302	2,358	949	917	1,409	169	5.43
Slovakia	67	2,328	1,387	496	453	892	133	3.41
Serbia	62	1,811	750	333	453	417	102	4.44
Switzerland	51	3,520	2,251	729	591	1,522	146	4.05
Bosnia & Herzegovina	48	790	317	104	159	213	67	2.37
Croatia	48	1,168	477	205	272	272	75	3.63
Lithuania	47	1,119	520	200	248	320	79	3.14
Latvia	45	875	526	159	155	366	71	2.18
Denmark	43	3,016	1,279	505	630	774	111	5.68
Estonia	32	532	379	118	101	261	47	2.15
Slovenia	30	1,616	763	305	331	458	69	4.80
Ireland	27	2,171	950	276	404	675	75	5.39
Macedonia	27	533	275	158	169	117	36	4.69
Belgium	26	3,635	2,082	702	633	1,379	117	5.41

Country	Number of suggested charging areas	Sum of daily parked BETs	Sum of charged energy (MWh)*	Charged energy with CCS chargers (MWh)	Number of CCS charging points	Charged energy with MCS chargers (MWh)**	Number of MCS charging points	Ratio of CCS to MCS charging points
Luxembourg	12	1,345	776	186	164	589	49	3.35
Moldova	11	14	8	3	12	4	11	1.09
Montenegro	10	4	2	0	5	1	10	0.50
Albania	6	3	1	0	3	1	6	0.50
San Marino	3	143	100	12	10	89	8	1.25
Andorra	2	43	28	4	5	24	4	1.25
Liechtenstein	2	146	87	25	23	62	6	3.83

*Energy (MWh) from both MCS and CCS chargers.
** Energy from MCS chargers with power rate of 1.1 MW/hr.
*** U.K. of Great Britain and Northern Ireland

A.3 Charging points allocation

Figure A.2 and Figure A.3 show details of CCS and MCS charging point distribution and daily use in all European countries. The number of daily BETs utilizing each charging area is shown for both types of chargers. CCS chargers serve BETs stopping at rest locations, i.e., stop period of nine hours, while MCS chargers serve BETs stopping at break locations, i.e., stop period of 45 minutes.

Figure A.2: Number of daily HDVs utilizing CCS chargers at charging areas

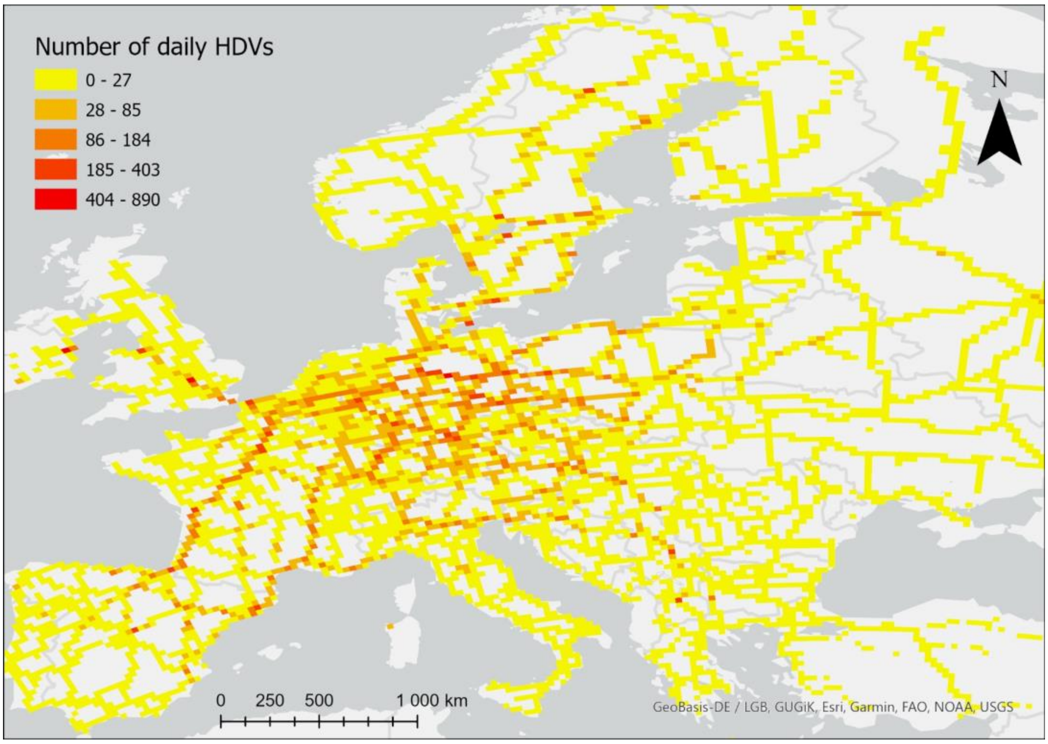

Figure A.3: Number of daily HDVs utilizing MCS chargers at charging areas