36th International Electric Vehicle Symposium and Exhibition (EVS36)
Sacramento, California, USA, June 11-14, 2023

Locations for Battery Electric Truck Charging based on Truck Stop Location Data

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Executive Summary

A significant fleet of battery electric trucks (BET) is expected to be on the roads in Europe within a few years to curtail CO_2 emissions from commercial vehicle operation, with large share from heavy-duty vehicles (HDV) in long-haul operation. However, the limited range of the battery HDV will make megawatt-charging necessary at stop locations but little is known empirically about long-haul truck stop locations. Here, we analyze a unique data set of 550,000 stop locations from 230,000 trucks in long-haul operation covering 35 European countries. We find stop locations are concentrated on densely populated areas in central Europe and close to large industrial areas as well as major roads. A small share of today's truck stop locations as potential future charging locations and a network of 1,400 public charging locations across Europe would lead to only 2 – 5 km mean distance per country from all of today's stop locations.

Keywords: electric vehicle, heavy-duty, truck, charging, infrastructure, Electric vehicle supply equipment

1 Introduction

Reaching European climate targets and eventually climate neutrality by 2050 requires the rapid decarbonization of road freight transport by heavy-duty vehicles (HDV). In 2018, transport was responsible for about one-quarter of energy-related greenhouse gas (GHG) emissions in the EU, whereas HDVs generated about 8 % of the total GHG emissions [1]. Manufacturer offers and announcements on sales targets for zero-emission trucks are promising, with battery-electric trucks (BET) in a primary position [2]. Thus, a significant BET fleet is expected to operate on European roads within a few years. However, owing to the limited all-electric range and insufficient charging infrastructure their technical feasibility in logistics is under discussion [3]. This implies the necessity for the coordinated deployment of charging infrastructure to safeguard commercial electric vehicle operational schedules while infrastructure profitability, sufficient utilization rates, and low charging costs are ensured [3, 4].

Indeed, multiple studies have already examined infrastructure modelling for plug-in electric vehicles (PEVs) in road networks. Typically, planning PEV charging infrastructure covers location planning, station sizing, and defining power requirements [4], whereas our work concentrates on location planning and partly touches power requirements. Here, [4] and [5] provide quite recent and comprehensive overviews for PEVs in general, while [6] synthesize key challenges and future work with an emphasis for commercial vehicles. Among others, [5] highlight differences in the underlying data source for location planning, namely (1) freight transport statistics, (2) real-world PEV travel data, (3) real-world travel data from fossil-fueled vehicles, (4) surveys or (5) or synthetic data sets. [4] identify four different approaches on how and from where charging demand is obtained, namely: (1) nodes, (2) paths or flows, (3) itineraries or trips, and (4) hybrid approaches. To determine potential locations, different optimization problems are given, e.g. p-median, set covering location model (SCLM), maximum covering location model (MCLM), flow-capturing or flow interception location problem (FCLM / FILP), and flow-refueling location model (FRLM). On top, different optimization targets, e.g. (1) minimize infrastructure costs for a given demand, (2) maximize the number of PEVs charged, (3) maximize charger utilization, (4) minimize the number of failed trips, or even (5) multi-objective problems may be distinguished. While some optimization approaches identify a minimal required infrastructure (e.g. FRLM), others aim for homogeneous distribution of charging locations along the road network (e.g. SCLM) [7]. Furthermore, various problem extensions add further characteristics like temporal dependencies (e.g. dwell time, vehicle queuing), detours, capacity restrictions, or stochastic processes and uncertainty. To enhance practical feasibility, geospatial data analysis may integrate additional aspects such as power grid distance, available parking space, or surrounding service facilities [8].

However, most studies concentrate on private or commercial passenger cars, buses, or taxis as these applications benefit from either their fixed tours within a precise schedule (buses), their urban driving patterns and charging times (taxis), or their significant share in the total vehicle fleet (private passenger cars) [3]. For HDVs, literature on modelling an electric charging infrastructure is scarce. In [9], freight-flow data are used to determine a potential traffic intensity and derive infrastructure needs across the TEN-T network in Europe yet without any precise location and by assuming charging station archetypes for private, semi-public, and public charging infrastructure. Similar to [9], [10] use freight-flow data and allocate freight flow to individual vehicles while assuming a hub-spoke vehicle movement and synthetic operational vehicle schedules along the US national highway network to determine on-route charging locations. [11, 12] use a coverage approach (50 km distance) to locate charging stations along one highway by using current traffic intensity. Similar to [9] and [10], [13-15] use freight-flow data but derive their dense network for public fast charging infrastructure across the TEN-T network by using a coverage approach and a queuing model for station sizing. The Alternative Fuel Infrastructure Regulation (AFIR) proposes a similar approach with different distances along the TEN-T core (50 km) and comprehensive (100 km) network and supplements these locations with infrastructure at urban nodes and secure parking areas. Recently, [16] have developed a driving regulation-based charging demand model on the TEN-T network from O-D-Matrices of [17]

In contrast, studies like [18] or [19] focus on the techno-economic feasibility of battery electric trucks for long-haul transport yet assume a potential charging infrastructure as given by using the European driving times regulation (4.5h maximum driving time) as distance metric. Furthermore, [19] uses statistics on the number of parked trucks at truck stops along German highways and determines a generic split with 82 % slow charging stations and 18 % high-power stations that is potentially adaptable to all investigated truck stops.

Overall, no study uses real-world GPS data but generates possible yet synthetic stopping points with varying spatial resolution using different approaches, optimization models and targets, and data sources while typically different types of HDV charging infrastructure are assessed separately. However, would it not be easiest to build charging infrastructure where trucks already stop? To ensure smooth integration into the operational schedules of electrified HDVs, charging infrastructure should ideally be chosen at places where trucks park (depots, retail stores, truck stops) to enable charging overnight, during mandatory breaks, or between shifts, as well as at public places to ease on-route charging along daily tours. This necessitates in-depth real-world GPS truck data analysis of with high spatial resolution instead of synthetic data sets and statistics. To the best of the authors' knowledge, such an approach for HDVs is missing to date.

The aim of the present paper is to analyze current truck stop locations from GPS data and derive conclusions for future truck charging locations.

The outline of this paper is as follows. Section 2 describes the GPS data and its aggregation. Section 3 contains the results and is followed by a discussion in section 4 and conclusions in section 5.

2 Data and Methods

2.1 Data

Seven truck manufacturers (OEM) provided GPS coordinates of truck stop locations. Locations from all trucks in VECTO vehicle classes 1-16 (gross vehicle weight (GVW) >= 7.5t) were included. Two groups of vehicles were distinguished: vehicles in "regional" operation are vehicles for which 90 % of its geo-coordinates are within 200 km from the vehicle's home base. "Home-base" is the most common last destination per day of a vehicle. Vehicles that are not in regional operation are classified as "long-haul". Data was provided separately for regional and long-haul vehicles.

In the data, "stops" are defined as at least 30 minutes with less than 5 km/h speed. Each OEM collected the stop duration in classes "½ – 1 hour", "1 – 3 hours", "3 – 8 hours", "8 – 23 hours", "23 – 44 hours", and "more than 44 hours". The OEMs aggregated locations within a radius of 10 – 100 m (varying between OEMs). To limit the analysis to locations with many stops, OEMs provided only data with at least 10 stops per year per location.

As the focus in the present data is on Europe, only locations in the area covered between 10.5° Western longitude and 31.6° Eastern longitude as well as 34.5° Northern latitude to 70° Northern latitude were kept. Table 1 provides summary statistics of the truck location data.

Table 1: Summary statistics for long haul truck data

	Summary statistics
Number of trucks involved	230,000
Number of locations before aggregation	550,000
Number of locations after aggregation	31,145
Countries in Europe covered	35
Mean number of stops year	1678
Standard deviation number of stops year	3615
Median number of stops year	596

2.2 Methods

The data described above was sent to the authors as an independent third party for further aggregation and analysis. We checked consistency of the data sets and variables and aggregated the individual OEM data to larger clusters. For clustering, the DBSCAN algorithm as implemented in the dbscan package [20] of the R statistical software was used. The maximal distance to form clusters (epsilon parameter) was set to 200 m, the minimal number of points in a cluster (minPts parameter) was set to 3, and border points were included. The algorithm forms new clusters, only clusters meeting the following conditions were kept, and cluster mid-points were calculated as the average of the geo-coordinates of all cluster-affiliated points(see [21] for details):

1. Stop locations from at least three different OEMs are in the cluster.
2. The cluster has at least 100 stops (sum over all time classes) per year.

. As the focus is on Europe on transport between European countries, data was kept from all EU member countries as well as the UK, Norway, Switzerland, Albania, Bosnia and Herzegovina, Liechtenstein, Macedonia, Monaca, and Moldova. Geo locations from Ukraine, Turkey, Belarus, and Russia have been deleted from the data.

The choice of clustering radius in defining the clusters has an effect on the final number of clusters and the share of locations that are inside clusters and thus potentially kept in the data set (a location even with a large number of stops is not kept, if trucks of only one or two OEMs are present as we imposed the condition of at least three OEMs' trucks should be present). We stress that the epsilon parameter has an significant effect on the final number of clusters, the cluster affiliation of individual points and the cluster size.

In a second step, only the best locations per country were kept. As the truck age and the availability of GPS devices in trucks varies across Europe, some countries contain more locations than others not because there are more trucks on the road but because there are more trucks with GPS devices on the roads. The number of locations per country was taken from [3], which suggest several important truck stop locations for charging in the individual EU member states (we added the UK, Norway and Switzerland) based on truck sales, truck stock and GDP per capita.

3 Results

3.1 Stop locations

Figure 1 shows all clustered truck stop locations for long-haul trucks in Europe. The locations often follow densely populated areas and major highways.

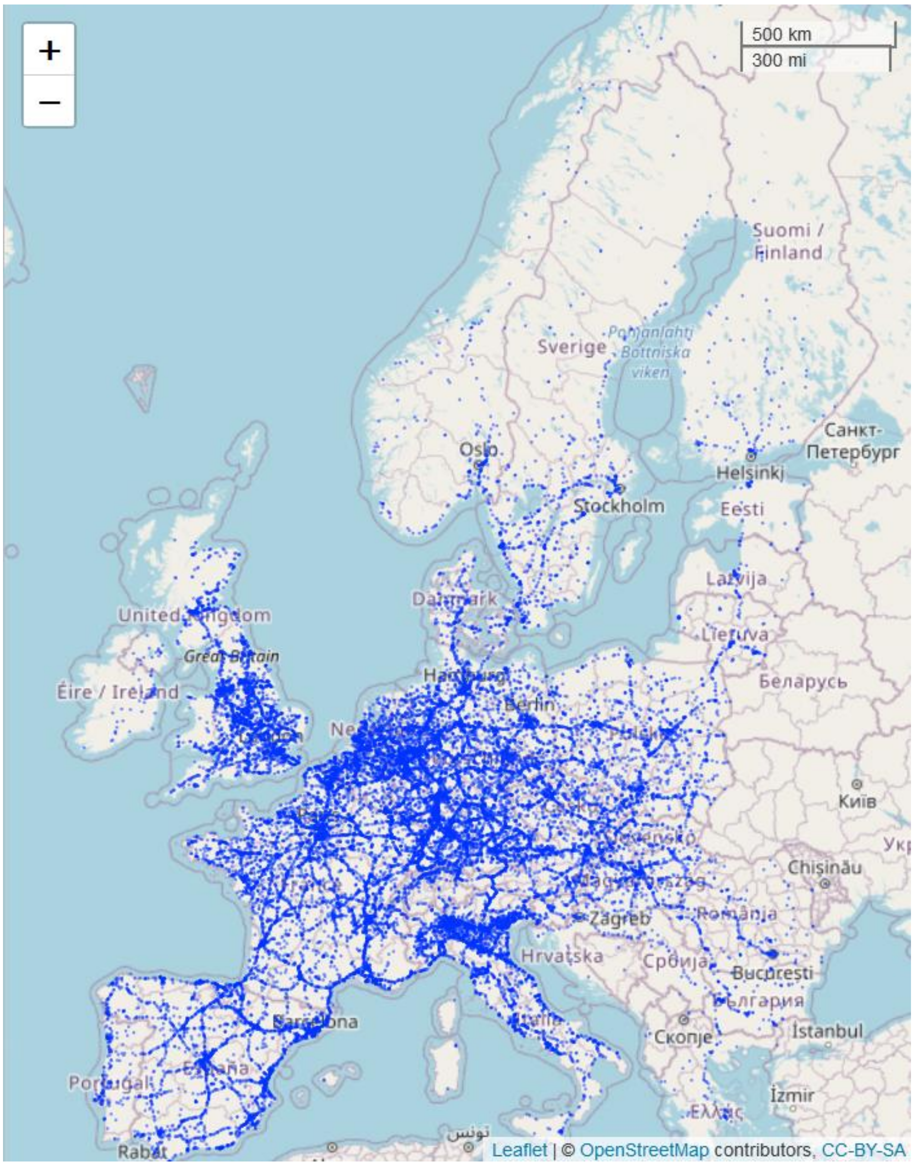

Figure1: Truck stop locations in the data set

We selected the 10% most visited locations per country from the long-haul data set with the number of total locations per country limited to the target number of charging points according to [4]. This leads to a few hundred locations for large countries (Germany, UK, and France), a few dozen locations for most of Europe, and less than ten locations for smaller countries or those with limited truck location data. We then analyzed the distance to the nearest potential public charging location from all other locations in the country. The minimal, mean, and maximal distance per country are shown in Figure 2. Shown are the minimal (black), mean (red), and maximal (blue) distances of all locations in the top 10% long-haul locations per country to the nearest potential charging point. For countries with only one location (Estonia, Bulgaria, and Greece), min, mean, and max coincide.

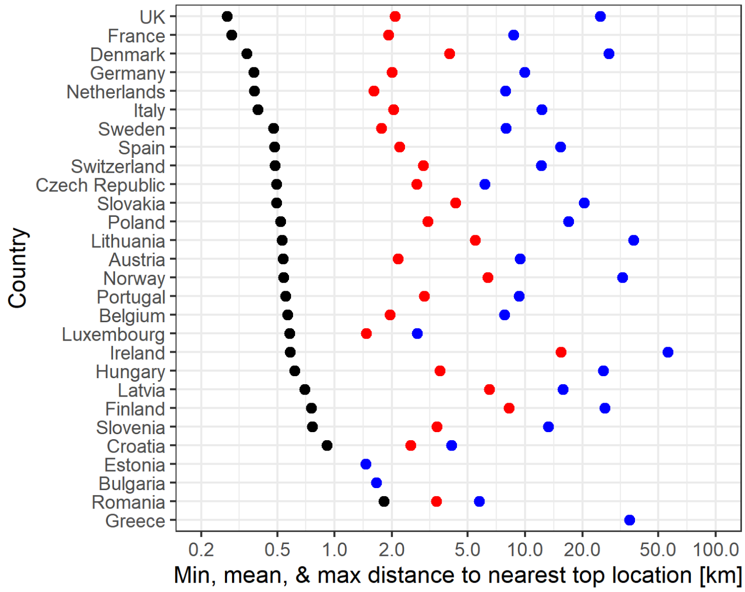

Figure 2: Minimal, mean, and maximal distances to top 10% locations

The mean distance to all other truck stop locations from these potential first public charging stations is typically 2 – 5 km. The mean distance is larger than 5 km only in a few countries with a very small number of locations in total, such as Ireland, Latvia, Lithuania, Norway, and Finland.

Figure 3 shows the minimal, mean, and maximal distance to the nearest potential charging point if the number of potential charging points is even further reduced. In this case, only those locations out of the top 10% locations per country are taken with at least 1/3 of stops below one hour duration (except for countries with less than six locations as this would reduce the number of locations to zero or close to zero). Shown are the minimal (black), mean (red), and maximal (blue) distances of all locations in the top long-haul locations per country with at least 1/3 of stops shorter than one hour to the nearest potential charging point. For countries with only one location (Estonia, Bulgaria, and Greece), min, mean, and max coincide.

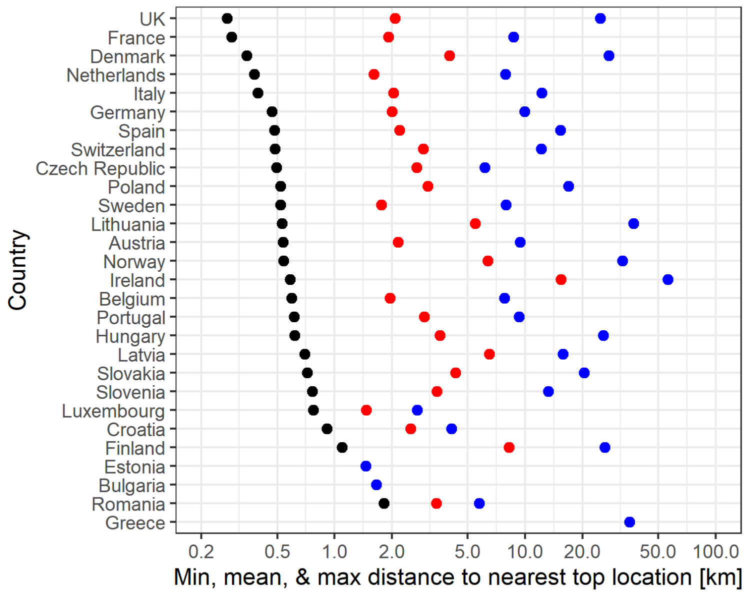

Figure 3: Minimal, mean, and maximal distances to top 10% locations with many short stops

Table 2: Number and distance in km to potential charging locations.

Country	Potential charging locations	Top 10% locations				Top 10% locations with >33% <1 h			
		#locations	Min	Mean	Max	#locations	Min	Mean	Max
Germany	3750	375	0.4	2.0	10.0	168	0.5	2.0	10.0
UK	2450	245	0.3	2.1	24.8	154	0.3	2.3	24.8
France	1500	150	0.3	1.9	8.7	68	0.3	1.7	5.3
Netherlands	900	90	0.4	1.6	7.9	39	0.4	1.5	6.7
Italy	900	90	0.4	2.0	12.2	46	0.4	2.2	10.7
Spain	750	75	0.5	2.2	15.4	50	0.5	2.3	6.2
Poland	550	55	0.5	3.1	16.9	43	0.5	3.3	16.9
Austria	400	40	0.5	2.2	9.4	22	0.5	2.5	9.4
Switzerland	400	31	0.5	2.9	12.1	21	0.5	2.7	12.1
Sweden	300	30	0.5	1.8	7.9	20	0.5	1.9	7.9
Belgium	300	30	0.6	2.0	7.8	13	0.6	1.2	2.3
Denmark	250	25	0.3	4.0	27.5	23	0.3	3.0	21.0
Czech Republic	250	25	0.5	2.7	6.1	23	0.5	2.9	6.1
Norway	250	22	0.5	6.4	32.3	15	0.5	6.0	32.1
Slovakia	150	15	0.5	4.3	20.4	10	0.7	5.8	20.4
Hungary	150	15	0.6	3.6	25.7	12	0.6	4.2	25.7
Lithuania	250	12	0.5	5.5	37.0	6	0.5	7.6	37.0
Portugal	100	10	0.6	3.0	9.3	3	0.6	3.6	9.3
Finland	100	10	0.8	8.2	26.3	7	1.1	7.6	23.7
Slovenia	100	10	0.8	3.4	13.2	8	0.8	4.0	13.2
Luxembourg	100	6	0.6	1.5	2.7	4	0.8	1.4	2.3
Ireland	100	5	0.6	15.4	56.0	5	0.6	15.4	56.0
Latvia	50	5	0.7	6.5	15.8	5	0.7	6.5	15.8
Romania	50	5	1.8	3.4	5.7	5	1.8	3.4	5.7
Croatia	20	2	0.9	2.5	4.1	2	0.9	2.5	4.1
Estonia	10	1	1.5	1.5	1.5	1	1.5	1.5	1.5
Bulgaria	10	1	1.7	1.7	1.7	1	1.7	1.7	1.7
Greece	10	1	35	35	35	1	35	35	35
Mean		**49**	**2**	**5**	**16**	**28**	**2**	**5**	**15**

In summary, the typical distance from any truck stop locations to the nearest potential charging locations is around 2 – 5 km. The mean distance is larger than 5 km only in a few countries with a very small number of locations in total.

3.2 Stop Durations

We also analyze the durations of stops. Figure 4 shows a two-dimensional histogram of the share of short stops (up to 3 hours) and long stops (more than 8 hours). The overall average is 59% up to three hours and 35% over eight hours (the residual is three to eight hours) or about 2/3 short and 1/3 long stops.

The duration of stops is crucial in determining the power required for charging electric trucks in the future. Therefore, the charging infrastructure should be designed to provide low, medium, or high power for charging, depending on the duration of stops. Furthermore, it is important to note that not all stops are equally visited by trucks. Thus, charging infrastructure should be constructed in locations where most trucks benefit from it.

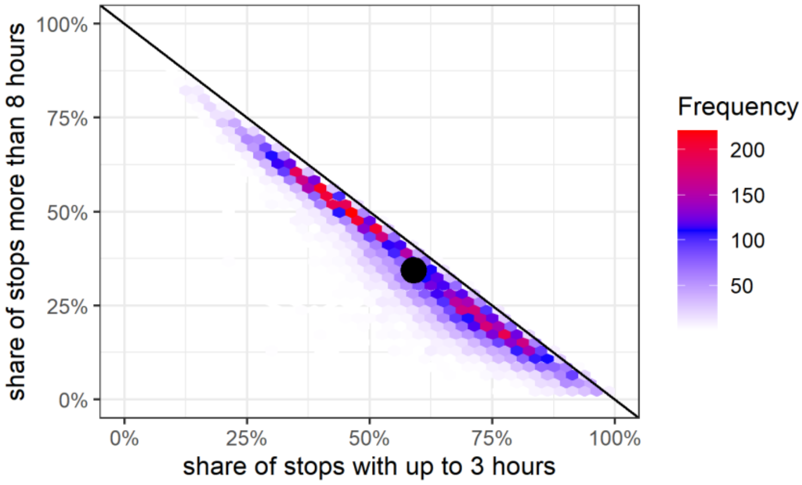

Figure 4: Minimal, mean, and maximal distances to top 10% locations with many short stops.

Figure 5 illustrates the cumulative share of stops as a function of the cumulative share of locations, with the locations sorted by the total number of stops. The figure indicates that the top 10% of locations account for approximately 50% of stops, while the top 5% of locations account for about 40% of stops. The figure demonstrates that a few stops are heavily frequented, whereas many locations are visited by only a few trucks. It is important to note that locations with less than three OEMs present and with less than 100 stops per year were excluded from the analysis.

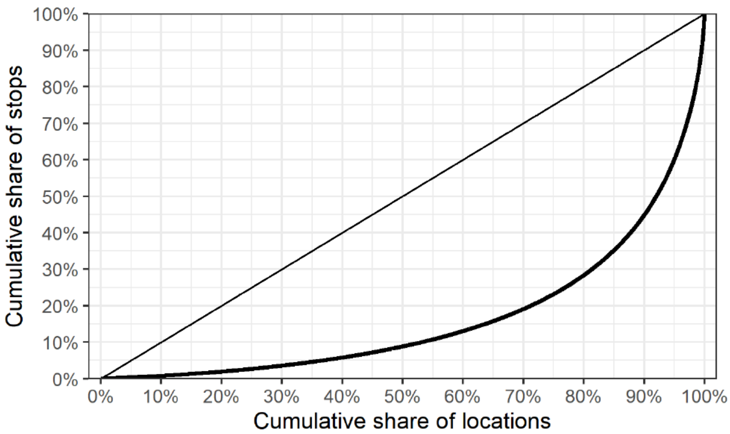

Figure 5: Minimal, mean, and maximal distances to top 10% locations with many short stops.

Table 3 presents information on the number of locations in Europe and Germany, categorized by their distance from a highway and thestop durations. Specifically, the table is divided into two distance categories: locations within 100 meters of a highway, and locations more than 100 meters away from a highway. For each category, the table shows the number of locations and share of stops with different duration under one hour and one to three hours).

In Europe, there are 25,974 locations within 100 meters of a highway. Among these locations, 35% of the stops are under one hour, while 27% take between one and three hours of stopping time. For locations more than 100 meters away from a highway, there are 5,171 locations. At these locations, 34% of the stops are under one hour, while 12% are between one and three hours. In Germany, there are 6,321 locations within 100 meters of a highway with 35% of stops under one hour and 27% between one and three hours. For locations more than 100 meters away from a highway, 30% of stops are under one hour, while 10% are between one and three hours. Overall, the table provides insights on the stop durations on and off the highway. Most short stops on the highway are very short but 10 – 12 % of stops are between one and three hours.

Table 3: Share of very short (< 1h) and short (1 – 3 h) stops in Europe and Germany

	Europe					Germany				
Distance to highway	No. locations	½-1h	1–3h	3-8h	>8h	No. locations	½-1h	1–3h	3-8h	>8h
> 100 m	25974	35%	27%	7%	32%	6321	35%	27%	6%	32%
< 100 m	5171	34%	12%	5%	49%	1131	30%	10%	5%	55%

Figure 6 shows that these mean shares are part of two clusters. Short stops on the highway with less than 100 m distance to the highway (here: the TEN-T network has been used) are usually very short (20 – 45 % are under one hour) with a small but apparently constant share of stops with one to three hours duration of 10 – 12 % of all stops. Further away from the highway, a second cluster appears where very short (1 h) and short (1-3h) stops are evenly distributed, each with shares of25 – 50 %, depending on the location.

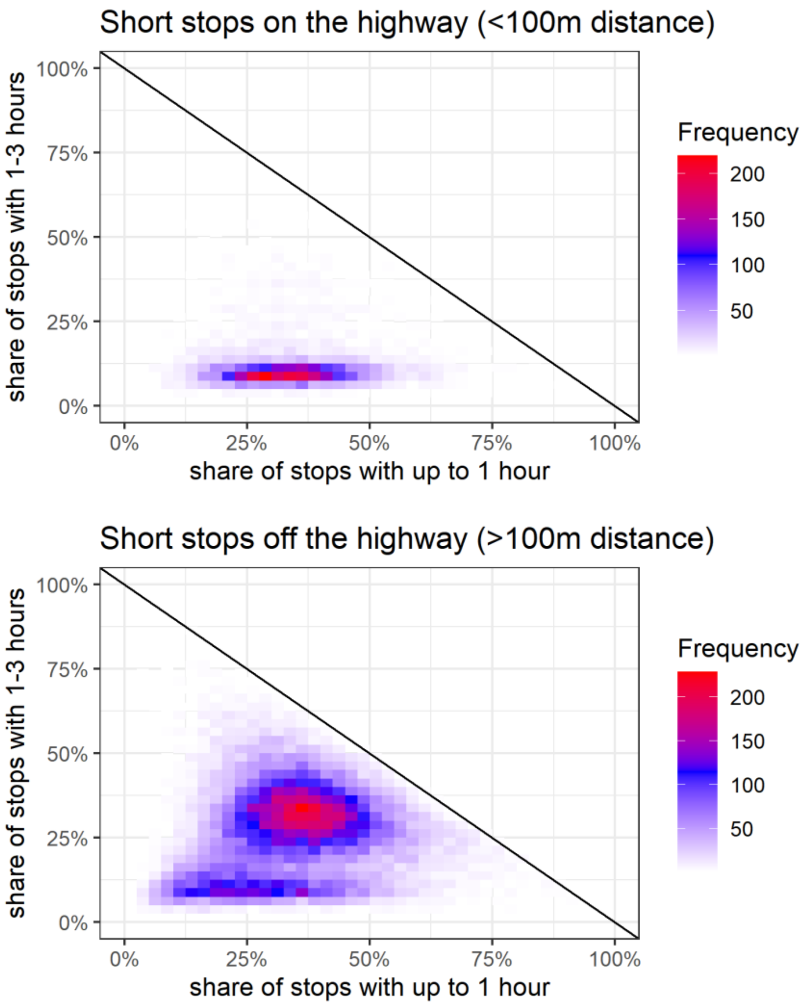

Figure 6: Share of stops with up to one hour vs. one to three hours duration for stops on the highway (less than 100 m distance to highway, top panel) and for stops off the highway (more than 100 m distance, bottom panel).

Likewise, there is a difference between the shares of stops for overnight to MCS charging on the highway and off the highway. Figure 6 shows the shares of stops with under one hour duration (keep in mind that the data only contains stops of at least 30 min duration) as well as the share of stops with at least eight hours duration by distance of the location to the highway. Very short stops of ½ - 1 h duration would be suitable for MCS charging whereas very long stops (>8 h duration) would be suitable for overnight charging.

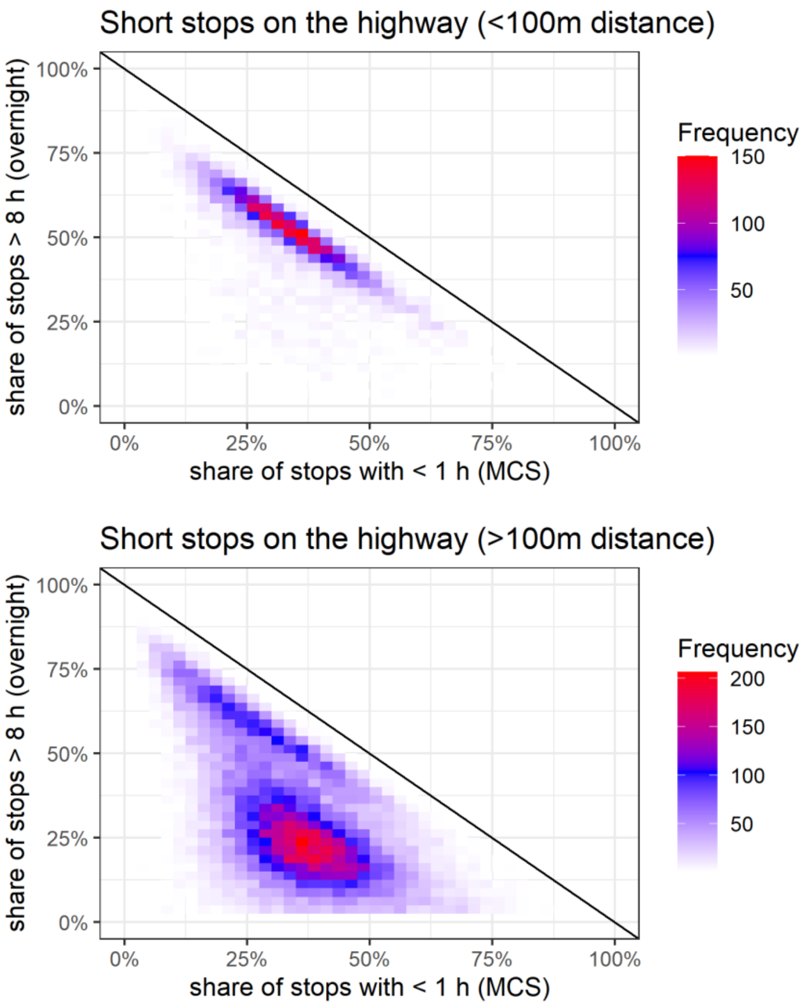

Figure 7: Share of stops with up to one hour vs. more than eight hours duration for stops on the highway (less than 100 m distance to highway, top panel) and for for stops off the highway (more than 100 m distance, bottom panel).

Table 3 also indicates a clear increase in the share of overnight stops (> 8 h) is much larger on the highway than off the highway. In summary, about one-third of stops on the highway are under one hour and would be suitable for MCS, whereas about of the stops are overnight and suitable for slow CCS charging.

4 Discussion

The aim of the present paper was to obtain insight from today's truck stop locations on future charging locations for battery electric trucks. We analyze over 30'000 truck stop locations from over 400'000 trucks in Europe. However, our results come with some uncertainty.

First, the literature on the distribution of stops is scarce; very few sources such as [17] on origin-destination matrices and EU-wide traffic count data can be used to check the distribution of locations.

Second, the individual locations have been clustered with the DB scan algorithm. A different cluster algorithm, such as k-means, would lead to slightly different locations, but the main idea is not to identify one location but a relevant area. Here, the used DB scan algorithm has the large advantages of allowing for non-convex areas and it is deterministic. A different cluster radius would result in a larger number of smaller locations, but there would probably be a loss of locations due to the minimum requirement of three manufacturers.

Third, the identified 10% most frequented locations do not aim to create a nationwide network, but rather to show particularly attractive locations. Also, please note that the data quality is different for different countries. The results should rather be seen as an indication where public charging infrasctructre for trucks would be helpful and how many locations are sufficient for which type of coverage.

Lastly, the analysis could be enriched with location data to gain deeper insight either before or after clustering.

5 Conclusion

This study presents a unique data set of truck stop locations based on approximately 400,000 trucks in Europe. The data set contains more than 30,000 aggregated long-haul truck stop locations covering all of Europe. The data set is rich and unique, and it covers Europe fairly representatively, especially if the number of locations per country is predetermined. The rank of locations within a country by the number of stops at a given location is probably close to reality, although the absolute number of stops might be inaccurate for some countries. It is important to note that the identified locations are suitable for establishing charging infrastructure from a logistics point of view. However, deciding which locations to use and how many charging points each should have requires additional analysis and an evaluation of additional criteria, such as available electricity grid power, existing local initiatives, already present DC electric passenger car charging infrastructure, and many more. The present data alone is insufficient to decide abouthigh-power fast chargers placement, but it is an important first step.

In summary, the present data set is a comprehensive and useful source to plan charging infrastructure deployment for battery electric trucks in long-haul operations.

Acknowledgments

We would like to thank the ACEA truck members for the data, funding and many discussions. This paper was supported by EU STORM project funded from the European Union's Horizon 2020 research and innovation program under grant agreement No 101006700 and by The Federal Ministry for Digital and Transport within the project HOLA (FKZ 03EMF0404A).

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Presenter Biography

Patrick Plötz studied Physics in Greifswald, St. Petersburg and Göttingen. Doctorate degree in Theoretical Physics from the University of Heidelberg. Since 2011 researcher in the Competence Center Energy Technology and Energy Systems at the Fraunhofer Institute for Systems and Innovation Research ISI. Since March 2020 Coordinator of Business Unit Energy Economy. Since 2020 private lecturer at the Karlsruhe Institute of Technology (KIT).