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# An optimal capacity-constrained fast charging network for battery electric trucks in Germany

Daniel Speth *, Patrick Plötz, Martin Wietschel

*Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48 76139 Karlsruhe, Germany*

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ABSTRACT

Battery electric trucks (BET) reduce greenhouse gas emissions in the transport sector but require public charging infrastructure. Truck fast charging networks have been planned in various studies and countries. However, existing charging infrastructure optimization studies ignore relevant actual constraints, such as the size of parking areas or available grid power, leading to unrealistic results. Here, we derive a minimal public fast charging network for BET in Germany with actual real-world capacity limitations. We add capacity constraints to a flow refueling location model (FRLM) which makes the optimization more challenging as it is no longer sufficient to ensure that every path can be travelled but it must be determined which vehicle uses which charging location. The constraint is implemented as hourly maximum number of vehicles that can be served at each location and obtained via queuing theory from local traffic flows. We apply the model to 236,000 origin–destination traffic flows. For 300 km BET range, we identify 124 optimal charging locations. For 15 % BET in stock, e.g. by 2030, this would require 2 to 30 charging points per location with an average of 16 charging points using 17 % of the available truck parking lots per location. Our findings provide input for governments and public charging infrastructure planners. These results indicate that well positioned large initial charging locations can already cover significant shares of BET traffic.

## 1. Introduction

### 1.1. Motivation

The transport sector, which is responsible for a quarter of the European Union's (EU) greenhouse gas emissions, is the only sector where greenhouse gas emissions have not decreased in the last two decades. Heavy-duty vehicles (HDV) exceeding a gross vehicle weight of 3.5 t are responsible for 7 % of the EU's greenhouse gas emissions (Eurostat, 2022). To reduce emissions in the transport sector and become climate-neutral by 2050, the EU has also implemented measures for heavy road freight transport. These include, inter alia, a firm-level emission performance standard of new vehicles and infrastructure mandates (Ovaere and Proost, 2022). The 2030 emission performance standard requires a 30 % reduction of $CO_2$ emissions generated during operation of newly registered HDV with a laden mass of 16 t compared to current levels (EU, 2019). Analysis show that a share of 4 to 22 % of zero-emission trucks (ZET), i.e. fuel cell electric trucks (FCET) or battery electric trucks (BET), is necessary to reach the target (Breed et al., 2021). In parallel, the European Union (EU) highlights the importance of public infrastructure for ZET and proposes the installation of hydrogen refueling

* Corresponding author.
*E-mail address:* daniel.speth@isi.fraunhofer.de (D. Speth).

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stations and charging stations along the most important European corridors, i.e. the TEN-T network (EU, 2023).

User surveys show the need for a properly developed infrastructure for alternative fuel vehicles (AFV) from a trucking industry perspective. A survey among 70 logistics companies in Germany identified infrastructure as one of the central user requirements (Kluschke et al., 2019). In California, a survey among 20 logistics companies also identified the fuel infrastructure as one of three most recurring factors influencing alternative fuel adoption (Bae et al., 2022). Using a Delphi study, Anderhofstadt and Spinler (2019) identified missing infrastructure as a main barrier for ZET in Germany.

Different studies show that ZET can be competitive with diesel vehicles from an economic point of view (c.f. Noll et al. (2022), Speth et al. (2022a), Phadke et al. (2021), Burke and Kumar Sinha (2020), Basma et al. (2022), Basma et al. (2021), Link et al. (2024)). According to Noll et al. (2022), cost competitiveness is exhibited in certain application segments already today. Comparing BET, FCET and hybrid electric truck (HET) to conventional drivetrains, they find that especially BET show great potential, even in long-haul applications.

Due to the necessity of ZET to achieve EU's climate targets as well as the important role of infrastructure, this paper deals with the modeling of public fast charging infrastructure (0.8 – 1.2 MW peak power) for BET in Germany. Given the smaller range as well as the economic advantages, the focus is on BET infrastructure, but the analysis can be transferred to FCET.

### 1.2. Literature

In the following, basic developments in infrastructure modeling are presented and relevant work related to trucks is outlined. According to Metais et al. (2022) and Deb et al. (2018), there are three major groups of charging infrastructure modeling approaches: node-based models, path-based models, and tour-based models. The following literature review is based on the aforementioned work and supplements publications with particular relevance for the modeling of charging infrastructure for trucks.

Node-based models assume demand at specific locations represented as nodes in a network, e.g. buildings or traffic hubs. Facilities at the nodes can serve the demand in a particular distance. The Set Covering Location Model (SCLM), a subgroup of node-based models, places facilities such that a minimum number of facilities can serve all demands. Using a SCLM, Toregas et al. (1971) placed emergency service facilities. Regarding charging infrastructure, Hosseini and MirHassani (2015) used a SCLM with a heuristic to place recharging locations in Phengu County (China). They combined the model with queuing theory to scale the single stations. As a variation, the Maximum Covering Location Model (MCLM) places a given number of facilities to cover as much demand as possible (Church and ReVelle, 1974). Today, p-median models that position p facilities such that the transportation costs from each node to the facilities are minimized are commonly used. They were introduced by Hakimi (1964) to identify optimal locations for police stations and switching stations in communication networks. To avoid unrealistically large facilities, node-based models can include a capacity restriction. For example, Gavranović et al. (2014) developed a p-median model for Turkey in which charging stations for electric vehicles can cover a maximum of 100,000 inhabitants per station. Zhu et al. (2017) combined a p-median model with a queuing model to account for waiting times when choosing charging locations for electric vehicles. Since node-based models are NP-hard problems with high computational effort in large scale applications, heuristics are often used to determine approximate solutions (Metais et al., 2022). For example, Speth et al. (2022b) and Speth et al. (2022c) place charging locations for BET at regular intervals along German and European highways and use local traffic volumes as an indicator for node-based charging demand. Using a queuing model, they determine the necessary number of charging points for each location. Already in an early phase with 15 % battery electric trucking, Speth et al. (2022c) foresee 660 public fast charging stations at a distance of 100 km with 3,679 charging points in Europe. Single charging stations require up to 18 charging points. Without considering local parking capacities, the model tends to calculate unrealistically large charging stations. However, node-based models place charging infrastructure mainly at locations where many citizens live or many vehicles drive (Capar and Kuby, 2012). The information about the actual charging need of the vehicles, based on the distance travelled, is neglected. Therefore, node-based models are only partially suitable for modeling fast charging infrastructure for BET.

Path-based models do not consider the traffic volume at nodes, but the traffic flow on an origin–destination-path. Hodgson (1990) introduced the Flow Capturing Location Model (FCLM), which is basically a flow-based model of the MCLM. A path is recharged or refueled, if at least one node with a refueling or charging infrastructure is passed. In contrast to the MCLM with road count data, vehicles are not considered multiple times for infrastructure positioning. To take the necessity of multiple stops into account, Kuby and Lim (2005) invented the Flow Refueling Location Model (FRLM). The FRLM, as originally formulated, is based on considering every possible combination of refueling locations. Lim and Kuby (2010) proposed several heuristics to keep the computation time manageable. Capar and Kuby (2012) and Capar et al. (2013) reformulated the problem. Instead of computing every possible combination of refueling locations, they determined for each arc in a path at which nodes a refueling location could be constructed to pass the arc. This allows the solution of larger, real-world problems. Jochem et al. (2019) used this approach to calculate a European charging network for battery electric cars with several hundred charging stations, 128 of them in Germany. To reduce the problem size, they considered only paths that are driven by at least 5,000 vehicles per year. He et al. (2019) calculated a fast charging network for the United States of America, using flows between 4,486 regions. To reduce complexity, they clustered them into 196 regions. Overall, problem size remains a crucial factor for the solvability of an FRLM. Upchurch et al. (2009) criticized that in the FRLM the presence of one charging station is sufficient to supply all passing paths. They introduced a Capacitated Flow Refueling Location Model (CFRLM) that restricts the number of vehicles refueled at one station. In order to avoid too much refueling at one station, the CFRLM – in contrast to the FRLM – must determine exactly at which location each vehicle is actually refueled. This makes optimization much more difficult, especially since Upchurch et al. (2009) still used the by now deprecated form of the FRLM as basis. They placed four refueling stations in a simplified road network of Arizona (USA) consisting of 50 nodes, with the aim of maximizing the traffic covered by the stations. Cross-border traffic was excluded, and the system was designed to handle peak hour traffic. However, they stated that "the amount of refueling capacity that could be built at each node is potentially infinite " (Upchurch et al., 2009). In the basic version of the model, they limited the number of vehicles per station, but not the number of stations per node. Wang and Lin (2013) used an CFRLM to design a charging network for scooters in in Phengu County (China) and took 12 paths into account. Zhang et al. (2018) included a power supply network as restriction to the CFRLM and applied it to a network with 25 nodes. While previous models typically limited the maximum number of vehicles per station, Hosseini and MirHassani (2017) limited the amount of energy delivered from one station and improved performance. Rose et al. (2020) transferred the FRLM to FCET and designed a hydrogen refueling network for Germany with a capacity constraint for every node in the network. To run the whole German truck fleet above 26 t gross vehicle weight on hydrogen, they considered 2,655 origin–destination paths and identified 142 potential refueling stations with up to 30 t of hydrogen per day. Since the dataset focuses on German traffic, it contains only few paths that have to be refilled multiple times during one trip. To further reduce model complexity, Rose et al. (2020) have refrained from calculating the exact fuel level at each node and estimated an average value before the actual calculation. As shown by Böhle (2021) this may lead to exceeding the maximum tank level. However, Böhle (2021) avoids an adjustment in favor of computing time and combines the model of Rose et al. (2020) with a multi-period approach. So far, the problem of unrealistically large stations has thus been solved for small datasets or by simplifications. Simulative modeling, shown for example by Shoman et al. (2023) to design a European truck charging network and Menter et al. (2023) for Germany, is also possible.

Tour-based models typically rely on large datasets, e.g. driver's logs or GPS data. Methodologically, they are not really categorized. However, streams can be identified (Metais et al., 2022). For example, GPS data can be used as node data or path data. Using GPS data from eight million vehicle trips for a MCLM and 116 possible charging locations, Whitehead et al. (2021) identified up to 10 optimal charging locations for short-haul trucks in South East Queensland (Australia). Simulation of vehicle trips, sometimes in combination with optimization approaches, is also typical for tour-based models. For example, Xi et al. (2013) used trip data to simulate the charging behavior of potential battery electric cars and identified optimal slow-charging locations in the city of Columbus (OH, USA). Since tour-based data is hard to access for privacy reasons (Metais et al., 2022) and can be biased, it is complicated to use for country-wide infrastructure modelling.

An overview on node-based, path-based, and tour-based models is given in Table 1.

In summary, the various location models (SCLM, MCLM, FCLM – see above) are the standard to design charging and refueling networks for vehicles in the literature with path-based models exceeding node-based models due to the knowledge of actual refueling requirements for every path. The same applies for tour-based models, but the creation of an appropriate dataset is more difficult. However, the higher level of knowledge is associated with an increase in computational effort. Therefore, previous calculations are usually based on small datasets and simplifying assumptions. In addition, the FRLM without a capacity limitation often leads to unrealistically large refueling stations and the exact refueling demand cannot be shown. CFRLM further increases the computational requirements. To the best of the authors' knowledge, that's why no large-scale FRLM has been performed so far.

### *1.3. Objective*

The aim of the present paper is to design a capacity-constrained high-power fast charging network for BET ($>$ 12 t gross vehicle weight) in Germany. The single stations are sized so that the truck fleet can be fully converted to BET. The analysis can help policymakers as well as industry representatives to estimate the infrastructure needs in a greenhouse gas neutral Germany, foreseen by 2045.

This work differs from previous research in several aspects. First, compared to previous studies, the analysis uses a large synthetic dataset with 236,000 heavy-duty truck traffic paths throughout Germany. A more detailed description can be found in section 2.1. Second, the paper shows the difference between a CFRLM and an FRLM in their application on real-world data. Thus, it contributes to an improved interpretation of model results in terms of their practical relevance. Third, the CFRLM was adjusted methodologically: We integrated a queuing model, considered traffic flows beyond the area under investigation, and applied a node-constraint that takes every single vehicle into account. Fourth, we used a server with 196 GB RAM and 8 cores to make a more realistic CFRLM solvable.

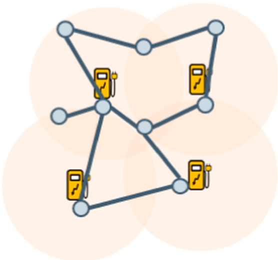
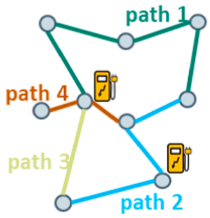
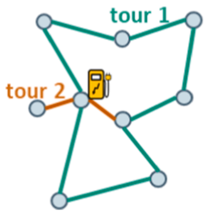
The outline of this paper is as follows: In section 2.1, we present our data and the most relevant assumptions. Afterwards, section 2.2 contains the model description. Section 3 presents the model results. The results are discussed in section 4. Finally, section 5 sums up the key findings and contains recommendations.

## 2. Data & methods

### *2.1. Data and assumptions*

The modeling presented in this paper is based on European origin–destination traffic flows. For this purpose, updated data from the ETISplus project is used. In 2010, the ETISplus project used several EU and EU country sources to model Europe-wide origin–destination freight volumes. The project calibrated the origin–destination flows using traffic count data (Szimba et al., 2012). Using current EU statistics, Speth et al. (2022d) have updated the project's truck data. A three-step procedure was used in which (1) country-specific growth rates of freight transport volumes since 2010 were determined, (2) the origin–destination freight transport volumes

**Table 1**
Overview on approaches to model charging infrastructure from a data perspective.

| | Node-based | Path-based | Tour-based |
|---|---|---|---|
| **Methods** | • set covering (SCLM)<br>• (Toregas et al., 1971)<br>• maximum covering (MCLM) (Church and ReVelle, 1974)<br>• p-median<br>• (Hakimi, 1964)<br>• heuristics / simulations | • flow capturing (FCLM)<br>• (Hodgson, 1990)<br>• flow refueling (FRLM)<br>• (Kuby and Lim, 2005)<br>• heuristics / simulations | • Similar to node-based or path-based approaches, SCLM, MCLM, p-Median, FCLM, and FRLM can be used<br>• heuristics / simulations |
| **Draft** |  |   |   |
| **Data** | • traffic count data at nodes<br>• transports statistics for<br>• calibration / scaling | • traffic flow at paths<br>• transports statistics for calibration / scaling | • traffic flow at tours (driver's logs or GPS))<br>• transports statistics for calibration / scaling |
| **Effort** |   | | |
| **Truck literature** | • Speth et al. (2022b) used node-based data and a heuristic to model a charging infrastructure for electric trucks in Germany<br>• Speth et al. (2022c) used node-based data and a heuristic to model a charging infrastructure for electric trucks in Europe | • Rose et al. (2020) used 2,655 paths and an capacitated FRLM to model a refueling network for fuel cell electric trucks in Germany<br>• Shoman et al. (2023) used European truck traffic flows to simulate a charging infrastructure network<br>• Menter et al. (2023) used a subsample of European truck traffic flows to simulate a German truck traffic charging infrastructure network | • Whitehead et al. (2021) used GPS data from eight million vehicle trips and an MCLM to define charging locations for short-haul electric trucks in South East Queensland |

were converted to origin–destination heavy-duty truck flows, and (3) the truck flows were allocated to an updated European road network using Dijkstra's algorithm. Finally, a forecast for 2030 was added. For more details, please refer to Speth et al. (2022d).

For our calculation, we use the 2030 forecast of Speth et al. (2022d). The dataset contains 1.5 million directed heavy-duty truck traffic flows between 1,675 NUTS3 regions[1] in Europe. Traffic flows within a NUTS3-region are not considered. In accordance with Speth et al. (2022b), we assume that trucks drive on average 300 km during one driving period of 4.5 h. Traffic flows shorter than 300 km therefore do not need to be publicly recharged and are therefore not relevant. Across Europe, 1.4 million flows with a total of 172 billion kilometers travelled remain. Of these, around 1 million flows with 72 billion vehicles kilometers travelled pass Germany. In order to keep the optimizations problems solvable, we focus on flows that are served at least weekly (>50 trucks/a). For Europe, we thus reduce the problem to 374,000 flows and 156 billion kilometers travelled. For Germany, we receive 236,000 flows and 61 billion kilometers travelled. By following the idea of Jochem et al. (2019), we have significantly reduced the problem size, while still considering more than 85 % of the vehicles' kilometers travelled. The level of detail is also well above Rose et al. (2020), who considered 2,655 flows in Germany.

In this paper, the available parking spaces along German highways serve as capacity constraint as actual charging stations cannot contain more charging spots than parking spots. We use a list with parking areas, typically public rest areas, from the German Autobahn GmbH. The parking areas are assigned to the nearest node in the German road network from Speth et al. (2022d), if the distance is less than 2 km. Multiple parking areas are aggregated at one node. The average aggregated parking area has got 36 parking spaces. But there are also areas with more than 300 parking spaces, as shown in Fig. 1. In total, we identified 689 aggregated parking areas.

The capacity of a charging infrastructure location depends on the maximum number of vehicles that can be served per unit of time. Speth et al. (2022b) show that during the busiest hour of the day, 6 % of daily truck traffic can be expected to pass the charging infrastructure. Therefore, we follow their assumptions and design the charging infrastructure using queuing theory. The charging points are designed so that the typical range of 300 km for 4.5 h can be recharged within 30 min. In addition, an average waiting time

[1] Nomenclature des unités territoriales statistiques.

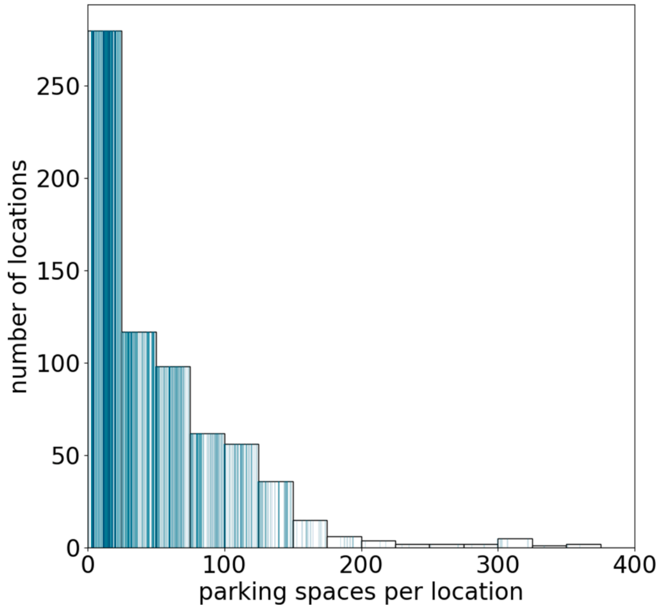



**Fig. 1.** Aggregated parking spaces at nodes of the German highway network, based on data from Autobahn GmbH. Color intensity indicates the distribution within the bins.

of 5 min is accepted. This means that the mandatory break of 45 min after 4.5 h of driving can be used for public recharging. On average, this requires a charging power of 720 kW per truck; the peak power is even higher (Speth et al., 2022b). A simplified assumption of approximately 1 MW peak power can be made. The presented charging infrastructure thus corresponds to the planned Megawatt Charging System (MCS), which is currently being tested (HoLa, 2021). To show the challenges of battery electric trucking and its infrastructure, a 100 % electrified fleet is assumed, similar to Rose et al. (2020). Table 2 sums up the most important parameters.

The geographical focus of the case study is Germany. However, since truck traffic is international, we first calculate a Europe-wide network without a capacity restriction. In our case, Europe refers to the 27 countries of the EU as well as the United Kingdom, Switzerland and Norway. For international origin–destination-paths, the results from the first step serve as the minimum available infrastructure outside Germany and can be used by the vehicles. Afterwards, we calculate a German charging network with capacity constraints.

### 2.2. Model description

To model a capacity-constrained high-power fast charging network for trucks in Germany including international traffic, we use a two-step approach. First, we calculate a European network without a capacity restriction. On the one hand, this network serves as the minimum usable infrastructure for international transports outside Germany. This is essential, as otherwise the infrastructure in the transit country Germany is overestimated. On the other hand, it represents a benchmark for Germany, to be able to assess the impact of the capacity restriction. Second, we calculate a new formulation of a CFRLM for Germany. Both steps as well as the related details are presented in the following.

#### 2.2.1. Problem formulation FRLM

With regard to the FRLM without capacity restriction, we follow the approach presented in Capar et al. (2013). Whenever necessary, we slightly adjust the assumptions by Capar et al. (2013) and add additional assumptions. Substantively adjusted assumptions are printed in italics:

1. Traffic between an origin–destination pair follows a single path from the center of the origin area to the center of the destination area.
2. The traffic volume for every single origin–destination path is known in advance.
3. Drivers have full knowledge of locations of charging stations along the path and recharge efficiently *to complete a single trip*.
4. Only nodes of the network are considered as possible locations of charging stations.
5. All trucks have similar driving ranges.
6. The fuel consumption is directly proportional to the distance travelled.
7. All potential recharging stations are uncapacitated.
8. *Each truck starts the trip fully charged and can be recharged at the destination.*

**Table 2**
General parameters, based on Speth et al. (2022b).

| Parameter | Abbreviation | Value |
|---|---|---|
| Electric energy demand | $cons_e$ | 1.2 kWh/km |
| Range in 4.5 h | $range_{BET}$ | 300 km |
| Share of daily charging events in peak hour | $s_{peakhour}$ | 6 % |
| Average charging time | $t_{charging}$ | 30 min |
| Average waiting time | $t_{waiting}$ | 5 min |
| Average charging power to recharge 300 km in 0.5 h | $p_{average}$ | 720 kW |
| Peak charging power | $p_{peak}$ | 1,000 kW |
| Share of battery electric trucking | $BET_{share}$ | 100 %[a] |

[a] The traffic volume considered corresponds to a forecast for 2030 and reflects currents developments. Full electrification is not expected in 2030, but rather in 2045. Since future traffic volume depends in fundamental decisions, such as the share of rails transport, current trends were not extrapolated beyond 2030.

The first assumption corresponds to the original model. As suggested by Capar et al. (2013), we use the shortest paths provided by Speth et al. (2022d). Since only the ETISplus road network is modeled, the proposed travel distances to and from the center of the origin and destination region are also considered. The second assumption also corresponds to the original model. As indicated by the third assumption, we assume a vehicle to complete a single trip instead of a round trip. As explained in Rose et al. (2020), a single trip better characterizes truck driving behavior than the originally assumed round trip. Assumption 4 also follows the original problem formulation, even if this is a simplified representation of reality. However, identifying real parking locations across Europe would be very complex. The following assumptions 5–7 are also taken from the original model. As indicated by Rose et al. (2020), waiving the assumption of a roundtrip requires an assumption regarding the charging behavior at the origin and destination of the trips. As indicated by assumption 8, we expect that charging infrastructure is available at every depot and therefore we consider that trucks can be fully charged at the origin and the destination. This also implies that trips with a distance shorter than the vehicle range do not have to be considered. The formulation of the uncapacitated FRLM reads (Capar et al., 2013; Rose et al., 2020):

$$\min \sum_{i \in N} z_i \tag{1}$$

s.t.

$$\sum\nolimits_{i \in K_{i,j}^q} z_i \geq y_q, \forall q \in Q, a_{j,k} \in A_q \tag{2}$$

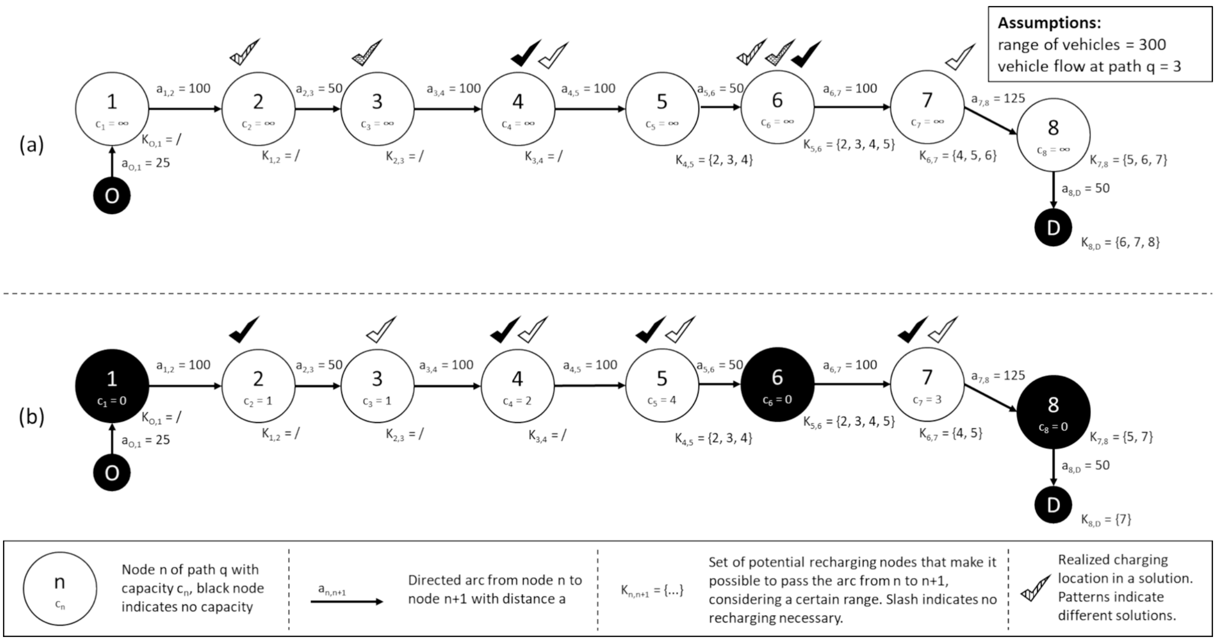



**Fig. 2.** Illustration of an origin–destination path with (b) and without (a) a capacity restriction.

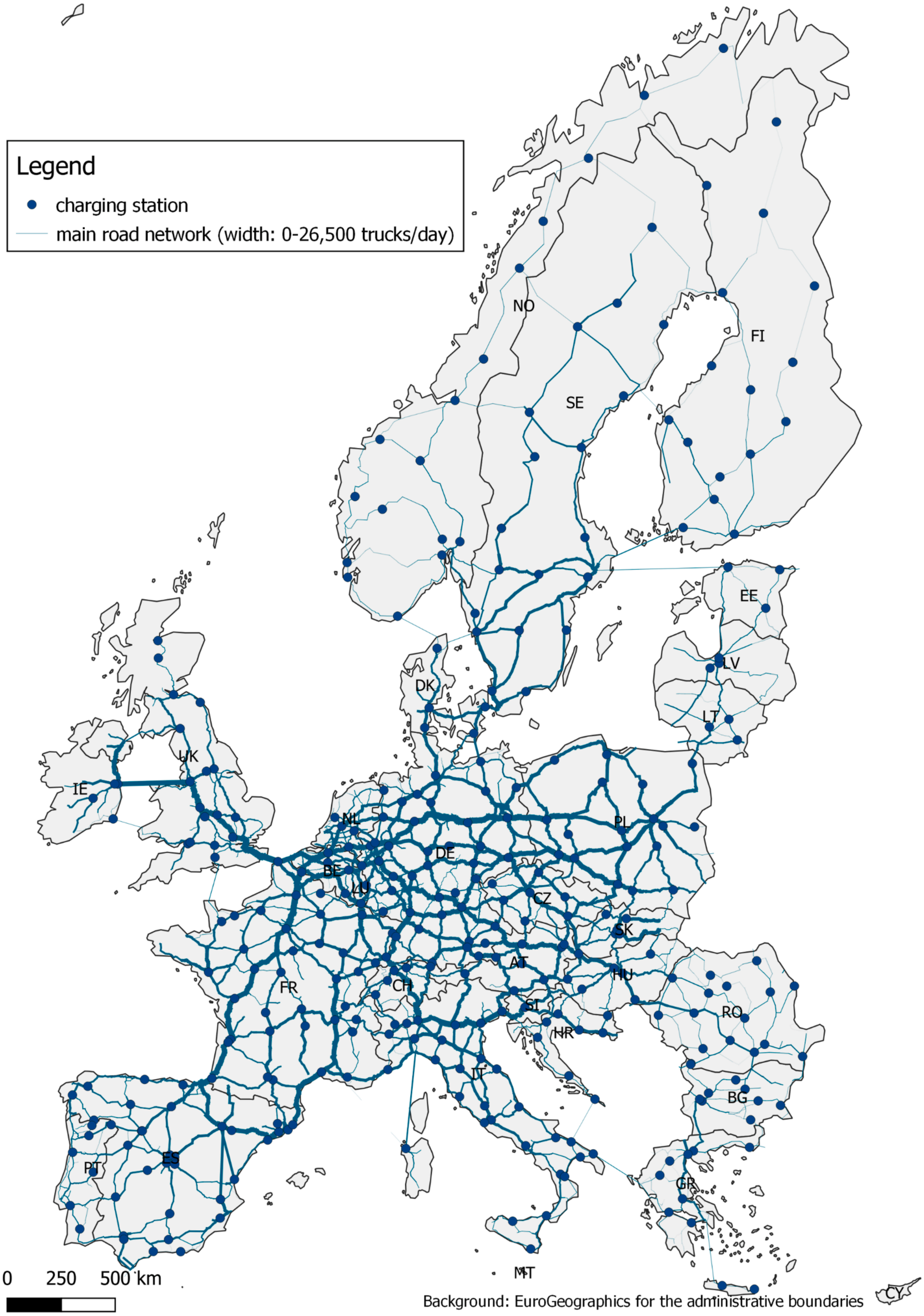



Fig. 3. Europe-wide charging network with 339 charging stations, based on FRLM.

$$\sum_{q \in Q} f_q y_q \geq s \sum_{q \in Q} f_q \tag{3}$$

$$y_q, z_i \in \{0, 1\}, \forall q \in Q, i \in N \tag{4}$$

| | |
|---|---|
| **Sets and indexes** | |
| $A_q$ | Set of all directional arcs on a shortest path $q$, sorted from the origin to the destination |
| $K_{i,j}^q$ | Set of all potential nodes that can refuel the arc $a_{j,k}$ in $A_q$ |
| $N$ | Set of all nodes in the modelled network |
| $Q$ | Set of all origin–destination pairs |
| $i, j, k$ | Indices, indicating nodes |
| $q$ | Index of origin–destination pairs |
| $a_{j,k}$ | Index of a directed arc from node $j$ to node $k$ |
| **Parameters** | |
| $f_q$ | Vehicle flow at path $q$ |
| $s$ | Share of recharged vehicle flows, in our modelling always 1 |
| **Decision variables** | |
| $y_q$ | $=1$ if the flow on path $q$ is recharged, 0 otherwise |
| $z_i$ | $=1$ if a charging station is built at node $i$, 0 otherwise |

Equation (1) formulates the objective to minimize the number of charging stations ($z_i$) at all nodes $i$ in the network. The constraint in Equation (2) ensures that a path can only be recharged ($y_q = 1$) if there is a charging infrastructure for each arc in the path ($a_{j,k}$) that makes it possible to pass the arc. For this, a candidate set ($K_{i,j}^q$) is calculated for each arc ($a_{j,k}$) of a trip ($q$). As an example, this is shown in Fig. 2: For example, assuming a range of 300 km, the arc $a_{4,5}$ can only be passed, if a charging station is established at one of the nodes 2, 3, or 4 ($K_{4,5}^{example}$={2, 3, 4}). Equation (3) ensures that a certain share ($s$) of all vehicles flows ($f_q$) can be realized. For our purpose, we always assume that all paths must be realized.[2] As shown in Fig. 2a, four possible solutions exist for the example path, each with two stations to be built. Which solution is realized depends on which potential stations are also located favorably for other paths.

### *2.2.2. Problem formulation CFRLM*

In the following, we present the CFRLM we use to calculate the German charging infrastructure network. First, we introduce the new assumptions. Afterwards, we present the mixed-integer optimization problem (MIP). Finally, we explain the model using an example path and address special effects.

Assumptions 1, 2, 3, 5, 6 and 8 remain unchanged and are consistent with the assumptions of the FRLM in section 2.2.1. Adjustments to assumptions 4 and 7 introduce the capacity constraint. Thereby, each node in the road network receives a capacity limit. The new formulation is shown in the following:

4. Only nodes with an assigned parking capacity are considered as locations of potential charging stations.
7. *All potential recharging stations are capacitated.*

$$\min \sum_{i \in N} z_i \tag{5}$$

s.t.

$$\sum_{i \in K_{i,j}^{q_s}} x_{i_{q_s}} \geq 1, \forall q_s \in Q, a_{j,k} \in A_{q_s} \tag{6}$$

$$\sum_{q_s \in Q} f_{q_s} x_{i_{q_s}} \leq c_i z_i, \forall i \in N \tag{7}$$

$$\sum_{i \in N} x_{i_{q_s}} \leq l_{q_s}, \forall q_s \in Q \tag{8}$$

[2] This means $y_q = 1 \forall q \in Q$. Thus equation (3) can be omitted and equation (2) becomes $\sum_{i \in K_{i,j}^q} z_i \geq 1 \forall q \in Q, a_{j,k} \in A_q$. However, we have decided to keep the formulation from the literature for comprehensibility.

$$x_{q_s}, z_i \in \{0,1\}, \forall q_s \in Q, i \in N \tag{9}$$

| | |
|---|---|
| **Sets and indexes** | |
| $A_{q_s}$ | Set of all directional arcs on a shortest path $q_s$, sorted from the origin to the destination |
| $K_{i,j}^{q_s}$ | Set of all potential nodes that can refuel the arc $a_{j,k}$ in $A_{q_s}$ |
| $N$ | Set of all nodes in the modelled network |
| $Q$ | Set of all origin–destination pairs |
| $i,j,k$ | Indices, indicating nodes |
| $q_s$ | Index of origin–destination pairs. Extended to identical origin–destination pairs for each subset. Flows are split, if the vehicle flow exceeds the capacity of a single parking space. |
| $s$ | Index, indicating a subset of a path $q$ |
| $a_{j,k}$ | Index of a directed arc from node $j$ to node $k$ |
| **Parameters** | |
| $f_{q_s}$ | Vehicle flow at path $q_s$ |
| $c_i$ | Capacity restriction in node $i$ |
| $l_{q_s}$ | Number of maximum stops to drive path $q_s$ |
| **Decision variables** | |
| $x_{i_{q_s}}$ | =1 if the flow on path $q_s$ is recharged at node $i$, 0 otherwise |
| $z_i$ | =1 if a charging station is built at node $i$, 0 otherwise |

Again, the objective function (Equation (5)) minimizes the number of charging stations ($z_i$). As described by Upchurch et al. (2009) and Böhle (2021), it is not sufficient for the capacity-constrained infrastructure to ensure that every arc on a path can be travelled (Equation (2)). Instead, it must be determined which vehicle uses which charging location. Therefore, the bivariate parameter $x_{i_{q_s}}$ indicates, if the path $q_s$ is recharged at node $i$. Equation (6) ensures that each arc if a path is drivable by requiring the path's vehicles to recharge at least at one candidate set location. Similar to the FRLM and as shown in Fig. 2(b), the Candidate sets $K_{i,j}^{q_s}$ contain all nodes that make an arc drivable, as long as the node is a suitable charging location. The hourly maximum number of vehicles that can be served at node $i$ ($c_i$) is calculated using queuing theory based on the methodology presented in Speth et al. (2022b) and with assumptions given in 2.1. A short description can be found in Appendix A. Equation (7) ensure that no more vehicles charge at a node $i$ per hour than the capacity $c_i$ allows. In addition, charging is only possible if a location is opened in node $i$ ($z_i = 1$). Equation (8) limits the maximum number of charging stops on one origin–destination-tour. As shown in Fig. 2b, capacity constraints may necessitate additional stops. In the example, all vehicles need to recharge in node 7 to reach the destination. Node 7 can be reached by recharging either in node 4 or in node 5. Since the capacity in node 4 is not sufficient for all vehicles, some vehicles must recharge in node 5 and therefore need to stop in either node 2 or node 3 to reach node 5. This means that some vehicles have to stop three times to cover 700 km, although they have a range of 300 km and start with a fully charged battery. Therefore, we allow one additional stop and calculate the maximum number of stops $l_{q_s}$ according to Equation (10).

$$l_{q_s} = \left\lfloor \frac{distance_{q_s}}{range_{BET}} \right\rfloor + 1 \forall (q_s \in Q) \cap (distance_{q_s} > range_{BET}) \tag{10}$$

$l_{q_s}$ Number of maximum stops to drive path $q_s$
$distance_{q_s}$ Length of path $q_s$
$range_{BET}$ Vehicle range within one driving session of 4.5 h

Due to the increased computational effort and the incomplete Europe-wide data on available parking capacities, the CFRLM is restricted to Germany. This means that paths are considered, if their distance is longer than the assumed minimum range of 300 km and if they are driven at least partially in Germany. For cross-border traffic, we assume that vehicles can use the foreign charging stations calculated by the FRLM. Thus, the origin of the path is the last charging station before the border, and the destination is the next charging station after the border.

To solve the problems, we use a server with 196 GB RAM and 8 cores. The implementation is done in Python 3.10, integrating CPLEX 12.6 via Pyomo.

## 3. Results

In the following, we present the results of the FRLM for Europe (chapter 3.1) and the results of the CFRLM for Germany (chapter 3.2). For the CFRLM results, we address the actual locations, the required charging points and the recharged amount of electricity. Additionally, we evaluate the suitability of the identified German charging stations for an early market phase in chapter.

### 3.1. European charging infrastructure (FRLM)

Fig. 3 shows the distribution of 339 charging stations in Europe, according to the FRLM. Especially along road with few junctions, for example Norway or Sweden, charging stations are placed at the maximum possible distance of 300 km. To serve traffic of several streets with one station, stations are often built at intersections. For every road section in the updated ETISplus dataset, the average daily traffic volume of the relevant origin–destination paths (>300 km, >= 50 trucks/a) is plotted in the background. It can be clearly seen that the traffic volume does not affect the charging infrastructure density. Highly trafficked routes, for example from North Spain via France to Belgium, also have charging stations with about 300 km distance. The number of charging stations required per country is thus essentially defined by the density of the road network. Appendix B shows the number of charging stations per country. Germany has 42 charging locations in the optimized network without capacity restriction. The charging infrastructure outside Germany serve as input for the modeling of cross-border traffic in the CFRLM for Germany. For example, there is a charging station in the south of Denmark. Therefore, even in the capacity-constrained case, charging infrastructure in Germany will not be built directly across the border. The next station will be located near Hamburg in both the FRLM and the CFRLM.

In order to maintain a reasonable computation time, the presented solution of the FRLM accepts a maximum tolerance of the MIP of 5 %. This means the optimal solution could theoretically be 323 charging stations.

### 3.2. German charging infrastructure (CFRLM)

Fig. 5 shows the distribution of 124 charging stations in Germany, according to the CFRLM. To keep the computation time reasonable, the solver tolerance is set to 15 %. Using IBM CPLEX on a virtual machine with 8 processors (AMD EPYC 7742) and 256 GB RAM, the computation time is still several days. The theoretically possible best solution would therefore be 106 charging stations. This shows the importance of the capacity restriction. Even if the theoretical lower bound could be reached, 2.5 times as many stations as in the FRLM without capacity restriction would be needed. In the networks shown, the demand triples.

Despite the capacity restriction, minimizing the number of charging stations in total still results in large locations. As shown in Fig. 4a, stations with up to 334 charging points are being built. In total, 12,323 charging points are needed. On average, this corresponds to 99 charging points per location. The median amounts to 83 charging points per location. Fig. 4b indicates that the individual stations are typically almost fully developed, meaning that almost every available parking space receives a charging point.

Similar to Fig. 3, Fig. 5 also shows the local traffic volume in the background. Comparison shows that the CFRLM does not distribute stations evenly, but places large stations with close distance along highly trafficked long-haul routes. A good example is the transit route from the Netherlands – via Essen, Hanover, passing Berlin – to Poland. As part of this route, the German highway A2, connects major European ports (Amsterdam, Rotterdam and Antwerp) to Eastern Europe.

The assignment of individual charging events to charging stations in the CFRLM allows an evaluation of the utilization of the infrastructure. As shown in Fig. 6a, the average charging station is occupied 43 % of the day. The utilization rate is lower for smaller stations, since fluctuations in the arrival rate have stronger influence and make oversizing necesarry. Since the trucks usually do not need to charge at the maximum power of 1 MW, the energetic utilization is lower than the temporal utilization. As shown in Fig. 6b, the average charging station provides 19 % of the theoretically maximum possible amount of energy.

Finally, we briefly present the amounts of energy required. At vehicle level, an average of 263 kWh is recharged per charging stop (median = 282 kWh). This corresponds to a range of 218 km (median = 235 km). As shown in Fig. 7a, there are charging events that nearly exhaust the demand of 360 kWh resulting from the maximum range of 300 km. However, other stops are made after short driving distances and result in low charging demands. Nevertheless, they are necessary to make paths drivable. In total, trucks charge 25 TWh annually at the modeled infrastructure. Fig. 7b shows that large station account for more than 0.6 TWh per year.

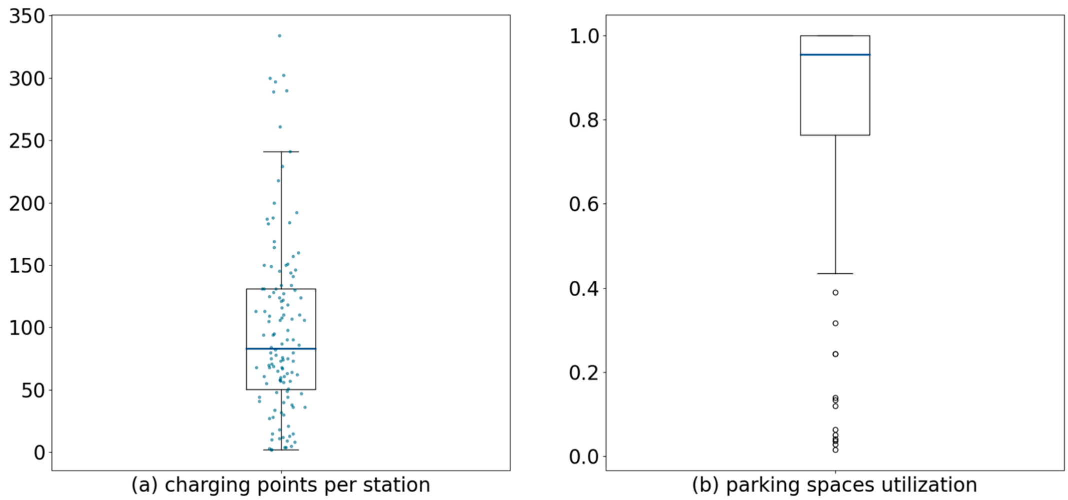



**Fig. 4.** (a) Number of charging points per station in the CFRLM and (b) utilization of available parking spaces at parking areas where a charging station is installed. Both panels for 100% share of battery electric trucking.

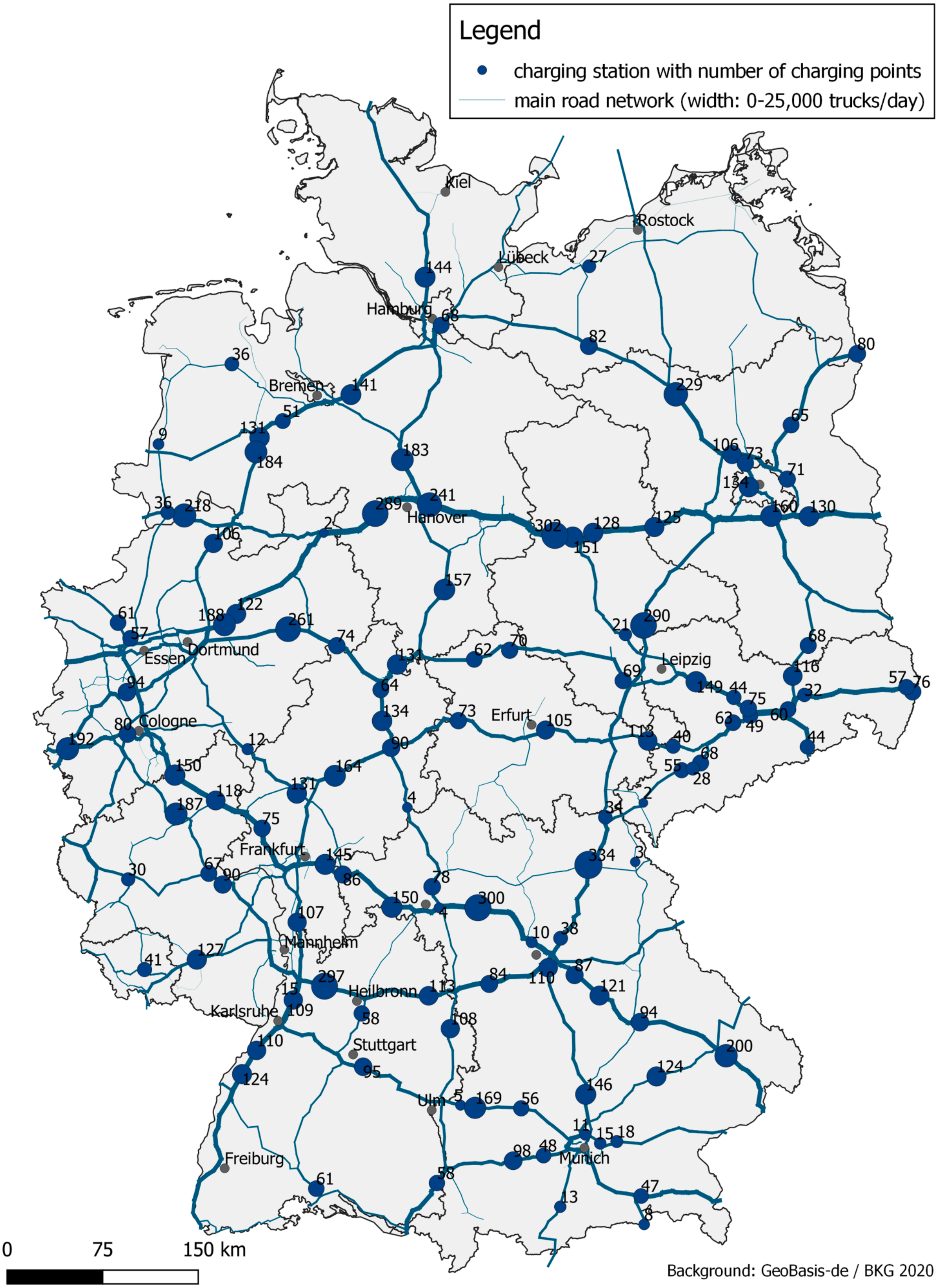



**Fig. 5.** German charging network with 124 charging stations, based on CFRLM.

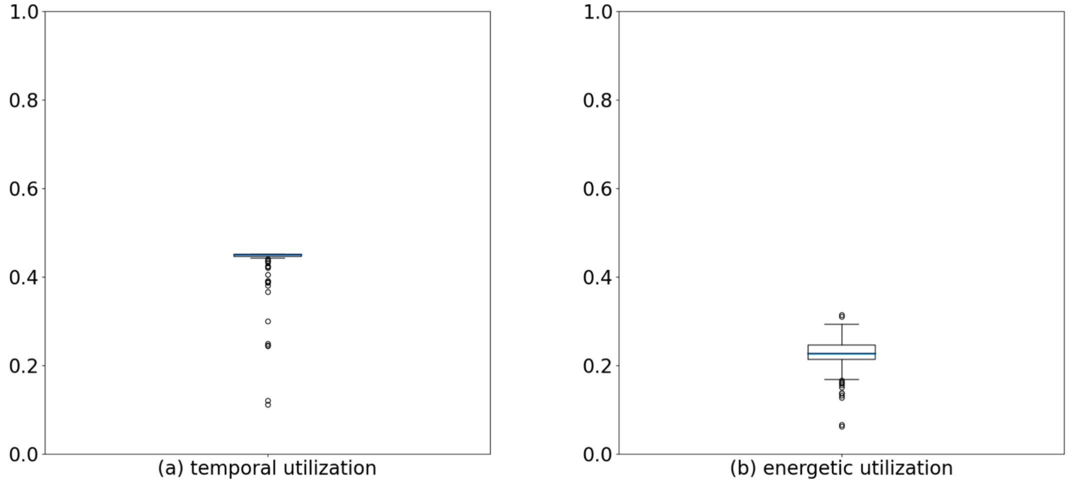



**Fig. 6.** (a) temporal and (b) energetic utilization of charging stations.

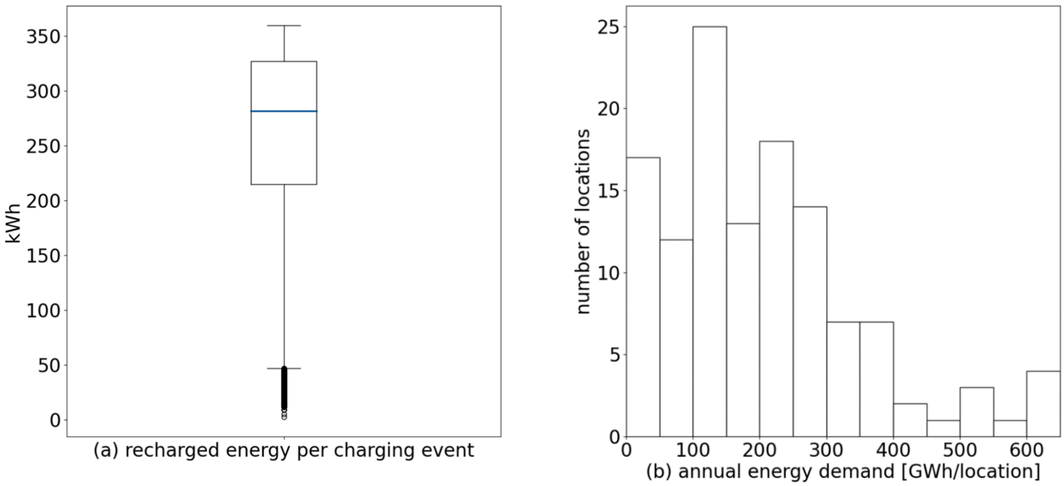



**Fig. 7.** (a) recharged energy per charging event and (b) annual energy demand of charging stations.

### *3.3. Suitability of identified German charging locations in an early market phase with limited grid connection*

The scenario presented in chapter 3.2 assumes a full conversion of heavy-duty truck traffic to BET. As indicated by Kippelt et al. (2022), it can take up to 10 years to install a new high-voltage grid connection with a newly built substation in Germany. Such a grid connection would be needed to supply more than 30 MVA. Assuming a power factor for reactive current of 0.95, an efficiency of 0.95, and a simultaneity factor of 0.6 – known from light-duty vehicles charging –, more than 30 MVA are needed to serve more than 45 megawatt charging points at one location (own calculation, based on Kippelt et al. (2022) and Burges and Kippelt (2021)). In the short to medium term, for example by 2030, integration into an existing medium-voltage substation with up to 20 MVA will be the main option at many locations (Kippelt et al., 2022). We therefore ran additional optimization models with tightened capacity restriction to the minimum of the local parking spaces and a maximum of 30 charging points at each location. We checked whether the stations identified in chapter 3.2 are sufficient to supply 15 % share of battery electric trucking – a likely electrification rate for 2030 (Breed et al., 2021; Speth et al., 2022b): The results show that the identified stations (n = 124) are sufficient to supply the vehicles. An average of 16 charging points per stations is required (mean = 16.4, median = 16, minimum = 2, maximum = 30, σ = 9.0). In total, 2,032 charging points are required. A possible distribution of charging points to charging stations is given in Fig. 8a. Fig. 8b shows the parking space utilization of the charging stations. On average, 17 % of all available parking spaces at a location that is used as a charging station need to be equipped with fast charging infrastructure (mean = 0.17, median = 0.15, minimum = 0.02, maximum = 0.77, σ = 0.13). Please note that this is only one possible solution, other distributions of charging points to charging stations are also possible. In total, 3.8 TWh would be publicly recharged each year.

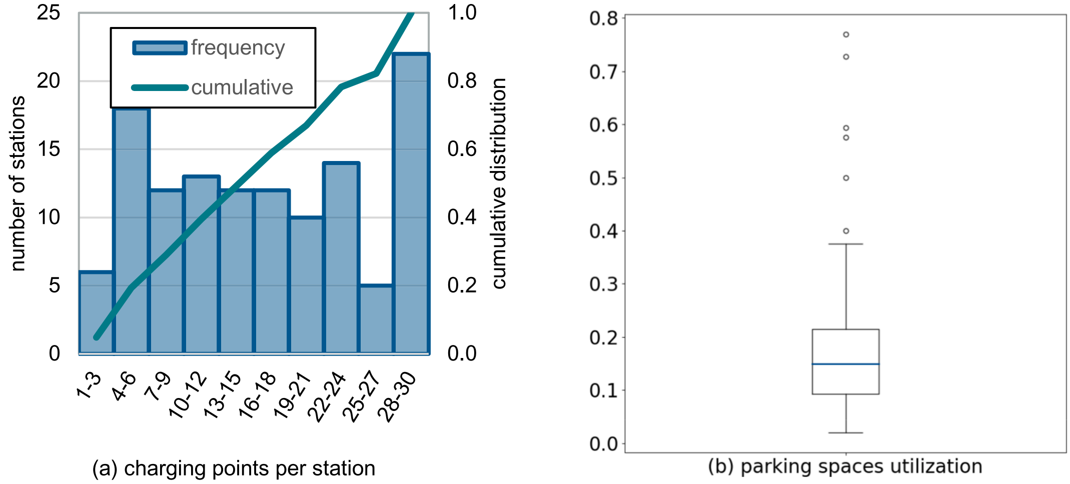



**Fig. 8.** (a) Frequency distribution of the number of charging points per station and (b) utilization of available parking spaces at parking areas where a charging station is installed. Both panels for 15% share of battery electric trucking.

## 4. Discussion

To the best of the authors' knowledge, this paper is the first to apply a capacity-constrained FRLM (CFRLM) to a dataset with more than 200,000 traffic flows and real-world parking capacities for the first time. The results show that the capacity constraint more than doubles the required number of charging stations compared to a traditional FRLM. Furthermore, the distinct assignment of each charging event to one charging station allows additional evaluations regarding the amount of energy required locally. However, the results presented here are also dependent on methodological framework conditions and the data we used. Therefore, these will be discussed in more detail.

The literature review shows that optimization methods are very popular for location planning from a methodological point of view. However, the optimality of the solution often comes with significant simplifications, to keep the problem solvable. The multiplication of required charging locations by the introduction of a capacity constraint shows that the result of an uncapacitated, large-scale FRLM are of limited relevance in practical applications. However, this additional accuracy comes with a significant additional computational effort – in our case several days.

Another methodological aspect is the integration of cross-border traffic. Unlike previous studies, cross-border traffic is integrated into the model in high resolution. Yet, the assumption of charging events at charging stations of the unrestricted FRLM in foreign countries is a simplification. The simplification results in less stations being built in the border area. More restrictive assumptions could further improve the results.

Finally, minimizing the number of charging stations results in a solution that includes few but large stations. In our case, the objective function was chosen to keep CFRLM and FRLM comparable. Future studies could focus even more on real-world relevance. On the one hand, this can be done by adapting the objective, for example by integrating a cost function. On the other hand, additional restrictions, for example restrictions derived from the power grid, could also be considered. Furthermore, one should note that many local details such as grid operator, landowner, existing car charging etc. will impact the decision to build truck charging at a given location. However, these additional costs aspects are generally not available for all locations and their inclusion goes beyond the scope of the present paper. However, the method presented here could easily integrate difference in local costs as the target function (minimize the total number of stations covering a given flow) can be expanded to include local weights (minimize the total weighted number of stations covering a given flow).

In terms of the data used, the origin–destination flows we use represent a broad database. However, they are also a simplification, as shown by Speth et al. (2022d). They do not represent driving profiles. This means that a trip with multiple stops is reflected as multiple independent paths. The charging behavior may differ as a result. Especially, long parking periods cannot be distinguished from short parking periods. Therefore, we modelled all public charging events as fast charging events. However, this leads to an overestimation of the fast-charging infrastructure demand. If available, future studies could build on extensive real-world driving profiles including time stamps. We covered 85 % of the traffic volume in the dataset. But we had to ignore some flows with a low traffic volume to keep the problem solvable. However, in their German section, these flows typically correspond to other flows included in the analysis. So, in principle, they are drivable. Due to their low traffic volume, they would have only a minor impact on the infrastructure. Yet, future analyses may converge parallel flows to include them.

The assumed range represents a central parameter, which is conservatively estimated at 300 km. Increasing the range would reduce the need for charging infrastructure. Additionally, we assumed that vehicles travelling less than 300 km can charge at their home depot. As stated by Speth and Plötz (2024), depot charging for trucks can reduce the public energy demand by approximately 80 %. However, if depot charging is not available, the public charging demand will increase significantly. Future research could further elaborate on this.

Finally, the optimization approach benefits from the low requirements regarding additional assumptions. Thus, in contrast to the heurist presented in Speth et al. (2022b), no assumptions on the share of public charging are needed. The model used there indicates lower infrastructure needs compared to the analysis in this paper, which – however – strongly depends on the assumptions made.

As the computational requirements of CFRLM are significant, future research could also test other optimization approaches for capacity constrained recharging networks such as machine learning or evolutionary optimization algorithms. However, in the present study, we followed the broad academic literature on this existing topic and extended the standard existing methods to meet actual and new constraints for battery electric trucks.

## 5. Summary & Conclusions

The aim of the present paper is to design a capacity-constrained high-power fast charging network for BET in Germany. In summary, the capacity-constrained CFRLM used in this paper builds on existing optimization charging infrastructure modeling approaches. However, the introduced capacity constraint clearly further develops the model to make the results more realistic. The shown tripling of required charging stations compared to the non-capacity-constrained case highlights this. At the same time, this additional degree of realism involves considerable computational effort, especially for large-scale applications.

In terms of content, the study shows that a total conversion of road-based freight transport in Germany comes with high requirements for a public charging infrastructure. With the assumptions chosen in this study, 124 charging stations with approximately 12,000 charging points were identified to fully electrify truck traffic in Germany. As explained in section 4, the assumptions regarding the vehicle range and the possibility of slow charging are worst-case estimates. Higher energy consumption, for example in adverse weather conditions, could be compensated for by larger batteries, taking into account the manufacturer's announcements of well over 600 km range by 2030 (NOW, 2023). The range of 300 km used in our calculations is a regulatory assumption, which – conservatively estimated – arises from the drivers' mandatory breaks. Higher consumption would lead to a higher energy demand and larger batteries. However, it can be assumed that the charging time will remain constant, as larger batteries and the MCS standard will allow a higher charging power over a longer period of time. All in all, the energy demand and the average charging power would increase, while the total number of charging points would remain constant. Therefore, the requirement of 12,000 fast charging points should be interpreted as an upper bound. Nevertheless, the findings result in requirements for various stakeholders. Policymakers should develop overall concepts for the electrification of road freight transport. Energy suppliers must consider the additional energy and power demand in their infrastructure planning. This relates especially to electricity network expansion planning.

The analysis presented in this paper offers scope for further research activities. From a methodological point of view, a systematic comparison of different modeling approaches on a common case study could provide further insights into the necessary complexity of modeling. Node-based, path-based and tour-based approaches as well as optimization, heuristics and simulation could be compared. With respect to the CFRLM, additional framework assumptions, such as cost curves for charging infrastructure or power system constraints, could provide additional insights. In terms of data, switching from origin-destination-flows to tour-based data with actual time stamps could further improve the model results.

## CRediT authorship contribution statement

**Daniel Speth:** Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patrick Plötz:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Martin Wietschel:** Writing – review & editing, Supervision, Funding acquisition.

## 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.

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## Appendix A:. Queuing model

The following is based on Speth et al. (2022b).

We convert the available parking spaces at one location into vehicles that can be served per hour. The calculation is based on the queuing theory. To define the queuing system, we use the Kendall notation (A/S/c/d/k/m).

The arrival process A is defined by Poisson-distributed arrivals (Gnann et al., 2018). We assume the following arrival rate for the peak hour: $\lambda = traffic_{daily} * s_{peakhour}$ with $s_{peakhour} = 0.06$. The inter-arrival times are therefore exponentially distributed (Markovian

Distribution M). This means A = M.

Gnann et al. (2018) show that the service process S can be approximated with a General distribution with normally distributed service times. This means S = G. The average number of vehicles that can be served per hour $\mu$ is defined by the average charging time $t_{charging}$. For example, an average charging time of 30 min means that on average 2 vehicles can be served every hour ($\mu = 2trucks/hour$).

The maximum possible number of service units c – or in our case of charging points – is determined by the number of parking spaces available at the location.

The parameters d, k and m remain at their default values. We implement the First-In-First-Out principle as queue discipline d. The number of trucks waiting in the queue can be infinite. This means k is assumed to be infinite. The total amount of vehicles served m is also assumed to be infinite.

To sum this up, we calculate an M/G/c queuing system. Unfortunately, there is no exact solution for such a system. Following Funke (2018), the M/G/c system can be determined approximately using the following: $W_q^{M|G|c} = \frac{C^2+1}{2} W_q^{M|M|c}$. C represents the variation coefficient of the service time. We assume a standard deviation of 5 min and a mean service time of 30 min. This means C = (5/30).

The average waiting time of the original M/M/c system can be calculated as $W_q^{M|M|c} = \frac{1}{1-\rho}\frac{1}{c\mu}\frac{(c\rho)^c}{c!}\left((1-\rho)\sum_{n=0}^{c-1}\frac{(c\rho)^n}{n!}+\frac{(c\rho)^c}{c!}\right)^{-1} with p = \frac{\lambda}{c\mu}$. Given an average waiting time of $t_{waiting} = 5min$, the average arrival rate $\lambda$ can be calculated. This allows the maximum possible arrival rate to be determined for any given number of parking spaces.

## Appendix B:. Charging stations per country in the FRLM

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**Table 3**
Charging stations per country in the FRLM, used as input for the CFRLM.

| Country | Country code | Number of stations |
|---|---|---|
| Austria | AT | 8 |
| Belgium | BE | 4 |
| Bulgaria | BG | 10 |
| Croatia | HR | 8 |
| Cyprus | CY | 0 |
| Czech Republic | CZ | 7 |
| Denmark | DK | 5 |
| Spain | ES | 33 |
| Estonia | EE | 3 |
| Finland | FI | 16 |
| France | FR | 39 |
| Germany | DE | 42 |
| Greece | GR | 10 |
| Hungary | HU | 7 |
| Ireland | IE | 4 |
| Italy | IT | 29 |
| Latvia | LV | 3 |
| Lithuania | LT | 3 |
| Luxemburg | LU | 1 |
| Malta | MT | 0 |
| Norway | NO | 17 |
| Netherlands | NL | 4 |
| Poland | PL | 18 |
| Portugal | PT | 6 |
| Romania | RO | 15 |
| Slovakia | SK | 5 |
| Slovenia | SI | 1 |
| Suisse | CH | 5 |
| Sweden | SE | 19 |
| United Kingdom | UK | 17 |

## Data availability

Data will be made available on request.

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