

A techno-economic analysis of fast charging needs in Germany for different ranges of battery electric vehicles

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Abstract

Political action supports the built-up of public charging infrastructure to increase market shares of battery electric vehicles (BEV). For a cost-effective deployment of public charging infrastructure, a detailed knowledge of charging infrastructure needs is necessary. However, the effect of increased vehicle ranges on charging infrastructure needs is not yet sufficiently understood. The aim of the present paper is to determine the number of fast charging points needed in Germany for different ranges of BEV. We use information on daily driving distances of real-world driving data from 6,339 German conventional passenger cars to deduce yearly charging demands for different ranges of BEV. Finally, we determine fast charging infrastructure needs in Germany by combining a coverage-oriented with a demand oriented approach and take differences in local charging demands into account. For Germany, we find that 500 fast charging points could meet charging demands of up to 500,000 BEV. In addition, we see charging demands decreasing with higher vehicle ranges as the resulting effect of a lower number of charging events on charging infrastructure needs outweighs the effect of increased charging times per charging event.

Keywords: charging infrastructure, fast charging, BEV

1 Introduction

Battery electric vehicles (BEV) are considered as an instrument to reduce greenhouse gas emissions. However, their market shares are still low and users demand for higher driving ranges as well as for a higher public charging infrastructure density [1]. While higher driving ranges could be attained by higher battery capacities at (currently) high cost [2], the determination of public charging infrastructure needs is complex. First, the estimation of public charging needs requires a detailed analysis of individual driving behavior as BEV can generally be operated independently from public charging infrastructure due to the possibility of home

charging. In addition, higher vehicle ranges – which could be expected in the future as indicated by increased ranges of actual BEV models (see e.g. [3]) – lower public charging needs and therefore directly affect public charging infrastructure demand. Second, an analysis of public charging infrastructure has to take geographical differences of charging demands into account as in areas with higher charging demands a higher charging infrastructure density is desirable to avoid high waiting times at charging stations.

Current studies either focus on the placement of charging stations based on local traffic data but do not take into account the number of needed charging points [4, 5] or determine the number of

needed charging points but neglect for local differences in charging demand [6, 7].

The aim of this paper is to present a modeling approach to determine the need for public charging points in Germany while taking into account locally diverging charging needs as well as the effects of different vehicle ranges on charging infrastructure needs. We focus on fast charging infrastructure (≥ 50 kW charging power). Furthermore, we determine charging infrastructure needs by combining a coverage-oriented and a demand-oriented approach. While the demand oriented approach ensures that each charging station is sized to limit waiting times, the coverage-oriented approach guarantees a minimum standard of service [8].

2 Data and Methods

2.1 Data

First, we estimate the number of needed charging events per year based on mobility data of conventional vehicles. To be able to represent variation in daily driving, we need a data basis with an observation period of several days. We use the German Mobility Panel (MOP). In this annual survey about 1,000 households report their daily travel patterns over a period of one week [9]. We use data from 1994 until 2010. The average annual vehicle kilometers travelled (VKT) of the vehicles in the dataset is 13,800 km (median 12,000 km).

Second, we use traffic volume data of the German highway network to determine local differences in charging demand. Here, we use data from the Federal Highway Research Institute [10]. For each of the 2,570 street-segments of the German highway network, the data set contains average daily traffic volumes (in thousand vehicles per day). There are 121 different highways in Germany with a total network-length of 13,000 km.

For BEV with vehicle ranges of 150 km we model charging times based on empirical data which was collected in the context of the US-American “EV project”. The project comprised the built-up of 12,000 charging points in 20 metropolitan areas (see theevproject.com). According to [13, 16], energy charged at public fast charging stations are mostly between 25 and 70% of vehicle battery capacity (see also Figure 1). In our analysis, we neglect for charging energies below 30% of battery capacity as we

expect these to be caused by BEV drivers wanting to try out public charging without an actual charging need.

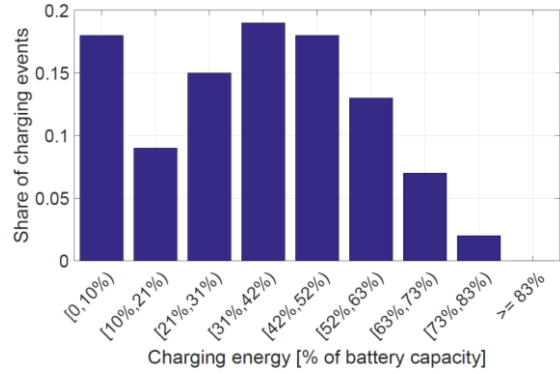


Figure 1: Distribution of charging energy (shown as proportion of battery capacity) at public fast charging stations. Data source: [13].

These charging data stem mostly from Nissan Leaf users. As the Nissan Leaf with a battery capacity of 24 kWh has a range of approximately 150 km (Model year 2015, see e.g. fueleconomy.gov) we directly use these charging data to model charging behavior of vehicles with a range of 150 km.

In this paper, for a BEV with a range of 150 km we assume a minimal charging energy of 7.2 kWh (30% of 24 kWh), a mean charging energy of 12 kWh and a maximum charging energy of 16.8 kWh (70% of 24 kWh). In combination with a presumed net charging power of 135 kW this results in a mean charging time of 5.3 min (and a variance of 0.9 min^2 for the assumed truncated normal distribution; for the assumption of normally distributed charging times see Section 2.2).

2.2 Methods and Assumptions

We first determine the number of charging sites that are needed for geographical coverage. For fast charging infrastructure, we presume the usage for interim charging to enable long distance trips. An interim charging event is comparable to a today’s refuelling stop. As long distance trips happen mainly at highways [11], we assume that fast charging infrastructure is built exclusively next to highways. For the geographical coverage we assume a maximum distance between two charging sites of $D_{CS} = 100$ km along every highway and calculate the number of needed charging sites for every highway BAB as function of its length l_{BAB} :

$$\#CS_{BAB} = \left\lceil \frac{l_{BAB}}{D_{CS}} \right\rceil \quad (1)$$

We assume one charging site to serve both directions of a highway and charging sites to be located every D_{CS} kilometer.

For the demand-oriented approach, charging infrastructure needs are mainly determined by two parameters: (1) the average fleet charging demand (given as number of charging events per BEV and year) and (2) the average charging times at a charging station as these directly influence waiting times of following BEV.

We first calculate the average fleet charging demand. For every vehicle, we assume the yearly number of fast charging stops to equal the number of days $D(L)$ on which driving distances exceed the electric range L of the BEV. Following [12], we assume daily driving distances to be log-normal distributed. For every user, we use the mean μ and the standard deviation η of his logarithmized daily driving distances (see [12] for details) to calculate $D(L)$ as

$$D(L) = \frac{\alpha 365}{1 + \left(\frac{L}{e\mu}\right)^{\eta\sqrt{3}}} \quad (2)$$

In a second step, we calculate the fleet average charging demand per BEV and year $\lambda_\emptyset$ as the arithmetic mean of the user specific yearly charging demands $D_i(L)$ of all N analyzed driving profiles:

$$\lambda_\emptyset = \frac{1}{N} * \sum_{i=1}^N D_i(L) \quad (3)$$

This implies that we assume the driving behavior of a potential BEV fleet to equal the driving behavior of the actual German vehicle fleet (see previous section for the used dataset). While in the short term actual charging needs might be higher as vehicles with higher yearly VKT are needed to economize the high investment of BEV, on the medium to long term it can be expected that all driving profiles are potentially willing to adopt a BEV due to lower battery cost and thus lower vehicle prices.

Finally, we assume that local charging demands at each charging site are not identical but differ according to the traffic intensity TI of the particular Highway-segment next to it (traffic intensity data acc. to [9], see previous section). The yearly charging demand CD_i at a specific charging site i thus results from its relative traffic intensity $\frac{TI_i}{\sum_i TI_i}$, the assumed total BEV stock $\#BEV$ and the average charging demand $\lambda_\emptyset$ as:

$$CD_i = \frac{TI_i}{\sum_i TI_i} * \#BEV * \lambda_\emptyset \quad (4)$$

We assume that 10% of daily charging demand happen in rush hour (e.g. [13]) and that charging events are distributed equally over the year.

For the modeling of charging behavior at public fast charging infrastructure, we analyze empirical charging data [13]. We find that the exponentially distributed charging times, as it is often used in queuing modeling [14], does not agree with actual charging behavior (see Figure 1). Therefore, we apply a queuing model with the Kendall-notation $M/G/s^1$ using normally distributed charging times to size each charging site such that average waiting times at all sites do not exceed five minutes in rush hour. We assume every charging site to have a maximum number s of eight charging points and multiple charging stations per charging site if needed. As $M/G/s$ -Systems do not allow for analytical solutions, we determine average charging times based on the approximation described in [15]. The approximation relies on $M/M/s$ -Systems² and is an extension of the Pollaczek-Khinchine-formula. Resulting waiting times of a $M/G/s$ -System are given as:

$$W_q^{M/G/s} = \frac{C^2 + 1}{2} * W_q^{M/M/s} \quad (5)$$

Here, C describes the coefficient of variation of the underlying charging time distribution. As for the assumed normally distributed service times $C \ll 1$, the resulting waiting times for the $M/G/s$ -System are lower than for an equally sized $M/M/s$ -System. Or in other words, to reach a certain predefined level of average waiting times, the system size of a $M/G/s$ -System can be smaller than that of a $M/M/s$ -System. To summarize, the modeling of charging sites as $M/G/s$ -Systems leads to a lower infrastructure need compared to the modeling with $M/M/s$ -Systems.

For vehicle ranges above 150 km empirical charging data is not available. However, higher vehicle ranges will also affect charging times as we expect the energy charged per charging event to increase with higher battery capacities (e.g. as an increased amount of energy is needed for a full recharge). As empirical data on charging behavior is only available for vehicle ranges up to 150 km

¹ The first letter describes the arrival process (here: M for Markovian), the second the service times (here: G for a General distribution) and there are s servers (see e.g. [14] for details).

² Queuing systems with exponentially distributed service times (M for Markovian).

(see Section 2.1), we quantify the effect of an increased vehicle range on charging times by assuming that the energy charged at a public fast charging station will depend on the user specific distance that should be enabled by the respective charging stop (“additional distance”). Note that we do not assume a proportional increase of publicly charged energy with vehicle ranges. We do so as we expect public charging to be more expensive than home charging so that BEV users will limit the energy charged publicly to a minimum that is necessary to reach their final destination (implying BEV users to be “homines oeconomici”).

We calculate the average of the aforementioned additional distances D_+ for every driving profile using the mean excess function of the log-normal distribution (for the parameters see above):

$$D_+ = \frac{\eta^2 L}{\ln L - \mu} \quad (6)$$

We use our results on additional distances D_+ (see Table 3) to scale mean charging times accordingly. For vehicle ranges of 300 km we get a mean charging time of 8.5 min and for vehicle ranges of 450 km the mean charging time is 9.6 min. For both vehicle ranges we assume the variance of the charging time distribution to be 1.98 min^2 . Note that the assumed mean charging energy of 50% battery capacity for BEV with an AER of 150 km – as deduced from empirical data (see Section 2.1) – can be confirmed by our results on additional distances (see Table 3).

3 Results

3.1 Geographical Coverage

For a geographical coverage of one charging site every 100 km on each highway, in total $\#CS = 211$ charging sites are necessary. Naturally, this number increases with smaller distances D_{CS} as shown in Table 1.

As shown in the last row, the number of charging sites $\#CS$ does not increase linearly with

decreasing distances D_{CS} . This is because at least one charging site for each Highway is considered. As a high share of Highways is shorter than the respective minimum distance between two charging sites D_{CS} , at these Highways one charging site is considered, regardless of the minimum distance D_{CS} . For example, ~50% of the Highways are shorter than 25 km. However, these Highways only comprise less than 5% of the length of the total Highway-network (own analysis based on [10]).

3.2 Demand-oriented approach

The average yearly charging demand per BEV $\lambda_\emptyset$ for the different all electric ranges (AER) of 150 km, 300 km and 450 km is given in Table 2.

Table 2: Average charging demand $\lambda_\emptyset$ per BEV and year for different AER.

AER	150km	300km	450km
$\lambda_\emptyset$	23.9	8.9	5.1

Especially the doubling of the AER from 150 km to 300 km causes a more than proportional decrease in yearly charging demand, therefore potentially reduces charging infrastructure demand. However, with increasing AER charging times presumably will increase, too. This assumption is supported by the fact that additional distances (for a definition see section 2.2) also increase with higher AER (see Table 3).

Table 3: Additional distances D_+ for different AER.

AER	150km	300km	450km
Mean D_+	115 km	147km	170km
Median D_+	67km	94km	120km

Regarding the median D_+ we see an increase of 40% for vehicle ranges of 300 km compared to vehicle ranges of 150 km. For vehicle ranges of 450 km, D_+ increases by a further 40%. The effect of increasing additional distances with higher battery capacities might be counterintuitive. However, an explanation might be that with higher battery capacities longer distances are feasible

Table 1: Number of needed charging sites for a geographic coverage of fast charging infrastructure along the German Highway network.

Distance between charging sites D_{CS}	25	50	60	75	100	125	150	175	200
Number of charging sites $\#CS$	586	337	296	252	211	188	171	161	153
Change w.r.t. base case $\frac{\#CS}{\#CS(D_{CS}=100km)}$	278%	160%	140%	119%	100%	89%	81%	76%	73%

without a recharging stop. As a consequence, recharging stops are needed only to enable very long distance trips, leading to an increase in the average additional distances.

To sum up, the increase of the all electric range of BEV has two opposite effects on charging infrastructure demand: (1) Higher vehicle ranges reduce the number of needed recharging stops per BEV an year thus reducing charging infrastructure demand (*ceteris paribus*) and (2) Higher battery capacities increase charging times thus leading to higher charging infrastructure demand (*ceteris paribus*).

The total effect of an increased vehicle range on charging infrastructure demand therefore is situation-dependent. For the analyzed German driving profiles, we find that the effect of decreased charging demand outweighs the effect of longer charging times. Accordingly, charging infrastructure demand decreases with higher AER as shown in Table 4. For a BEV stock of 50,000 charging infrastructure needs are determined by the geographical coverage and therefore are independent from AER.

Table 4: Charging infrastructure demand [charging points per 10,000 BEV] as function of BEV stock.

BEV stock	AER = 150km	AER = 300km	AER = 450km
50,000	42.2	42.2	42.2
250,000	12.6	10.6	9.0
500,000	9.4	7.6	6.2
1,000,000	7.8	5.7	4.4
1,500,000	7.2	4.9	3.8
2,000,000	7.0	4.6	3.4

The resulting total charging infrastructure needs along the German Highway-network is shown in Figure 2 as function of the assumed BEV stock.

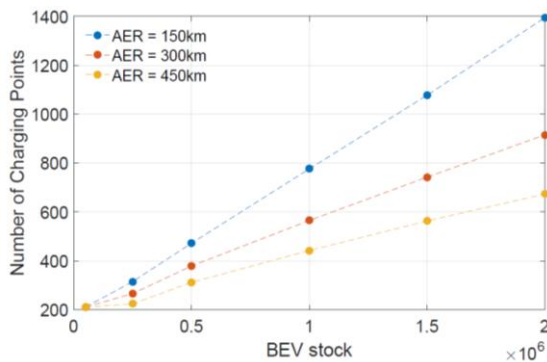


Figure 2: Number of Charging Points along the German Highway-network as function of BEV stock.

4 Discussion and Conclusions

4.1 Discussion

We model the availability of fast charging stations using M/G/s-queueing systems. The analysis of empirical charging data does not support the assumption of exponentially distributed service times as often used in queueing modeling (e.g. [14]). A sensitivity analysis shows that the application of a M/M/s-queueing model, i.e. the assumption of exponentially distributed service times, leads to approximately 10% higher charging infrastructure needs on the long term (BEV stock 2,000,000). In the short term, due to smaller station sizes, charging infrastructure needs would be overestimated by approximately 20%.

As empirical data on charging behavior is not available for higher vehicle ranges (see Section 2), we assume that BEV users will limit the energy charged at public fast charging stations to the minimum and we use the distance to be enabled by the fast charging stop (“additional distance”) to determine charging time distribution for higher vehicle ranges (see Section 2.2). If in contrast we assumed a proportional increase in charging times with vehicle ranges – supposing a mean charging energy of 50% of battery capacity and a normal distribution truncated at 10 and 80% of battery capacity regardless of vehicle range – this would result in approximately 20% (50%) higher charging infrastructure needs for vehicle ranges of 300 km (450 km).

4.2 Conclusions

We analyze fast charging infrastructure demands in Germany and find that 500 fast charging points – a number that is politically promoted to be available in Germany until 2017 (see e.g. [17]) – could meet charging demands of up to 500,000 BEV (vehicle ranges of 150 km). In addition, as charging infrastructure demands decrease with higher vehicle ranges, the long-term planning of fast charging infrastructure has to take into account that charging infrastructure demands might decrease with expected higher vehicle ranges in the future.

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