# Battery electric long-haul trucks in Europe: Public charging, energy, and power requirements



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# Battery electric long-haul trucks in Europe: Public charging, energy, and power requirements

Wasim Shoman [a,*], Sonia Yeh [a], Frances Sprei [a], Patrick Plötz [b], Daniel Speth [b]

[a] Department of Space, Earth and Environment, Chalmers University of Technology, 41296 Göteborg, Sweden
[b] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139 Karlsruhe, Germany

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ABSTRACT

Electric battery trucks (BETs) have the potential to significantly reduce emissions from heavy-duty vehicles. However, adopting BETs for long-haul operations depends on the availability of sufficient charging infrastructure. In this study, we use a trip chain model to assess the charging requirements for BETs in long-haul operations in Europe in 2030. Our model accounts for truck driving regulations and different stop types. We find that the number of overnight chargers (50–100 kW) required is 4–5 times higher than the number of megawatt chargers (0.7–1.2 MW) needed to support a BET share of 15% in long-haul operations. We estimate that approximately 40,000 overnight and 9,000 megawatt chargers are required, with an average of eight overnight and two megawatt chargers per charging area serving an average of two and 11 BETs daily, respectively. These findings provide insights for planning charging infrastructure for BETs in long-haul operations in Europe.

## 1. Introduction

Road transportation is a significant promoter of global economic activity and a major polluter to the environment, which presents a challenge in reaching a low-carbon sustainable future (Carrara and Longden, 2017; Mulholland et al., 2018). Road transport alone accounts for a fifth of global greenhouse gas emissions (Santos, 2017); a third 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 5% of the vehicles on European roads but contributed to 15–22% of CO2 emissions from road transport in 2019, and their CO2 emissions are increasing rapidly (+9% between 2014 and 2019) (Danese et al., 2021; Suzan and Mathieu, 2021). To substantially reduce greenhouse gas 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 many advantages, including zero tailpipe emissions and lower maintenance costs. Several truck producers have already manufactured models up to 350 kWh, with an expected range of 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 charging station network that can deliver enough 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

* Corresponding author. Tel.: +46 317721729; fax: +460317725944.
*E-mail address:* wasim.shoman@chalmers.se (W. Shoman).

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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 multiday intercity travel without daily return to the truck's home base. Thus, the electrification of HDVs presents distinct challenges from those for personal vehicles due to high-level 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 Europe's BET fleet in 2030. 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) origin–destination (OD) matrix for HDVs (Iww et al., 2012) and considers EU truck driving regulations (Ahlstrom 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, charging area capacity, and energy supply) of all BETs in EU member states. However, we do not go into details on exact charging station locations or design, this would need further analysis based on other constraints that are beyond the scope of our paper. 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. Sections 4 and 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 estimate the energy use for a transportation scenario. The model calculates the BET fleet's required battery size and charging infrastructure in Germany. Their simulation relies on real-world data of long-haul vehicles but from limited road segments. Çabukoglu et al., (2018) investigate the Swiss heavy-duty fleet's electrification requirements. They use a multi-agent simulation for each vehicle to simulate the required battery swapping stations and stationary charging infrastructure. Jochem et al., (2019) estimate the minimum number of fast-charging stations in eight EU countries, including France and Germany. Hurtado-Beltran et al., (2021) identify the electric charging requirements for trucks along the United States highways. The study is based on a GIS analysis of the network service area. Mishra et al., (2022) propose an agent-based charging station model with vehicle diaries obtained through real-world vehicle tracking data in five states in the United States. The framework elucidates the dependencies of fast charging station operation on traffic data, charging station characteristics, and electrification share. Al-Hanahi et al., (2021) study two major charging strategies for commercial vehicles: charging at depos, and on-route, i.e., at stops. They explore the challenging issues related to charging HDV at public charging stations. Danese et al., (2021) develop an approach to allocate static and dynamic charging infrastructure 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, two main approaches have been used for modeling the nationwide or international rollout of charging infrastructure along motorways (Speth et al., 2022a). One approach is distributing charging points uniformly 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 (COA) by Speth et al., (2022a). The other approach, referred to as the demand-oriented approach (DOA) by Speth et al., (2022a), is to position charging infrastructure according to charging demand to enable high utilization of charging points. The COA works with common traffic volume data, but the results lack important details such as a station's capacity and energy requirement. The DOA estimates the minimum charging infrastructure but requires detailed traffic data and high computational power (Speth et al., 2022a). The approach can be extended further by considering the charging stations' queuing effects (Jochem et al., 2019), which could yield better insights into charging requirements and the limitations of selected locations, such as charging station capacity. Neither COA nor DOA 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 original equipment manufacturer (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 reflect better the fleet's needs regarding charging types, station capacity, and energy supply.

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 impact (or are constrained by) other significant connected systems to the charging stations, such as the power grid. Other studies, for instance 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 truck travel-pattern heterogeneity and thus fails to capture the charging-point differences, such as the charging point's power rate.

This study fills the gap by proposing a trip-chain model that captures the HDV movements across European regions as BETs in long-haul operations. The model disaggregates the flows of the OD matrix into vehicle-based tours to identify the required charging stations' locations, the characteristics and number of charging points, and the daily energy requirements. Our trip chains method provides new perspectives for analyzing the charging demand from long-distance freight transportation (Duan et al., 2020).

## 3. Methods and data

We develop a method to identify of charging areas in Europe that meet the demand of goods movements between regions and the EU driving regulations (Ahlstrom et al., 2022). The spatial resolution of regions is based on the Nomenclature of Territorial Units for Statistics-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 traveling are explained in Section 3.2. Travel 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 travel 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 Sections 3.3 and 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 Nomenclature of Territorial Units for Statistics-3 region level of details for 2010 (Iww et al., 2012). The OD matrix comprises about 1,630 regions and 2.5 million origin–destination (OD) pairs. An OD matrix contains aggregated information about traffic flows between zones or regions, typically in tons. Our study considers connected trips between all regions. 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, rate of recurrence of visiting these locations, and the sequence in which they are visited (Joubert and Meintjes, 2015; Peterson and Michalek, 2013). 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 th 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 h. 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 h 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 places where drivers stop between two shifts or during long rest periods to avoid disrupting their operational schedules. Thus, deploying public charging infrastructure serves the required tasks and travel paths of commercial vehicles and is located around their destination and parking places (Al-Hanahi et al., 2021). Regulation (EC) No 561/2006 of the European Union states that the daily driving period must not exceed 9 h, and drivers should stop driving at least 45 min 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 (Ahlstrom et al., 2022). For comparison, in the US, truck drivers may travel more with fewer pause periods: up to 11 h of driving (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 stop types, total travel time on the road ($TTD_{o,d}$), 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 travel and rest time regulations. We apply 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., start, rest, break, and end locations. A trip chain is a sequence of such trips covering the distance between an OD pair.

For simplicity, we assume a uniform share of BET ($BET_{share}$) adoption across all regions. The total number of BETs ($N_{BETr}$) 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 ($\gamma$) 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 volume of goods 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. The study breaks the tour into multiple trips with trip duration $TD_i$ (travel time between the stops for trip $i$) $\leq$ 4.5 h. Total travel duration of the tour (the travel time using the fastest route 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 $TTD_{o,d}$ 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 (Fig. 1). An illustration of $B$ and $R$ allocation for a sample tour is illustrated in Supplementary Material (SM)1.

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 $\times$ 25 km$^2$ polygons. Each square presents a charging area that could include multiple charging stations and charging points, as further explained in the next subsection. We do not identify the exact location of the charging stations since this would need further information and to consider aspects such as existing infrastructure.

### 3.3. Charging infrastructure

Two types of chargers are assumed according to stop duration: a megawatt charging system (MCS, 0.7–1.2 MW) for the break stops with 30 min charging duration and a combined charging system (CCS, 50–100 kW), with nine hours charging duration for the longer rest stops. The number of MCS charging points must meet the peak traffic arriving to the charging areas. The remaining 15 min 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 suggests the number of required counters to maintain an average waiting time for a given arrival rate and service time (Salazar, 2020). We assume that an average waiting time of five minutes is to be retained; the number of counters relates to the number of charging points per charging area. The arrival rate is derived from the daily traffic and the service time from the charging time. The number of counters and queues determines the service mechanism. The supply of service times is a portion of the service procedure. Waiting refers to a counter's rule to select the following client from the queue when the counter completes serving the current client. In the following, we assume that clients are served in the order of arrival ("first-in, first-out"). For more details about the model and assumption, check SM 2.

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.

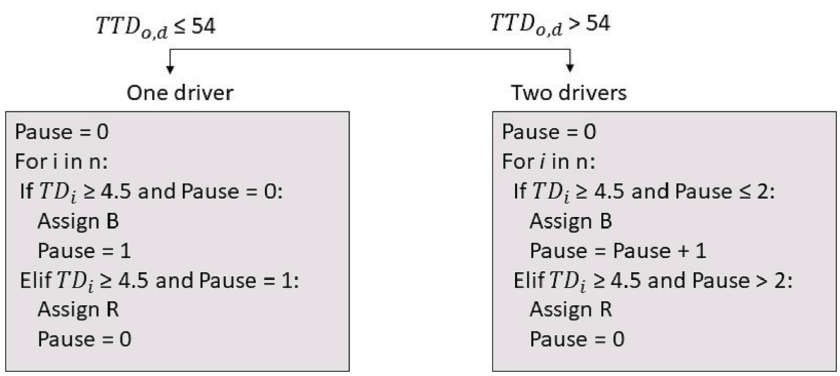


**Fig. 1.** Algorithm for assigning break and rest locations.

### 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 and 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. Accordingly, we calculate the required energy to fulfill each trip between stops. We assume that trucks meet the technical requirements of the trip and truck's battery capacity is selected according to the trip with the maximum energy requirement.

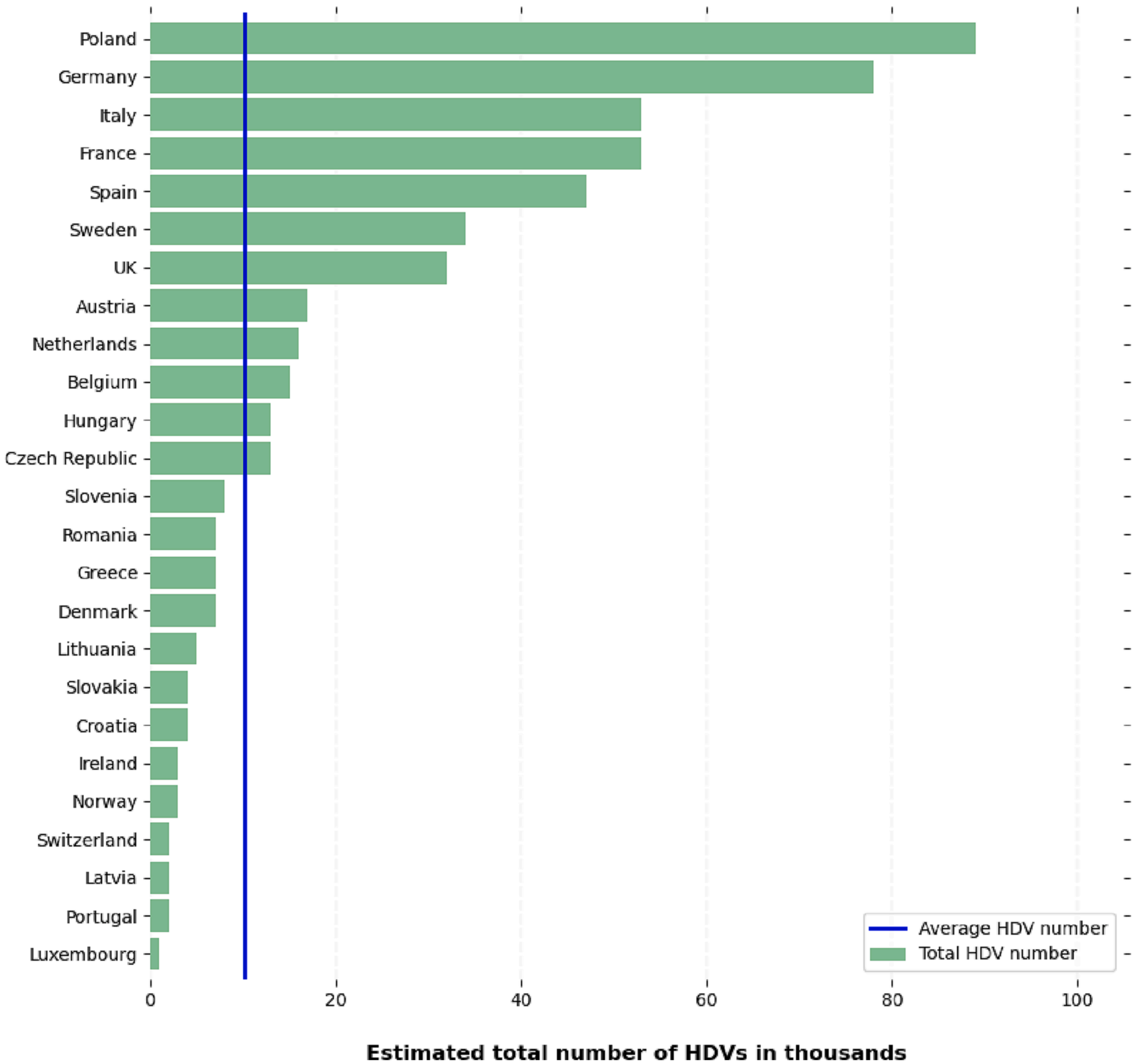


**Fig. 2.** The estimated number of HDVs in thousands (including both BET and non-electrified HDV) in long-haul operations originated from the 25 European countries with the most HDVs in 2030.

### 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 the 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 Fig. 2. Our calculated number of long-haul trucks for all OD pairs with over 4.5 h 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 originating trucks, see Fig. 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.

### 4.2. Required battery range and capacity

The total travel time, including rests and breaks, and the 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 h and 1,449 km, respectively; see Table 1. The medians are 27 h and 1,227 km, respectively. The total of travel time could reach up to 300 h for some trip chains, such as between the regions of Kamchatka, Russia, and Pohjois-Karjala, Finland. However, 99.9% of all trip chains take less than 106 h, ~ 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 h of total driving. Only 3% of the trip chains in our data have more than 54 h total driving time; these are allocated as two-driver trip chains.

The energy requirement 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 (see Section 3.4). We thus presume that BETs in our model meet these requirements.

### 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$^2$ 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 SM 3.

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 charging areas are approximately 25–35 km apart from their centroids, covering most of the European highways. For comparison, Speth et al., (2022a) 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 serves 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, Montenegro, and Finland have an average of less than ten

**Table 1**
Statistics summarizing the trip chain) and trips between stops for all BETs.

| Level | Variables | Mean | Standard deviation | Percentile | | | |
|---|---|---|---|---|---|---|---|
| | | | | 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 |

parked BETs per charging area per day. There are four charging areas with daily use (i.e., BETs parking for rest or break) of 1000 BETs or more. The highest number of BETs stopping at a charging area is found in Ireland, with 1410 BETs daily. 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 SM 3.

### 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 SM4 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 1100 and 60 kW, respectively, assuming that chargers deliver power at a fixed hourly rate within the corresponding charging durations, i.e., 30 min 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 (Fig. 3). For instance, Germany requires 10,300 and 1,360 CCS and MCS chargers, respectively. In contrast, countries on the margins with trade flow centers 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 UK and Ireland have some high-demand charging areas, the overall number of chargers in both countries is relatively low compared to neighboring 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 SM 3.

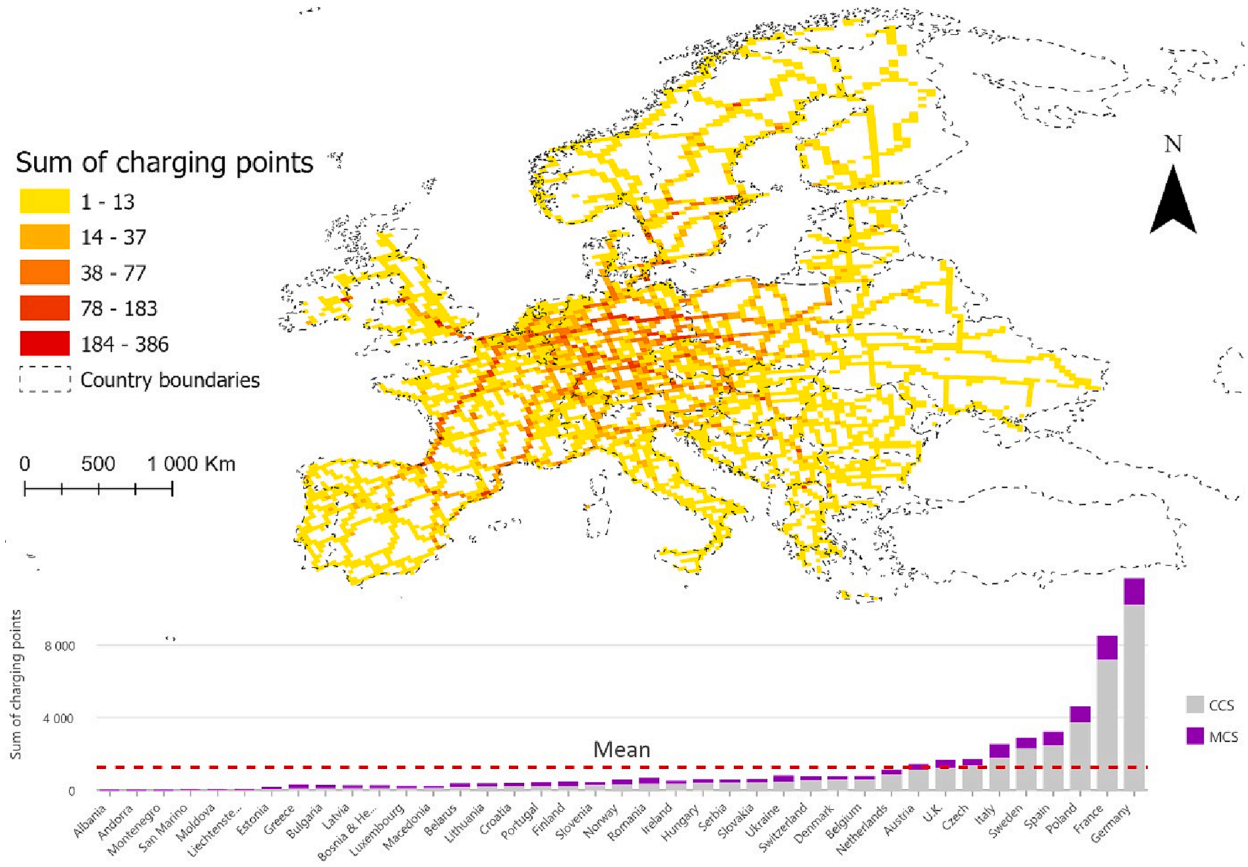


**Fig. 3.** Total number of CCS and MCS chargers by charging area and country in Europe.

### 4.5. The energy requirements at charging areas

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 Fig. 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.

Most energy requirement, i.e., 62%, arises from MCS chargers at break locations. BETs stop for breaks more than for rests due to the sequence of stop types identified in the travel pattern, i.e., trucks stop for a break after 4.5 h of driving and then for a rest after another 4.5 h of driving for one-driver tours. On a daily basis, this sums up to 68 GWh from BETs at their break stops. 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.

## 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

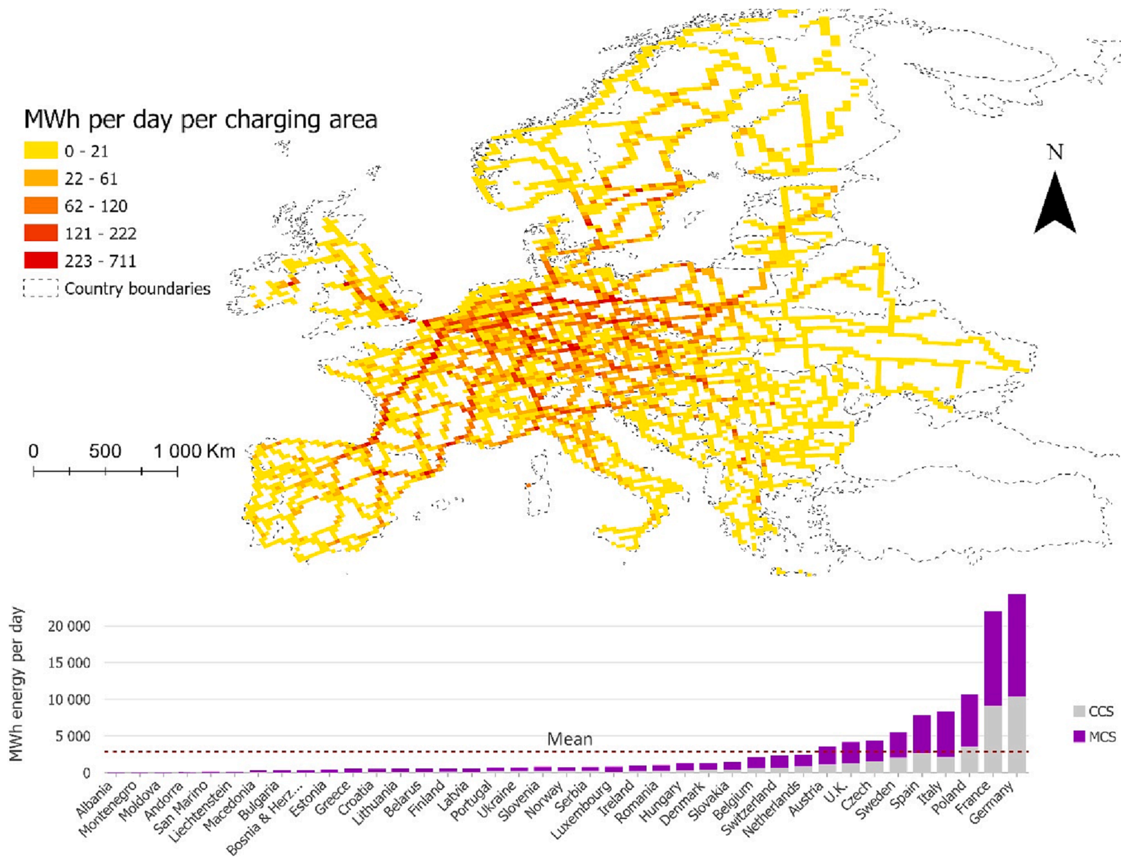


**Fig. 4.** Daily energy requirement for each charging area and country (MWh per day) from both CCS and MCS charging.

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. IEA, (2023)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. On the other hand, the model does not consider charging needs for other vehicle types, e.g., passenger cars and regional trucks, which might use the same parking spots. Future work could investigate charging needs for all vehicles to assign charging points accommodating different charging requirements from all stopping vehicles.

EU regulations allow HDV drivers to divide their break period into two shorter periods (i.e., two separate stops of 15 and 30 min). 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 min, plus the additional 15 min 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 25x25 $km^2$ area. The actual site selection could be allocated anywhere within this area depending on other aspects, such as existing parking or electricity grid. These must be evaluated individually for each area (Auer et al., 2023; Speth et al., 2022a). To help planners make informed decisions on the optimal siting of charging infrastructure for heavy-duty long-haul trucks, we recommend considering additional factors beyond siting locations. For example, we assume one break period after 4.5 h of driving. However, in cases where drivers divide their break period into two shorter periods, a charging area should serve at least one of the stops, with 15 min of driving between stops (~20 km assuming an average speed of 80 km/hour). In such cases, the locations of the second short break may differ from those of the first break. Our follow-up study will compare the impacts of different modeling and tools (e.g., optimization, coverage vs. trip chain approach) on charging infrastructure estimation, which will be valuable for planners in deciding siting of charging infrastructure, but it is beyond the scope of this study.

The assumed charging durations to fulfill the charging requirement influences the charging points' required number and power rates. 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 due to more break stops than the only one driver trip chains. Our motivation is to reduce travel time, thus saving costs 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 BETs transport average loads of goods between only one pair of ODs. Thus, a BET does not transport goods to multiple destinations within a trip chain. Our assumption overestimates the number of BETs required to transport the goods between ODs, but might underestimate the distance travelled for each truck. On the other hand, the same assumption underestimates the BET number if more than one truck is involved in transporting the goods between a pair of Ods. For instance, trucks meet at a depot between the origin and the destination to swap goods or if the same truck continues to another destination directly after having been at the first one. 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. Changing the BET share 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*

We use a trip chain approach to identify charging events along the highways, i.e., break and rest stops. To convert these stops into an understandable number of charging points, we aggregate the results to charging areas of $25 \times 25$ $km^2$ providing proper charging coverage along the highways. The charging areas could be modified to smaller or bigger aggregated zones. Increasing the size of the aggregation area does not change the overall number of CCS charging points per area. However, the total number of MCS charging points is more sensitive to the selected aggregation distance, which identifies the charging area. The aggregation distance affects the peak traffic arriving at charging points and the utilization of MCS chargers.

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 revealed a proposal to add a MCS charging network of 1 MW power capacity that can provide 640 km range in no more than 30 min of charging (Al-Hanahi et al., 2021). Mohamed et al., (2022) consider MCS facilities that can quickly charge large battery sizes (i.e., ~ 800 kWh) in less than 30 min 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 for BETs with long travel (i.e., long trip chains). Thus, there is an urgent need to start planning since the deployment of the charging infrastructure network will depend on other processes such as grid development, permitting, and land use.

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 Fig. 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.

Deploying stations every 25–35 km goes beyond alternative fuel infrastructure regulations (AFIR) requirements, illustrating that more ambitious measures than those regulated might be needed to meet the electrification targets. The implications are that more policy instruments might need to be deployed at the national level or that more dense grids will evolve market-driven in the long term. Further studies should look into how the rollout of charging infrastructure can be accelerated to meet these needs. In contrast, the present study aims to improve understanding the magnitude of chargers needed.

## 6. Conclusion

In this study, we develop an innovative trip chain approach to estimate the charging infrastructure demand for long-haul electric trucks in Europe in 2030. The approach simulates truck travel distances, stop locations, durations, and energy requirements using publicly available origin–destination data and accounted for European truck driving regulations. Our research finds that an average charging area needs to have four to five times more overnight (CCS, 50–100 kW) chargers than megawatt (MCS, 0.7–1.2 MW) chargers to support a BET share of long-haul operations at 15%. The study estimates that approximately 40,000 CCS and 9,000 MCS chargers are required, with an average of 8 CCS and 2 MCS chargers per charging area serving an average of 2 and 11 BETs daily, respectively.

The study makes several assumptions that may affect the accuracy of the results, such as assumptions about BET energy consumption and travel patterns, and the flexibility of EU regulations allowing for breaks to be divided into two shorter periods. Future research could address these limitations by collecting more detailed data on HDV travel schedules and evaluating the impact of different charging durations on the required number and power rates of charging points. The results of this study provide valuable insights for the planning and deployment of charging infrastructure for BETs in long-haul operations in Europe.

## CRediT authorship contribution statement

**Wasim Shoman:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sonia Yeh:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Frances Sprei:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Patrick Plötz:** Formal analysis, Funding acquisition, Validation, Writing – original draft, Writing – review & editing. **Daniel Speth:** Formal analysis, Validation, Writing – original draft, Writing – review & editing.

## Declaration of Competing Interest

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

## Data availability

Data is shared at this link (https://zenodo.org/record/7866504#.ZEo6B3ZByUn)

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## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2023.103825.

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