
# Optimized demand-based charging networks for long-haul trucking in Europe

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### Notes

# Abstract

Battery electric trucks (BETs) are the most promising option for fast and large-scale CO2 emission reduction in road freight transport. Yet, the limited range and longer charging times compared to diesel trucks make long-haul BET applications challenging, so a comprehensive fast charging network for BETs is required. However, little is known about optimal truck charging locations for long-haul trucking in Europe. Here we derive optimized truck charging networks consisting of publicly accessible locations across the continent. Based on European truck traffic flow estimates for 2030 and actual truck stop locations we construct a long-term minimum charging network that covers the expected charging demand. Our approach introduces an origin-destination pair sampling method and includes local capacity constraints to compute an optimized stepwise network expansion along the highest demand routes in Europe. For an electrification target of 15% BET share in long-haul and without depot charging, our results suggest that about 91% of electric long-haul truck traffic across Europe can be enabled already with a network of 1,000 locations, while 500 locations would suffice for about 50%. We furthermore show how the coverage of origin-destination flows scales with the number of locations and the size of the stations. Ideal locations to cover many truck trips are at highway intersections and along major European road freight corridors (TEN-T core network).



### Key words

charging infrastructure; battery trucks; megawatt charging

# Contents

# 1 Introduction

As part of the "Green Deal" and to become climate neutral by 2050, the European Union (EU) passed measures to reduce greenhouse gas emissions in all sectors, including the transport sector (Ovaere et al. 2022). To achieve the target of climate neutrality and to fulfil current EU legislation, heavy-duty vehicles (HDVs), i.e. > 12 t gross vehicle weight, also need to become zero emission vehicles (ZEV) (Breed et al. 2021; Plötz et al. 2023). Battery electric trucks (BETs) powered by electricity and stored in batteries have developed as the most promising solution to reduce road freight transport emissions (IEA 2023; Plötz 2022). Although there are currently few HDV BETs on European roads, manufacturers expect a sales share of up to 50% in the EU by 2030 (NOW 2023).

Surveys among logistics companies and experts show that charging infrastructure is one key obstacle for a successful market diffusion of BETs (Anderhofstadt et al. 2019; Bae et al. 2022; Konstantinou et al. 2023). Technical analyses show that public charging infrastructure is needed for long-haul applications (cf. Speth et al. (2024) for Germany, Borlaug et al. (2021) and Borlaug et al. (2022) for the U.S., Nykvist et al. (2021)). Accordingly, the Alternative Fuels Infrastructure Regulation (AFIR - Regulation (EU) 2023/1804) requires EU member states to set up highway fast chargers quickly. By 2030, charging pools shall be installed every 60 km along the TEN-T Core network (47,000 km (one direction)) in both directions. Another 62,000 km (one direction) shall be equipped with charging pools every 100 km in each direction (EU 2023). The planned Megawatt Charging System (MCS) will allow for charging power in the megawatt range and therefore enable truck charging within 30 minutes (CharIN 2023). We use the terms "charging pool", "charging station", or "charging location" to denote one or more charging points at a specific location (EU 2023).

Previous attempts in the literature have analysed – and in general confirmed – the technical feasibility of BETs but without identification of optimal charging locations (Borlaug et al. 2021; Borlaug et al. 2022; Çabukoglu et al. 2018; Liimatainen et al. 2019; Nykvist et al. 2021; Speth et al. 2024; Tong et al. 2021). However, they did not define regionally resolved charging locations for BET.

Following the idea of the AFIR, Speth et al. (2022a) and Speth et al. (2022b) placed charging pools at regular intervals, for example every 50 or 100 km, and dimensioned single pools based on the passing traffic flow. They calculated that approximately 5,000 public megawatt charging points at 1,500 pools could serve 15% of truck traffic in Europe by 2030. Shoman et al. (2023) simulated a European truck fleet and defined public charging locations based on the mandatory break after 4.5 hours of driving. They found a need for approximately 9,000 megawatt charging points to serve 15% of the European truck fleet in 2030. Similar attempts can be found for smaller areas, for example for the relation Helsingborg-Stockholm (Sweden) (Karlsson et al. 2023) and for Ontario (Canada) (Dimatulac et al. 2023). But the analyses do not answer how to design a minimal network that ensures traffic along all relevant routes.

Jochem et al. (2016) designed a minimum charging network for passenger cars in Germany, using a flow-refuelling location model. Later, the approach was improved and adopted to the European highway network (Jochem et al. 2019). However, the approach did not consider parking capacities at rest areas. Furthermore, the analysis focused on highly trafficked origin-destination relations (at least 5,000 vehicles per year (Jochem et al. 2019)) to keep the problem solvable. Rose et al. (2020) added a simplified (Böhle 2021) capacity constraint to the flow-refuelling location model to calculate a hydrogen truck refuelling network for Germany, based on 2,655 origin-destination truck trips.

In summary, to the best of the authors' knowledge, no study has constructed minimal charging networks for battery electric trucks in Europe so far. From a methodological point of view, no prior work optimizes charging infrastructure for a wide range of geographical demands while applying a capacity constraint.

The present study aims to fill this gap in the literature by addressing the following research question: How much BET long-haul traffic in Europe can be enabled by optimally placed megawatt chargers? This work differs from previous research in several aspects. First, we use an optimization model that includes station capacity constraints to compute networks for all of Europe. Second, our results indicate the scaling of truck flow coverage in relation to the number of locations and station capacity. Third, we use a sampling technique to represent both large and small origin-destination truck flows while maintaining tractability of the optimization problem. This contrasts with, e.g., Shoman et al. (2023), who exclude truck flows that are individually small, although when aggregated they represent a significant share of the geographic distribution of total flow volume.

The outline of this paper is as follows. Section 2 introduces the truck traffic and stop location data used for the analysis and the optimization model used for placing the charging stations. Section 3 presents the results from our analysis, followed by a discussion in Section 4. We present our conclusions in Section 5.

# 2 Data and Methods

In this section, we detail the data used in our study and our methodology.

## 2.1 Data

Our approach to determine optimal charging locations builds on three main kinds of input data:

1) *Candidate locations for charging stations.* These serve as the ground set of options available for setting up charging infrastructure. Our model is going to pick among the candidate locations with the goal of minimizing the number of selected locations.
2) *Origin-destination pairs for HDV traffic demand.* As we follow a demand-based approach, the origin-destination (OD) pairs and the associated truck flow volume serve as the demand signal where charging stations are needed and/or should be prioritized.
3) *Distances and transit times.* To determine feasible routes for OD pairs that align with detour, range, and charging requirements, information on distances and transit times between locations is needed. The charging stations are then placed such that the selected locations enable feasible routes for OD pairs.

In the following sections, we describe the data sources we use for the inputs.

### 2.1.1 Charging Station Location Candidates

We construct a candidate set of charging locations with a focus on existing and publicly accessible sites. Most of these locations are extracted from the recently published data set (Link et al. 2023, 2024). In regions with insufficient density of candidates we augment the set with locations published by ACEA (European Automobile Manufacturers' Association) on their website (ACEA 2022). In total, the two data sets contain more than 50,000 actual truck stop locations across Europe. For this paper's purpose, we use a subset of over 10,000 locations as input candidates for the optimization model, which facilitates our approach's scalability. We construct the subset by selecting the most suitable locations while limiting their geographic density, as detailed below.

To be precise, we iteratively select locations to keep and remove any other candidates within a geodetic distance of at most 9 km, which conversely guarantees at least 9 km distance between any two locations in the remaining subset. In consequence, the optimization model effectively only places charging locations with a precision of at best about 5 km (in those regions where candidates are most dense). Therefore, we can think of each candidate as a representative for an area with 9 km diameter. This approach is justified by the assumption that any deviations within the candidate areas are negligible from a practical perspective.

To ensure we are picking the most suitable candidate locations as representatives, before filtering we initially rank the locations based on their attributes as a proxy for suitability. More precisely, we hierarchically sort the locations published by (Link et al. 2023) based on the provided attributes `truckParkingConfidence`, `type` and `totalArea_m2` in that order. For `truckParkingConfidence`, we rank `High` before `Medium`. For `type`, we rank in the order `Truck Stop/Rest Area`, `Fueling/Truck Stop`, `Parking/Rest Area`, `Fueling`, `Rest Area`, and finally, `Parking`. For `totalArea_m2` we rank in descending order. The ACEA locations are added at the bottom of the list such that they are only included in areas where there are no other public locations nearby.

After filtering as described above we are left with 8,116 public locations and 2,508 ACEA locations, which yields 10,624 candidate locations in total.

### 2.1.2 Origin-Destination Pairs

As a basis for HDV traffic demand, we use the publicly available data set published by Speth et al. (2021). We first briefly summarize the characteristics of that data set and then describe our preprocessing to make it suitable for our study.

The original data set contains HDV traffic flows between 1,675 NUTS3 regions all over Europe. In total, more than 1.5 million directed traffic flows are available. The flow data are based on an EU project from 2010 (Szimba et al. 2012) and have been updated using more recent statistics on road transport. Beyond that, a volume flow forecast for 2030 has been added. For this purpose, a growth rate for the volume of transported goods in tons was determined for each country. The individual good flows were then scaled accordingly. Finally, they were converted to vehicle traffic flows. A detailed description can be found in Speth et al. (2022c).

Based on the original data we prepare a set of OD truck flows that serve as input to our demand-based optimization approach. This section documents the preprocessing steps involved. First, we select OD pairs with origin and destination in EU27, Switzerland, Norway, and the UK, excluding some smaller isolated areas (e.g., Cyprus and smaller islands). We ignore countries that are not represented in the charging station candidate location set (see Appendix A.1 for details on the removed regions). Further, we remove any *trivial* OD pairs, i.e., those with an assigned 2030 truck flow volume of less than a single vehicle.

Next, we extract the subset of OD pairs that correspond to *long-haul* truck traffic. To this end, we define long-haul OD pairs as those where the associated direct transit distance is at least 335 km, which is approximately equivalent to a transit time of 4.5 hours for road travel. Note that the distance and transit time associated with each OD pair is determined by the distance and transit time of the fastest route between origin and destination, which we extracted from a separate data source (see below). After filtering we are left with 1,092,625 long-haul OD pairs (72% of all OD pairs) whose associated truck flow of 147,377,340 HDVs per year corresponds to about 17% of the total truck flow and 48% of total vehicle-kilometers in the estimate for 2030. The relatively small share of truck flow is because the majority of HDV traffic corresponds to urban and regional instead of long-haul transport.

Now, the number of OD pairs remaining is too large to simultaneously incorporate all of them in the optimization model. However, since there is considerable overlap between the routes of the individual OD pairs, it is not necessary to consider all of them at the same time. Instead, we rely on random samples from the distribution of all OD pairs. To ensure the samples are representative both in terms of geography and associated truck flow, we first transform the OD pair distribution as follows. Every OD pair that has truck flow $f > 100$ HDVs per year is split into $n = \left\lceil \frac{f}{100} \right\rceil$ copies with truck flow $\frac{f}{n}$ each. This results in a distribution of 2,290,498 OD pairs (each assigned a truck flow between 1 and 100). Our transformation enables the *partial* sampling of very high truck flow OD pairs in the original distribution. Therefore, we can draw representative samples in terms of truck flow while picking OD pairs uniformly at random from the transformed distribution. The latter is necessary to represent different regions proportionally, since the NUTS-3 region aggregation differs across countries (e.g., NUTS-3 regions in Germany are significantly smaller than in France and thus have more associated OD pairs but with less truck flow each).

Finally, we adjust the truck flow of every OD pair to the relative share of BETs, which we assume at 15% following Shoman et al. (2023). From the final OD pair distribution, we draw samples uniformly at random without replacement. As sample size we choose 1% of the data, which corresponds to 22,905 OD pairs for each optimization run. Section 2.2 details how we use the samples to construct optimized station networks.

### 2.1.3 Distances and Transit Times

Our model relies on distance and transit time information between geo-coordinates to determine feasible routes for HDVs. To provide these values, we use a custom Open Source Routing Machine server (OSRM, Luxen et al. (2011)) based on OpenStreetMap data (OSM 2024). We compute the distance and transit time for a fastest route (note that "fastest route" may not be unique) between all relevant location pairs via the table service of OSRM, which allows to query millions of data points in a matter of minutes. Based on the input locations considered we collect distance and transit time information for more than 80 million pairs of points.

## 2.2 Method

In this section we summarize the properties of the optimization approach to construct demand-based truck charging networks. A supplementary mathematical formulation of the involved optimization problem can be found in Appendix A.1.2. For further details on the formulation and optimization methods we refer to Arslan et al. (2019), Nordlund et al. (2023) and the references therein. For this paper, we use our own modified version of an optimization algorithm available as open-source implementation on GitHub (CHALET 2023). Our code employs only a subset of the techniques described in Nordlund et al. (2023).

For any given set of charging locations, we consider a station network that specifies the possible routes for OD pairs. Here, a route is a sequence of charging locations that are visited between origin and destination. An OD truck flow is called *feasible* (or *covered*) if a route from origin to destination through the station network exists such that the route satisfies several constraints. These are set in the model, and we summarize them as constraints i) – v) below. For our analyses in Sections 3.1 and 3.2 we only enforce constraints i) – iii), where iii) dictates charging stops in flexible distance intervals. This makes routes independent of vehicle and charger technology and approximately aligns the charging stop frequency with European driving break regulation. Then, in Section 3.3 we replace constraint iii) by iv) and v), which instead make the route dependent on vehicle range and charging time requirements. We use this approach to analyse the impact of technological parameters on minimal charging networks.

i) Detour constraint: The total driving time is limited to at most $\overline{\tau} = max\{1.05 \cdot \tau, 30 \text{ min} + \tau\}$ where $\tau$ is the direct non-stop driving time from origin to destination. In other words, we allow an extra 5% of driving time, but at least 30 minutes. This ensures the routes can accommodate charging stops by deviating within a small margin from the fastest route (which does not include any stops). Alternatively, the extra available driving time may also be spent on charging if applicable (cf. travel time constraint).

ii) Station capacity constraint: To avoid an overallocation of charging stops to a small set of locations, we limit the truck flow that can be associated with any individual location. Since the actual capacities per location are highly uncertain and can vary considerably, we use a simple capacity assumption across all locations that serves as a simple guardrail in the model. To be precise, we limit the truck flow per candidate location to a maximum of 100,000 HDVs per year by default.* To reflect the capacity assumption proportionally in each sample of OD pairs (compare Section 2.1), we down-scale the capacity accordingly by the sample size (to 1,000 as 1% of 100,000). In Sections 3.1

*At a high level this value can be motivated as follows. Assuming 250 – 300 driving days per year, it corresponds to at most 333 – 400 charging stops on average per day. For candidates that represent the most capable locations, e.g. service areas of both sides of a motorway with 10 charging points each, this corresponds to 17 – 20 charging stops per charger per day. If each charging stop is at most 45 mins, every charger is occupied for 13 – 15 hours per day, which implies a temporal charger utilization of around 60%.

and 3.3 we use the default station capacity value of 100,000 HDVs per year, while in Section 3.2 we analyze how the results from Section 3.1 change when the capacity value is varied between 0 and 150,000 HDVs per year.

iii) Charging stop constraint: The first stop after departure from the origin must be within 200 km from the origin and the last stop before arrival at the destination must be within 200 km of the destination. The transit distance between any two consecutive charging stops must be at least 200 km and at most 335 km (which corresponds to approx. 4.5 hours road travel). Apart from being similar to legally mandated driving breaks, this can also be interpreted as 400 – 500 km BET range without any depot charging and 50% state-of-charge (SOC) required on arrival. We use this constraint for the results in Sections 3.1 and 3.2 while in Section 3.3 we replace it by iv) and v).

iv) Range constraint: The distance between any two consecutive charging stops is limited to the maximum vehicle range $R$ (after subtraction of a 100 km safety margin). The first and last charging stop must be within a distance of $50\% \, R$ from the origin, respectively the destination. This implements the common *half-range assumption*, which means that the vehicle requires at most 50% max range when leaving an origin and at least 50% remaining range when arriving at a destination. Consequently, every OD trip requires at least one charging stop, and at the last charging stop the vehicle needs to recharge sufficiently to arrive with 50% battery at the destination.

v) Travel time constraint: The allowed total travel time (defined as sum of driving and charging time) may not exceed $\hat{\tau} = \beta(\overline{\tau})$, where $\beta$ is a function that adds 45 mins of break time for every full 4.5 hours of input driving time. For example, $\beta(2 \text{ hours}) = 2 \text{ hours}$ and $\beta(6 \text{ hours}) = 6 \text{ hours } 45 \text{ mins}$. In essence, this means the legally required driving break time (45 mins every 4.5 hours) must suffice for most of the charging time. Charging time itself is computed as a non-linear function of the charger power, starting battery state and the target battery state, which in turn depends on the distance to the next stop (and the final battery state at the destination if applicable).

The optimization model selects charging locations within a specified budget to maximize the OD truck flow that is feasible with respect to the selected locations (cf. Appendix A.1.2). In other words, it determines an optimal placement of charging locations to cover as much OD truck flow as possible given the route constraints. To compute OD coverage curves that show the tradeoff between the number of locations and the implied OD coverage, we initially compute the maximum possible coverage for an unlimited number of locations. Afterwards, we re-run the model with sequentially tighter budgets by steps of 100 locations, each time restricting the input locations to those that were selected in the previous run. This construction ensures that the determined locations are consistent across the curve, i.e., the locations for smaller budgets are subsets of the locations for higher budgets.

# 3 Results

The main result we present is a demand-based charging network expansion that places charging stops in alignment with European driving break regulation. In other words, the locations are computed with respect constraints i) – iii) described in the previous section. We evaluate the accuracy of our sampling approach and the station capacity parameter. Additionally, we construct charging networks based on technological constraints such as vehicle range and charging power. We analyse the impact of varying these parameters on the feasibility of OD routes and the number of required charging locations.

## 3.1 Optimized Charging Network Expansion

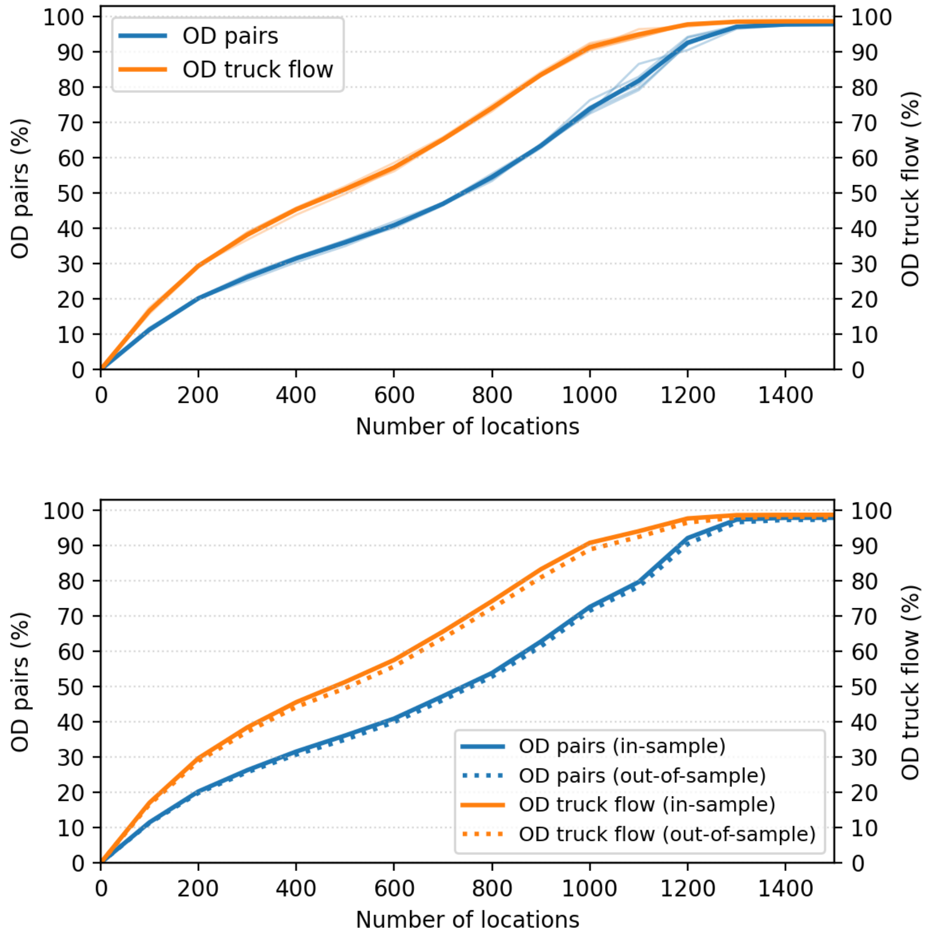
Here we present an optimal charging network expansion based on the long-term network constraints induced by driving regulations. We evaluate 5 samples from the OD distribution with a proportional station capacity that corresponds to (at most) 100,000 HDV visits per year and location. We find that on average 97.9% of OD pairs with an associated truck flow of 98.7% are feasible in this model. Moreover, about 1,300 locations are sufficient to achieve the maximal coverage.

We now check if all samples lead to equally representative solutions. To this end we compare the implied OD coverage across different samples in Figure 1. At the top we show the implied OD coverage on each sample individually (semi-transparent lines) and on average (solid lines). Overall, we see only minor deviations between the different samples. At the bottom we compare the estimated in-sample vs. out-of-sample OD coverage by re-evaluating all samples on the locations computed for the first sample. At any point on the curve, we observe that the deviation between in-sample and out-of-sample coverage is less than 2 percentage points for OD pairs and less than 3 percentage points for OD truck flow. This confirms that the locations computed for one sample achieve comparable OD coverage on other samples, which suggests that the results translate proportionally to the entire data.

Moreover, Figure 1 shows that for 15% BET in stock, 1,000 optimally placed megawatt charging locations in Europe could enable about 91% of electric long-haul trucking and 75% of OD pairs while 500 charging stations could enable about 50% of electric long-haul truck traffic.

**Figure 1: Share of covered OD pairs and OD truck flow versus number of locations.**

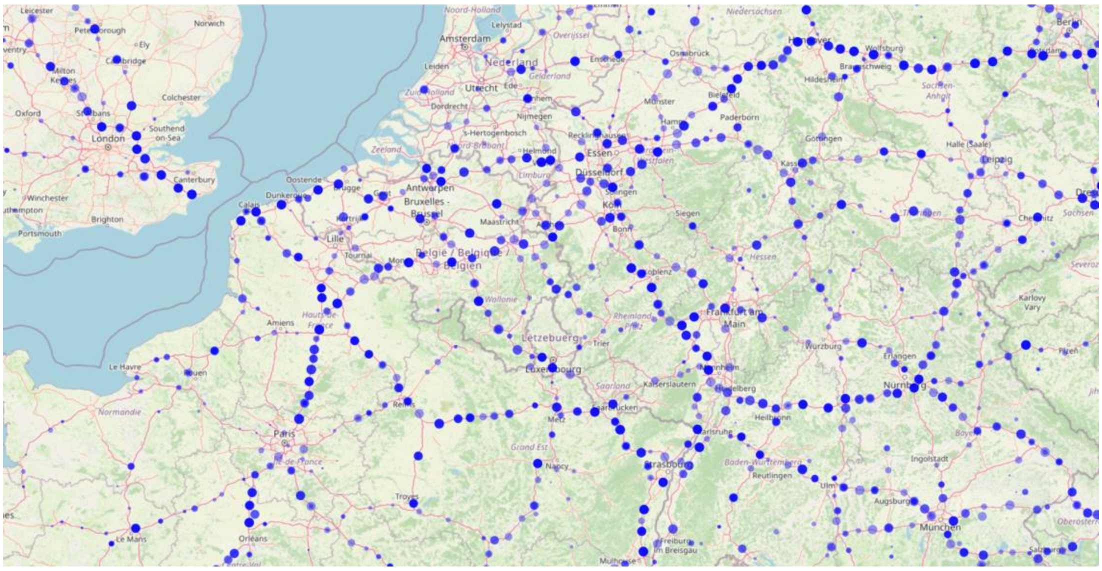
The top panel shows the results on 5 individual samples (thin lines) and the average (thick line). The bot-tom panel shows a comparison between in-sample (solid lines) and out-of-sample (dashed lines). In this scenario, each location can serve up to 100,000 HDV per year.




However, the precise locations computed for distinct samples can differ. This is expected to some degree, since many different, but similarly sized sets of locations can achieve the same OD coverage and thus are equally good in the sense of the model. In Figure 2 we show some of the locations selected by the model for maximal coverage across all samples. The opacity of the points is proportional to the number of samples that include them, and the size of the points is proportional to the OD truck flow assigned to them. We see that the locations are heavily concentrated along a few major roads. In the highest demand areas (e.g., between Hannover and Wolfsburg), almost all available candidates along the road are picked as their individual capacities are exhausted.

**Figure 2: Cutout of the selected locations in the long-term network to achieve maximum OD coverage.**

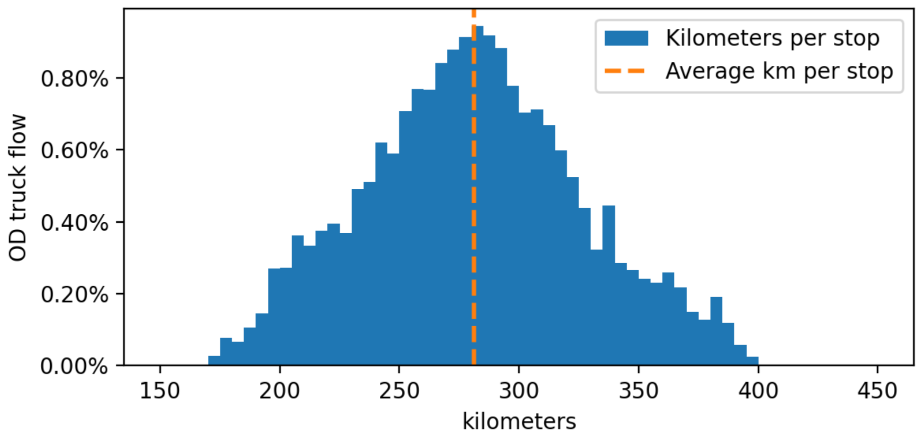
The opacity of the bubbles indicates the number of samples that include the location, while the size is proportional to the number of vehicle visits. Along the major highway corridors, many locations reach the maximum demand set by the station capacity constraint. Background: OpenStreetMap



Regarding the routes computed for each feasible OD pair, we analyse the number of charging stops per distance travelled. Figure 3 shows the distribution of the kilometre-per-stop ratio across all feasible truck flows. The values range (approx.) from 160 km to 400 km with an average of 280 km. This matches expectations from the charging stop constraint set in the model. With this constraint, one stop may suffice for trips between 335 km and 400 km distance, while for longer trips the distance-per-stop ratio should approach a value between 200 km and 335 km.

**Figure 3: Distribution of the average distance-per-stop ratios for all origin-destination trips.**

The result matches the constraint set in the model, which enforces charging stops in flexible distance intervals.



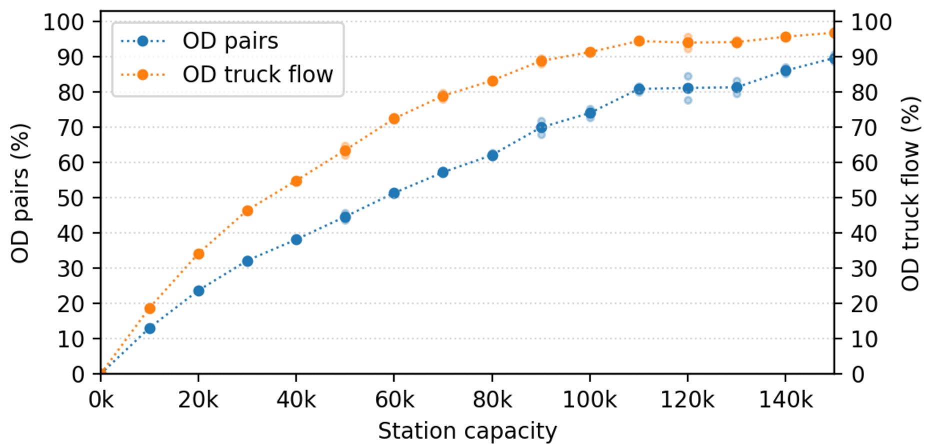
## 3.2 Impact of Station Capacity

In this section we show the impact of varying station capacity for a fixed number of locations. Recall that the station capacity expresses how many HDVs can visit each location per year. We repeat the prior experiment with two samples and station capacities as multiples of 10,000 between 10,000 and 150,000 HDVs. For every station capacity value this yields independently computed results.

Figure 4 shows the OD coverage curve for a fixed number of 1,000 locations. The OD coverage is mostly monotonically increasing, which is logical behaviour. Between capacities 110,000 and 130,000, we see small deviations due to suboptimal model results. One can further see a diminishing return pattern for the marginal benefit of higher station capacity. Nevertheless, for very large capacity values the OD coverage approaches maximum possible values even though the number of locations is fixed at 1,000.

**Figure 4: Share of covered OD pairs and OD truck flow versus station capacity for 1,000 locations.**

The semi-transparent dots represent results on individual samples and are independent between different capacities. The solid dots represent the averaged results over both samples.




## 3.3 Optimized Networks based on Vehicle Technology

In the construction of the charging network in Section 3.1, we assumed distance-based periodic charging stops inspired by EU driving break regulation. Therefore, those results were independent of vehicle range and charging power requirements. In this section, we compute instead charging networks that consider the range and travel time constraints iv) and v). The idle break time available for charging is set to 45 mins for every 4.5 hours, but we allow an arbitrary allocation of the break time during the trip. This enables longer distances between consecutive charging stops depending on the maximum vehicle range. In this model, while keeping station capacity fixed, we analyze the impact of varying charging power and vehicle range on OD pair feasibility and the number of required locations.

We define several scenarios corresponding to different parameter combinations. In terms of maximum vehicle ranges (before subtraction of a 100 km safety margin) we consider the values 500 km, 700 km and 900 km. The battery capacity is assumed to be proportional to the vehicle range based on a fixed battery consumption rate of 1.2 kWh/km, resulting in capacities 600 kWh, 840 kWh and 1080 kWh, respectively. In terms of charging power, we consider the values 350 kW, 650 kW and 1000 kW. Due to the half-range assumption at origin at destination, the energy that needs to be supplied during each trip must cover the entire trip distance and is the same in every scenario. For

350 kW charging power we found that the available charging time is mostly insufficient to supply enough energy under the present assumptions (no depot charging, only max. 45 min charging time). Accordingly, the share of feasible long-haul routes is less than 2%, and we exclude 350 kW chargers from the detailed results below.

For the remaining parameter combinations, we compute an optimal charging network expansion with the help of two OD samples. In Table 1 we report the OD pair and flow coverage in each scenario and the minimal number of charging locations required to achieve that. With 650 kW charging power 85% – 89% of trips are feasible and with 1000 kW charging power the OD coverage reaches its maximum at 97% – 99%. The maximum vehicle range affects route feasibility only indirectly, as it impacts the charging location selection. This can even lead to a decrease in OD coverage as higher vehicle ranges imply more restrictive battery energy requirements at the trip destination. We suspect that part of the 1% – 3% reduction of OD feasibility for 900 km compared to 700 km vehicle range is due to this effect. More importantly, higher vehicle ranges for the same charging power lead to a significant decrease in the number of required locations, because the vehicles need fewer charging stops. For instance, with 1000 kW charging power an increase in vehicle range from 500 km to 900 km leads to a 50% reduction of required charging locations while OD coverage is essentially unchanged. Finally, we observe that increasing charging power from 650 kW to 1000 kW reduces the number of required charging locations across all vehicle ranges while the OD coverage improves. Plots of the OD coverage curves for all scenarios can be found in Appendix A.1.3.

**Table 1: Summary of charging networks computed based on vehicle range and charging power.**

The coverage of OD pairs/flows increases with higher charging power. The number of required charging locations decreases with vehicle range.

| Charging power | 650 kW | | | 1000 kW | | |
|---|---|---|---|---|---|---|
| Vehicle range | 500 km | 700 km | 900 km | 500 km | 700 km | 900 km |
| OD pair coverage | 88.5% | 89.9% | 87.3% | 97.6% | 98.7% | 98.1% |
| OD flow coverage | 87.5% | 88.6% | 85.4% | 97.8% | 98.4% | 97.4% |
| Required locations | ≈1900 | ≈1600 | ≈1500 | ≈1200 | ≈900 | ≈800 |
| Average distance per stop | 269 km | 389 km | 437 km | 283 km | 408 km | 505 km |

# 4 Discussion

In this section we list potential caveats of our approach which may distort the results or limit their applicability. To this end, we mention issues related to the inputs and methodological shortcomings. Afterwards we discuss potential insights from our analysis.

First, the OD routes through the charging network that we determine rely on the availability of candidate locations in the relevant geographic area. In case there are not sufficient candidates available, the affected OD pairs are infeasible, i.e., no corresponding routes can be obtained.

Second, the geo-coordinates that define the locations usually map to one side of the road. Due to physical barriers between roadsides, this could render some locations only accessible from one side of the road, although there are parking areas on both sides. In such cases, the routes using the opposite direction of travel may require prohibitive detours to use that location.

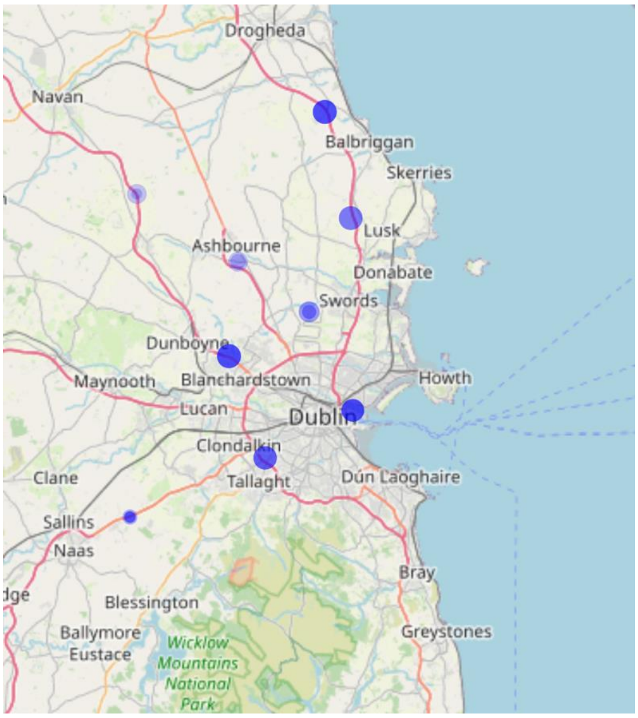
Third, although the candidate locations are generally publicly accessible, there is significant uncertainty around the suitability for HDV charging stations. In particular, there is insufficient information on power availability, which is essential for the purpose of megawatt charging. Besides the station capacity constraint described in Section 2.2, our optimization model prioritizes different locations purely based on geography.

Fourth, since the coordinates of origins and destinations correspond to geometric centres of NUTS-3 regions, they are sometimes in remote rural areas or far from the road network. This might bias the results towards selecting charging locations in areas that do not correlate to the relevant industrial and population centres.

Lastly, some OD routes may include sections corresponding to ferry (or rail) connections. However, this information is not included in our data as we only query distance and transit time values for the benefit of scalability. Thus, the distance and transit time for such routes are distorted in comparison to exclusive road travel. On the one hand, trucks do not consume (as much) battery while on a ferry, which leads to an overestimation of charging needs around ferry trips. On the other hand, the transit time (per km) is higher relative to road travel, which increases the proportionally allocated charging time (in case the travel time constraint is used). Overall, we observe that the model is biased towards placing charging stations at seaports on either end of ferry connections, e.g., as in Figure 5.

**Figure 5: Multiple charging locations around the port of Dublin as selected by the model.**

Background: OpenStreetMap




In general, the model almost always selects fully developed locations. This is obvious because it can then handle a lot of traffic with just a few locations. Within the trip distances (>335 km), almost every vehicle passes busy roads. This means that it may not be needed for the model to expand the networks along routes with little traffic. Ergo, if full coverage need not be achieved, almost all locations are located on high-traffic routes and are fully developed. Additionally, the model has candidate locations available at very short intervals on the major roads. This means that a high number of fully utilized charging locations can be selected there. As the model covers the entire charging needs (there is no unaccounted depot charging), the charging stop requirement is roughly proportional to trip distance. This explains why the coverage increases almost linearly with the locations. Only at the very end, when the most unfavourable routes (routes that avoid busy roads) must be electrified, less attractive locations away from major corridors are selected and we observe a diminishing return pattern. The map in Figure 2 then shows an intense case with large electrification, in which even the few trips that are often away from the busy roads must be electrified.

# 5 Summary & Conclusions

Based on a unique data set of European long-haul truck traffic and actual truck stop locations, we applied an optimization algorithm to identify the best locations to cover as much electric truck traffic flow as possible. We added local station size limitations to make our findings more applicable to the real world. Adding size restrictions makes the optimization problem significantly harder and we used a novel sampling approach to keep the problem tractable while still representing smaller traffic flows in the problem. With respect to an electrification share of 15% BET in stock and without depot charging, our findings show that already 1,000 optimally placed megawatt charging locations in Europe could enable about 91% of electric long-haul trucking while 500 charging stations could enable about 50% of long-haul truck traffic. We furthermore show how the OD coverage scales with station size for a fixed number of 1,000 locations.

For network planners and policy makers, our results indicate that one should place large charging hubs on high-traffic routes as sooner or later many trucks will pass by within their driving times. Second, one should expand the network step by step, adding locations along these corridors. We already observe similar results in real-life for battery electric passenger cars on long-distance routes: massive expansion along the major axes, mostly financed by companies, while the feeder roads and less frequented motorways tend to be developed with subsidized, small charging parks to achieve area coverage. Optimization as used here demonstrates similar findings for HDVs with their largely different usage patterns.

Likewise for truck operators, our findings indicate that already a limited network of a few hundred charging stations across all of Europe enables electrification of significant shares of truck traffic flows as the latter is often concentrated along major corridors and truck operators do not need to wait with electric long-haul trucking until the charging network is complete.

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# 6 List of figures

# 7 List of tables

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# A.1 Appendix

## A.1.1 Geographic OD pair filter

In the geographic OD pair filter, we remove the following regions:

- All regions in the following countries: *Russia, Belarus, Ukraine, Bosnia and Herzegovina, Morocco, Turkey, Montenegro, Kazakhstan, Macedonia, Cyprus*
- Any region south of 36 degrees parallel north (approx. latitude of Strait of Gibraltar)
- Additionally, the following remote single-region islands: *Jan Mayen, Regiao Autonoma dos Acores, Eivissa y Formentera, Mallorca, Menorca, Shetland Islands, Orkney Islands, Eilean Siar (Western Isles), Dodekanisos, Kyklades, Lesvos, Chios, Samos*

## A.1.2 Mathematical optimization problem

We consider a network graph $\mathcal{G}$ consisting of origin/destination nodes and (candidate) charging locations $\mathcal{L}$. For any subset of charging locations $L \subseteq \mathcal{L}$, let $\mathcal{G}(L)$ denote the subgraph of $\mathcal{G}$ induced by $L$, i.e., the network that only considers charging locations $l \in L$. Routes between origin and destination nodes are represented as paths in $\mathcal{G}(L)$ for any selection of locations $L$. We define $\mathcal{P}_{st}$ as the set of all feasible paths from origin $s$ to destination $t$. Here, feasibility means that any path $P_{st} \in \mathcal{P}_{st}$ satisfies the route constraints described in Section 2.2. For the sake of brevity, we omit the details on how these constraints are modelled mathematically.

Now we are given a set of origin-destination (OD) pairs $\mathcal{Q}$ and a cost budget $B$. Every OD pair $st \in \mathcal{Q}$ has an associated truck flow $f_{st} > 0$. Additionally, every candidate charging location has an associated selection cost $c_l > 0$ (in our case we set $c_l = 1$ for all locations $l$) and station capacity $\kappa_l$. The optimization problem we consider is stated mathematically as follows:

$$\max_{L \subseteq \mathcal{L}, Q \subseteq \mathcal{Q}, P_{st} \in \mathcal{P}_{st}} \quad \sum_{st \in Q} f_{st}$$

$$\text{subject to} \quad P_{st} \subset \mathcal{G}(L) \qquad \forall st \in Q \qquad (1)$$

$$\sum_{st \in Q : l \in P_{st}} f_{st} \leq \kappa_l \qquad \forall l \in L \qquad (2)$$

$$\sum_{l \in L} c_l \leq B \qquad (3)$$

The objective is to maximize the total truck flow that is feasible in the network induced by the selected charging locations (1), where the truck flow assigned to each individual location may not exceed its capacity (2). The total cost of the selected locations must be within the budget (3).

## A.1.3 Supplementary plots

The following plots show OD coverage curves that correspond to charging network results presented in Section 3.3. The left column corresponds to 650 kW charging power and vehicles ranges 500 km, 700 km, and 900 km (from top to bottom). The right column contains plots for 1000 kW charging power and the same vehicle ranges.