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# Building Up Demand-Oriented Charging Infrastructure for Electric Vehicles in Germany

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**Abstract**

Mobility offerings have never been as abundant and varied as the present. While users welcome new and innovative mobility options, this current paradigm shift presents a challenge for authorities that plan, organize, and operate such services. In particular, integrating new mobility services into existing infrastructure systems can generate problems of acceptance, co-operability, and compatibility. This problem is especially relevant for electric vehicles. Limited range and battery capacity of battery electric vehicles make them dependent on charging infrastructure, which in turn hinders their acceptance. In light of the German government's goal of one million electric vehicles by 2020, establishing a demand-oriented charging infrastructure is of crucial importance. However, numerous questions remain unanswered regarding the quantity, type, and location of electric vehicle charging stations in Germany. This article presents the findings of the project "LADEN2020: Concept to build up a demand-oriented charging infrastructure in Germany between today and 2020." The research project develops a systematically comprehensible and consistent strategy for electric vehicle charging infrastructure in Germany. The paper presents the methodological framework to estimate the charging demand for daily and long-distance travel, which is unique and innovative as similar comprehensive and consistent analytical tools do not exist to date.


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*Keywords:* Electric vehicles, electric mobility, charging infrastructure, daily travel, long-distance travel, Germany


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## 1. Introduction

In order to mitigate global climate change and reduce urban air pollution, many European countries (*1*), as well as the USA (*2*), China (*3*), and Japan (*4*), advocate for electric vehicle (EV) deployment. In Germany, the federal government aims to have one million electric vehicles – mainly battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) – by 2020 (*7*).

Given that there are three million new vehicle registrations per year in Germany, reaching the goal of one million EVs by 2020 requires that around 7% of all vehicle registrations between now and 2020 are EVs. This high market penetration requires that a large segment of new car buyers, not just early-adopters, opt for EVs (*2*). The successful mass commercialization of EVs requires sufficient charging infrastructure (*6*). This raises the question of how much infrastructure is necessary (*11*). One particular challenge in determining nation-wide charging infrastructure is the dissimilar characteristics of daily travel (DT) and long-distance travel (LD-travel). For DT, repetitive and short distances trips can be met with either one long over-night charge or fast charging during typically daily events (e.g., shopping). For LD-travel, the above charging pattern is not sufficient as charging events must occur during a very short time span.

In this paper, we introduce a new method to determine the number of charging points required for the German case study. Our method focuses on a flexible modelling approach without computational complexity, and aims for a straightforward analysis of a large amount of input data. The method has two separate approaches: one for the daily travel and one for the long-distance travel. In the following section (Section 2) we present a literature review of charging infrastructure planning. Section 3 describes charging infrastructure for daily travel outlining the methodology, data, assumptions, and analysis. Section 4 illustrates the methodology for charging infrastructure planning in long-distance travel. Section 5 summarizes the results of the research, and finally Section 6 presents the conclusions of the paper.

## 2. Literature review

For Germany, the National Platform for Electric-mobility recommends the development of 77,100 public charging points for normal and fast charging to fulfill the requirements of one million EVs (*13*). Alternatively, the European Commission suggests 1.5 million charging points in Germany by 2020, of which 150,000 should be publically accessible charging points (*11*). Funke et al. estimate a need for 15,000 charging points for on-street parkers and 2,000 fast charging stations in 2020 based on a user-need analysis model (*14*). Thus, there is substantial variation in the recommended quantity of charging infrastructure due to differences in analysis methodologies. Existing approaches to establish charging infrastructure use complex mathematical models, such as discrete, graph theory based methods (*15*, *16*), or diverse location models (*17*, *18*).

For the estimation of demand in long-distance travel, available studies also vary from relative simple estimation methods to complex optimization approaches such as capturing models (*29*). In the capturing approaches, a given number of refueling facilities are located such that the total vehicle flows refueled are maximized. These approaches also vary in spatial resolution, which means they cover partly freeway sections, small city-regions, and seldom countries as a whole. The main difficulty of estimation charging demand using capturing models in LD-travel lies in the contradiction that spatially detailed complex models are time and cost inefficient.

## 3. Charging infrastructure – daily travel

### *3.1. Methodology*

Based on the premise that electric mobility will be a mass market by 2020, we assume that EVs will be used similarly to today's relatively new conventional vehicles. Therefore, we utilize actual travel survey data (i.e., vehicle usage profiles, destination information, parking durations) for conventional vehicles to derive charging demand for EVs similar to other research (12). We also design charging infrastructure such that it allows people to charge in situations during which their cars park anyway (e.g., at work or during shopping). Further, we assume that users do not change their activity and travel patterns due to EVs. Rather, they just choose slightly different destinations.

### *3.2. Data and assumptions*

In order to provide an empirical basis for assumptions about charging demand, data from the most recent German National Travel Survey (MiD) from 2008 (*24*) are used. To match travel behavior of EVs in 2020 as closely as possible, vehicles older than six years (about the median age of the German passenger car fleet) were excluded from the analysis. This reduces the sample size of the vehicle data set to 16,419 vehicles. The MID 24-hour person diaries are rearranged into 24-hour vehicle usage profiles representing car use on a typical day.

We examine three major factors, and the resulting six scenarios, influencing infrastructure requirements (see TABLE 1):

- Fleet composition: In order to determine the influence of fleet composition on infrastructure requirements, two alternatives are evaluated: a BEV dominated EV fleet and a PHEV dominated EV fleet.
- Availability of private parking at home: Having a private parking spot at home assumes that the vehicle can be charged at home. The MiD data show that 73% of vehicles have a private parking spot at home. The first scenario evaluated is that only those persons with a parking spot at home purchase an EV (i.e., 100% home parking). The alternative is that 73% of vehicles have a private parking spot at home.
- Availability of on-street charging infrastructure: Curbside charging has a potentially large influence on total infrastructure needs, especially for those without private parking at home. Two scenarios are examined: charging infrastructure is not available for on-street locations at home and at work, and charging infrastructure is available at these locations.

TABLE 1 Scenarios for EV charging infrastructure requirements and the resulting charging points required (distance is to the next available charging point). Charging points are discussed later in the paper. (CI – charging infrastructure)

| **Scenario** | **Fleet composition** | **Home parking** | **On-street CI** | **Charging points (x $10^3$)** ½ km | 1 km |
|---|---|---|---|---|---|
| No. 1 | 2/3 BEV, 1/3 PHEV | 100% | No | 26.5 | 13.3 |
| No. 2 | 1/3 BEV, 2/3 PHEV | 100% | No | 28.6 | 14.7 |
| No. 3 | 2/3 BEV, 1/3 PHEV | 73% | No | 43.2 | 24.7 |
| No. 4 | 1/3 BEV, 2/3 PHEV | 73% | No | 49.8 | 29.5 |
| No. 5 | 2/3 BEV, 1/3 PHEV | 73% | Yes | 136.3 | 94.6 |
| No. 6 | 1/3 BEV, 2/3 PHEV | 73% | Yes | 161.7 | 114.6 |

### *3.3. Analysis*

**Determining charging demand**

In order to evaluate all the scenarios, we generate four hypothetical situations for each vehicle:

- *EV-technology:*
    1) Vehicle is a BEV: It has to cover its entire 24-hour mileage purely using battery energy; if single trip distances exceed the vehicle range, the vehicle stops for fast charging.
    2) Vehicle is a PHEV: On average, PHEVs cover two-thirds of their mileage using battery energy; if single trip distances exceed the vehicle range, the vehicle does not stop for fast charging.
- *Availability of on-street charging infrastructure:*
    a) There is on-street charging infrastructure available on the street at home and work.
    b) There is *no* on-street charging infrastructure available on the street at home and work.

Applying these charging rules to each vehicle for each of the four situations, our algorithm generates a detailed individual charging profile composed of single charging events defined by location/trip purpose, parking classification, charging speed, time of day, and duration. Having determined the charging demand for the 16,419 vehicles in the MiD dataset, we scale up the results for a fleet of one million EVs.

**Determining charging infrastructure**

In order to determine the supply of charging infrastructure, we combine geographic distances between charging points and utilization rates. We assume that charging demand is limited to the settlement and transportation area in Germany (13.5% of the total land area of Germany or 48,241 km$^2$). We idealize this area overlaid with a grid street system. Next, we assume that there is a charging point at each grid intersection. In this idealized situation, the average distance to the next available charging point represents the quality of supply of charging. Superimposing the demand and supply curves gives the number of charging points at the intersections (FIGURE 1). The intersection represents EV infrastructure that is attractive for users (i.e., the utilization rate of charge points minimizes wait times) and efficient (i.e., the utilization rate is not so low that points are underutilized).

### *3.4. Results and discussion*

The resulting EV charging infrastructure demand and supply curves are shown in FIGURE 1.

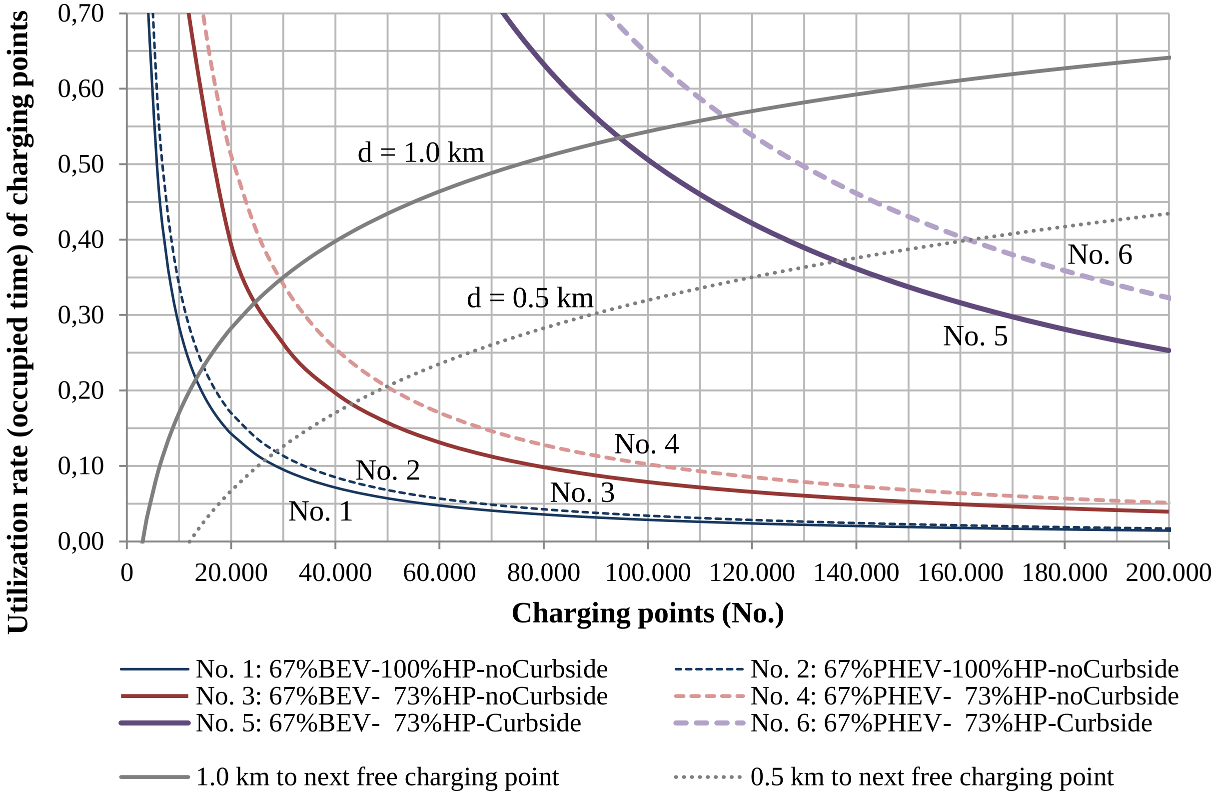


FIGURE 1 Infrastructure demand curves (downward sloping) superimposed with supply curves (upward sloping). Twelve solutions (i.e., intersections) for charging points are found. (HP – home parking, percentage of vehicles that have a private parking spot at home; Curbside – whether or not vehicles can charge on-street outside residential and work locations; d – the average geographic distance between charging points). See TABLE 3 for the results of the six scenarios.

The number of charging points is determined by the intersection of the demand and supply curves. TABLE 1 summarizes the number of charging points for each scenario. There are three factors affecting the demand curves (i.e., fleet composition, home parking, and on-street charging) and one factor affecting the supply curves (i.e., distance to next available charging point). While the exact number of charging points is of importance, the general lessons from the scenario analysis provide decision-makers with critical insights.

First, providing on-street charging in residential areas and at work dramatically increases required charging infrastructure. The reason for this is that cars park much longer than they need to be charged. This results in a charging infrastructure that is blocked much longer than being used efficiently for charging. Second, a high percentage of EVs with a private parking spot at home *notably* decreases the total number of charging stations. The findings show that if only individuals with home parking purchase EVs, charging points decrease between 39 and 51% compared to scenarios with lower home parking availability.

Third, the results illustrate that a larger proportion of PHEVs in the total EV fleet *slightly* increases charging infrastructure. This is due to the fact that the PHEVs are modeled to mainly use their electric engine, which have a lower range than BEVs (i.e., PHEV range – 50 km, BEV range 150km). In addition, PHEVs charged faster than BEVs but remain parked at the charging point, which results in an inefficient use of the infrastructure. Finally, the influence of the supply side shows that decreasing the distance to the next available charging point *markedly* increases the number of charging points.

## 4. Charging infrastructure – long-distance travel

The LD-travel patterns differ from daily travel. The short and repetitive characteristics of daily travel demand require a different approach than the estimation of charging infrastructure for the less frequent LD-travel. For this analysis, we considered only long-distance trips with a trip length of at least 150 km since we assume that BEVs can cover shorter distances without additional charging.

### *4.1. Methodology*

We combined three different methodological approaches for the estimation of EV charging infrastructure in LD-travel:

1. <u>Germany-wide macroscopic transport demand model</u>: We use the VALIDATE model to determine the Germany-wide car travel demand on an average workday on the street network (*30*). According to the assignment results we obtain at least one route with all used nodes and links as geo-referenced points for each assigned origin-destination (O-D) relation. The share of trips by EVs on these routes is also calculated at this step. These routes and their traffic volumes are then imported into Geographical Information System (GIS) software.

2. <u>Modeling in GIS</u>: We calculate the distances between each node on each route based on the list of routes from the VALIDATE model. By doing so, it is possible to measure the distance between the starting node and any other node on the route. This allows us to spatially locate each charging event on the freeway depending on the various ranges of EVs. According to the assumptions of a) the battery range, b) the charging state of the battery at the beginning of the LD-trip, and c) the amount of energy which can be recharged in 30 minutes, for each O-D-relation we display every charging event as a point on the relevant route. Afterwards all these charging events are cumulated along the routes. Thus, the total charging demand

along the routes (in kWh per day respective of number of charging events per day) is summed and mapped.

3. Spatial and temporal differentiation: The temporal distribution of the aggregated charging demand over 24 hours needs to be considered in order to convert the demand into the number of charging spots, since LD-travel demand varies over the day. We define typical temporal demand profiles of LD car trips based on the data of the German Mobility Panel (*31*). Our analyses indicate that the temporal demand profiles of LD trips do not have the typical morning and afternoon peaks, but rather demand is nearly constant between 8:00 a.m. and 6:00 p.m. Subsequently, the temporal distribution of the total demand in terms of densities is modeled using these temporal demand profiles. As a result, the number of charging spots required is determined. Comfort aspects in terms of waiting times while charging are also considered. We develop an analytical approach based on queuing theory assuming certain arrival and service rates to identify which excess charging infrastructure is required to achieve certain comfort levels.

*4.2. Data and assumptions*

The travel demand model VALIDATE contains a Germany-wide attributed digital street network which is comprised of around two million nodes, 120 million links, and 10,200 traffic zones. The model is calibrated with the data of around 70,000 traffic counters. The assignment results in eight million O-D-relations and supplies all necessary information to nodes and links in the form of georeferenced points (around 250 million) with attributes such as “from node,” “to node,” and “traffic volume.”

We assume that the usage of EVs in long-distance travel could be similar to conventional cars, if there is sufficient public charging infrastructure. However, primary survey data on car usage over longer periods for representative car fleets do not exist. Therefore, a model based representation of a conventional car fleet for each day of year is used. CUMILE (Car Usage Model Integrating Long Distance Events) *(32*) models usage patterns (in particular mileages) of a representative car fleet over a full year. The CUMILE model thus provides an essential basis for assigning EVs of different configurations (i.e., PHEV, BEV) in accordance with the interpersonal differing mobility requirements of the owner, and supplies information on the usage intensity and frequency of vehicles in LD-travel.

For the determination of the charging needs in LD-travel, assumptions on fleet composition and share described in section 3.2 are used. In addition, further assumptions regarding the charging time and range are:

- All vehicles have a 100% SOC (state-of-charge) before the journey starts.
- PHEVs drive first in an electric mode, then drive in conventional mode, and charge only when they refuel anyway (assuming after 400 km).
- BEVs recharge first when their SOC is below 20%.

- Only fast charging (i.e., 50 kW, 30-minute charging time and up to 80% SOC) occur. This means that vehicles reach only 60% of a theoretical range after their first charging event (i.e., a BEV with 150 km range will have only 90 km range after the first charge).
- A charging event just before the destination (ca. 20 km) does not take place. It is assumed that the driver will drive straight to their actual destination.

*4.3. Analysis*

**Determining charging demand**

The above methodology consists of three different components. First, the usage patterns of conventional cars in the LD-travel are modeled. This forms the basis for the use of EVs. According to trip length distribution of conventional cars only 1.2% of all trips are more than 150 km. For 1 million EVs, the total number of journeys with EVs is expected to be approximately 2.7 million for one day. Assuming a share of 1.2% of all trips are more than 150 km, around 30,000 EVs would have daily trips greater than 150 km. These rare long-distance events are of considerable importance for the development of a demand-oriented charging infrastructure.

Next, using the CUMILE model, trip length distribution for EVs depending on the first scenario (1/3 BEV, 2/3 PHEV) are calculated. According to this distribution, on an average day about 1% of the BEVs would be travelling between 150 and 200 kilometers. The resulting share of EVs per trip length classes thus constitutes input parameters for the calculation of the charging demand in the network model.

As mentioned, the core of the demand calculation is comprised of a Germany-wide traffic demand model and further processed in GIS. The first step of the analysis in this part is the assignment of demand on road infrastructure. After the assignment process approximately eight million relations have been created. Each relation has information on the actually used routes, which consist of a huge number of nodes and edges. By means of a link based listing of relations, the replication of each individual route at the node level is possible.

Subsequently, the entire listing of routes as nodes and their relevant information (e.g., coordinates of nodes, loads on the links, and length of each route) is exported to GIS. In this step, every single relation and their route selection are reproduced in form of points. The distances between two nodes along a route are then added cumulatively in GIS. Thus it is possible to locate any distance from the origin zone as certain points on the map. This node-following model forms the basis of the calculation procedure of charging demand. First, by means of trip length distributions and share of EVs, the number of relevant trips from each origin zone is calculated. For example, it is known from the trip length distribution in CUMILE model that on an average day 1% of the BEVs travel is between 150 and 200 km. It can be concluded that for each O-D relationship with a distance between 150 and 200 km, 0.0075% of the total demand would be traveled by BEVs (since 1 million EVs corresponds to 2.2% of the entire fleet and BEVs makes up 1/3 of the EV fleet). Afterwards the percentage of EV trips for each OD-relation is calculated as described above.

Next, the number of charging events for individual O-D-relations is determined. As an example we can analyze an O-D-relation of 250 km. Since we assume that charging events of an BEV (range assumption: 150 km) will take place first when the SOC is around 20%, the distance traveled until the first charging event is around 120 km. The second charging event would be around 90 km after first event (the amount recharged between first and second event is just 60% of actual battery capacity). Our BEV has a total of 210 km traveled with one charging event. Since the distance to the destination is more than 20 km, a second charging process must take place. Consequently, the number of all necessary charging events for each O-D-relation is calculated and each event is mapped on the network. Finally, the number of charging events and share of electric trips are multiplied. For each link on the route the total charging demand is calculated and summed. Furthermore, the links on highways are separated into equal parts of 50 km or 100 km. Thus, charging demand is displayed as densities on highways (charging point per 100 km). The mapping of densities allows for detecting different types of highway corridors.

**Determining charging infrastructure demand**

Traffic volume is not evenly distributed on a network, but there are significant and typical temporal patterns. The loads on weekdays, on weekends, in the morning, midday, and evening hours vary. This temporal variation in demand creates a heavy burden on the transport network. Moreover, these temporal variations play a crucial role by determining the demand for charging infrastructure. The number of required charging points is governed by the daily maximum of traffic volume, so that there are no bottlenecks in the quality of service. Thus, the quality of service has a decisive influence on the acceptance of the public charging infrastructure. In order to represent the temporal variability, generalized traffic load curves are used.

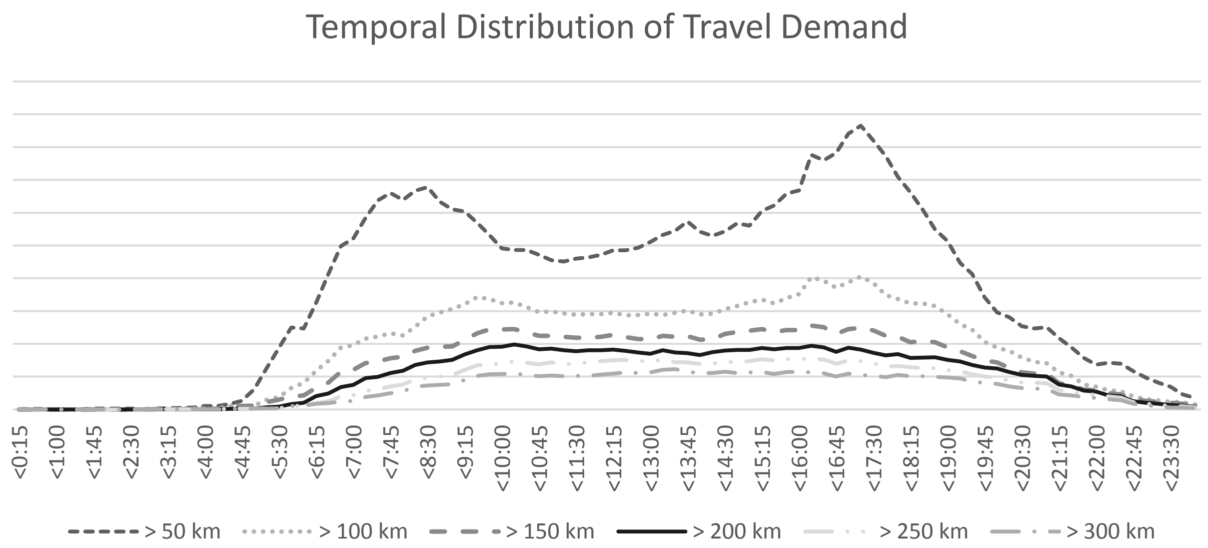


FIGURE 2 Temporal distribution of daily traffic demand differentiated by trip lengths. Each line represents the daily distribution of the given trip length

As can be seen in FIGURE 2, LD-travel shows a relative equal distribution of traffic volume between 8:00 am and 8:00 pm with an hourly distribution of 8% of total daily volume. This means that a relative homogenous charging demand during the day on highways is expected.

Another aspect of the temporal distribution of network volume is that despite the fairly homogeneous load, an hourly variation is to be expected. Since the traffic load curves are aggregated values and different routes can have a greater variability, hourly variations are expected. This aspect can be represented in queuing models. A queuing model helps in estimating the utilization of service points depending on arrival time distribution and waiting time. To calculate the charging infrastructure needed a queuing model is applied. This approach enables us to calculate the required number of charging points for different arrival rates and corresponding utilization rates. As an example, for an arrival rate of $\lambda = 10$ (10 vehicle arrivals at charging station per hour) and service rate of $\mu = 2$ (2 charges / hour per charging point), results in 5 charging points with 100% utilization rate and 18 minutes of wait time. Increasing the number of service points to 7 results in a 70% utilization rate and 5 minutes of waiting time.

*4.4. Results and discussion*

We calculate charging demand and infrastructure demand by use of the described approach. For a scenario of one million EVs composed of 1/3 BEVs and 2/3 PHEVs and 150 km and 50 km electric range respectively, we first determine the charging demand for highways. However, demand density does not allow conclusions on the total number of charging points. Therefore, the demand for infrastructure is calculated using the demand densities by means of temporal distributions (i.e., using load curves and queuing model). Considering the optimal capacity utilization of the charging stations and an acceptable waiting time (less than 5 minutes) the demand for charging infrastructure on German freeways yields the total number of 1,150 charging points. However, these are the results of just one scenario. Analysis with different range and fleet composition, waiting times, and utilization rates provide varying results. See FIGURE 3 for the results.

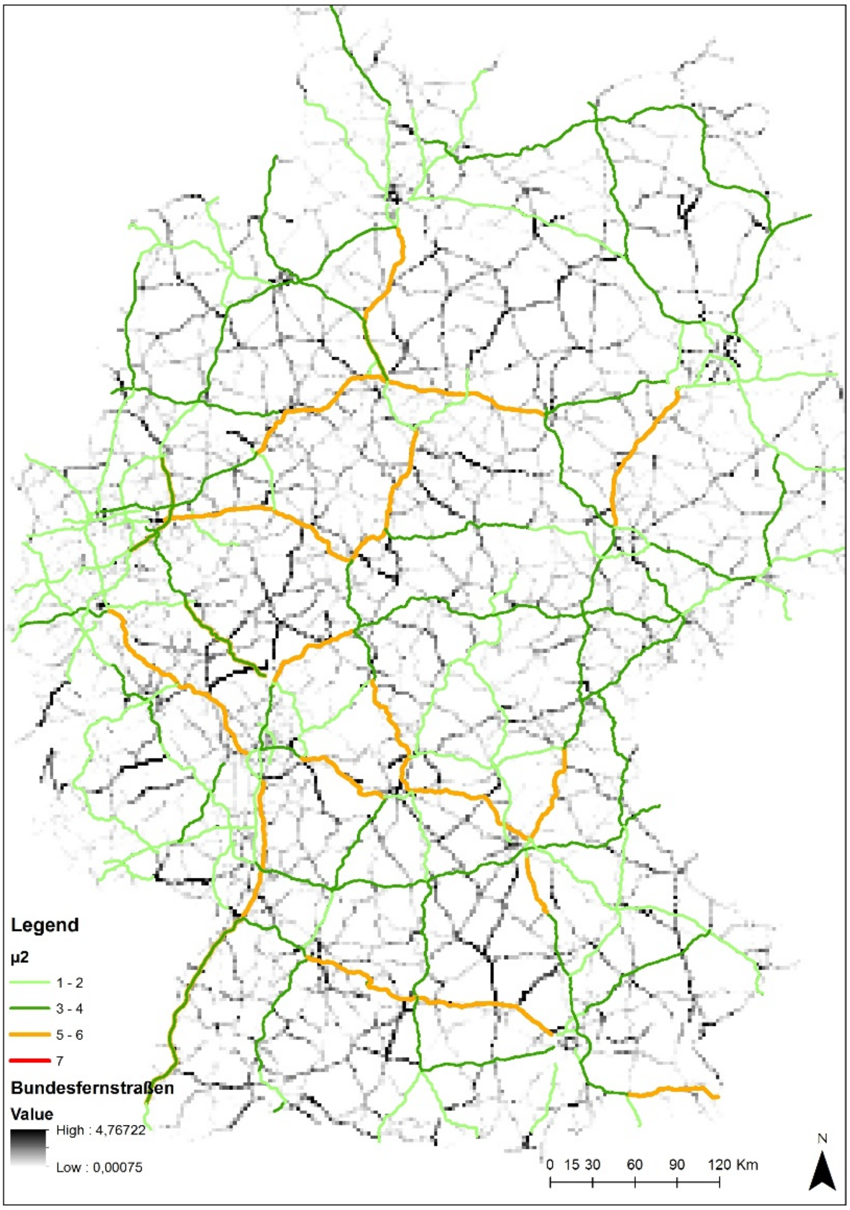


FIGURE 3 Number of charging points for LD-travel with waiting times less than five minutes. Different colors represent number of charging points needed on that section of highway. Highway sections are around 50 km on average. (Bundesfernstraßen – highways, μ = 2 (2 charges / hour per charging point).

Variations in the model parameters should be considered in future research. To date the modelling is based on the workday traffic demand data. Here the parameters such as holiday and weekend demand should also be taken into account. Currently it is assumed that EVs have the same usage patterns as conventional cars. However, a model based estimation of probabilities that certain trip lengths would be carried out by BEVs or PHEVs is necessary. A detailed spatial analysis is also necessary in order to differentiate and test for certain highway sections and for the options of clustering or homogeneous distribution of charging points.

## 5. Results

For one million EVs in Germany by 2020 we recommend between 14,700 and 29,500 charging points for daily travel and 1,150 charging points for LD-travel. For daily travel, the results show that infrastructure requirements are most influenced by on-street charging followed by home parking, and finally fleet composition. As on-street charging in residential areas dramatically increases the total infrastructure, we recommend a system without on-street charging in residential neighborhoods or at work. We also anticipate PHEVs to dominate the fleet composition in 2020 due to consumer demand. Thus, we recommend planning for Scenario No. 2 or No. 4. Finally, we think that a charging supply with an average distance of 1 km to the next available charging point is satisfactory. This results in 14,700 to 29,500 charging points for Germany in 2020.

Based on the analysis of LD-travel, the share of PHEVs would not change the demand dramatically on the highways because of the realistic assumption that most of the LD-travel would be done in combustion mode and a charging event would occur when the vehicle already refuels. BEVs, on the other hand, especially the ones with higher ranges and higher probabilities to be used in LD-travels, will drastically affect the demand structure.

## 6. Conclusion

In this paper we develop a demand-oriented approach to determine charging infrastructure for EVs examining both daily and long-distance travel. The methodology is based on the assumption that mass commercialization of EVs results in users maintaining their current travel behavior. Utilizing commonly available travel data, the methodology allows for the calculation of infrastructure demand.

For daily travel, we present four key findings from the German case study. First, offering on-street charging in residential areas and at work dramatically increases required charging infrastructure. Second, increasing the percentage of EVs with a private parking spot at home notably decreases the total number of charging stations. Third, PHEVs slightly increase charging infrastructure. Fourth, demand for charging infrastructure does not increase linearly with charging demand.

For LD-travel, both the model-driven approach with VALIDATE and the analytical approach using the car usage model CUMILE supply similar results at an aggregated level. Our main finding is that the comfort assumptions (i.e., waiting times) and fleet composition (i.e., share of BEVs) are crucial to infrastructure demand. The relation between the number of charging points, waiting time, and spatial distribution of charging points (i.e., allocating points in clusters in one point or distributing them along highway in equal distances) were analyzed in detail. However, first insights from the preliminary analysis illustrate a strong effect of spatial form on the number of stations.

Future work in the area of charging infrastructure should expand upon user preferences and infrastructure attractiveness. In particular, integrating pricing is a critical topic, which should be explored. Finally, the integration of EVs into the overall electricity network is crucial to achieve system wide energy savings and meet environmental objectives, and should be studied further.

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