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Fast charging infrastructure for electric vehicles: Today's situation and future needs

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ABSTRACT

Potential users of plug-in electric vehicles often ask for public charging facilities before buying vehicles. Furthermore, the speed of public charging is often expected to be similar to conventional refueling. For this reason, research on and political interest in public charging focus more and more on fast charging options with higher power rates, yet estimates for future needs are rare. This paper tries to fill this gap by analyzing current charging behavior from a large charging data set from Sweden and Norway and take the findings to calibrate a queuing model for future fast charging infrastructure needs. We find that the ratio of battery electric vehicles to public fast charging points can be similar to other alternative fuels in the future (close to one fast charging point per 1000 vehicles for high power rates of 150 kW). In addition, the surplus on the electricity prices for payoff is only 0.05–0.15 €/kWh per charging point. However, charging infrastructure needs highly depend on battery sizes and power rates that are both likely to increase in the future.

1. Introduction

Battery electric vehicles (BEV) can reduce greenhouse gas (GHG) emissions if powered with renewable energy (Nordelöf et al., 2014). A barrier to the market diffusion of BEVs is the limited range with current batteries. Though it is possible to find user groups who can fulfill their driving needs and for whom a BEV is economical without public charging (see e.g. Jakobsson et al., 2016), a broader introduction of BEVs would require an improvement of battery technology or a more extensive charging infrastructure setup. This is also postulated by potential vehicle buyers (Dütschke et al., 2011) and policy makers (D'Appolonia et al., 2016, NPE, 2015). On the other hand, fast charging stations imply a large investment (Schroeder and Traber 2012) which warrants the question of how many fast charging stations are actually needed. Here, we define fast charging if power rates are above 22 kW (BMWi, 2015) while a charging site may contain multiple charging stations with even more charging points (= outlets).

The European Commission suggested national targets for public charging points in 2013, which favored 150,000 public charging points in Germany and 14,000 public charging points in Sweden (EC, 2013). The later suggested German national action plan suggested 43,000 public points (of which 7000 should be fast) (BMWi, 2015). Although both numbers contain slow and fast charging options, they differ largely. The first calculations for these estimates were made based on small batteries and low charging power, but recent developments in charging points and vehicles put more relevance on the necessary number of fast chargers. By the end of

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2016, there were 1403 fast chargers in Germany, 523 fast chargers in Sweden and 1052 fast chargers in Norway.[1] In Sweden, the ratio of BEV in stock per fast charger is the lowest (15.3), compared to Germany (29.6) and Norway (78.9).[2] Norway has reached a BEV share of about 6% of the total vehicle stock.[3] These numbers show different market situations which are expected to change even more in the future. Still, today's ratio for Norway is a magnitude larger than the suggestion from the European Commission. This discrepancy is important to address since the initial public charging infrastructure might have to be largely subsidized by governmental bodies (Gnann, 2015).

In the literature, there are no estimates on the required number of fast charging points for large geographical areas (with the exception for some highway corridors) based on real-world driving data and existing charging data, even if the planning and placement of charging stations for electric vehicles has been the subject of various studies. The studies vary in methods and approaches. Shahraki et al. (2015) optimize the vehicle miles traveled. They use actual vehicle travel demand as input, but only from taxis and not private vehicles. Their study focuses on Beijing. For a review of optimization methods related to charging parameters see (Rahman et al., 2016). Xi et al. (2013) combine simulation and optimization to study the location of chargers. However, they only look at level-1 and level-2 chargers. Actual charging behavior in Ireland is studied in Morrissey et al. (2016). They find that fast charging infrastructure is most likely to become commercially viable in the short- to medium-term based on current charging frequency.

Different perspectives are also taken into account. Guo et al. (2016), e.g., look at the business perspective and the investment planning for charging station providers. Their model is theoretical with no real life case study. Similarly, Sadeghi-Barzani et al. (2014) look at how to minimize the total cost of charging station investment. They have a real life case: the city of Teheran. Still, they do not take into consideration driving patterns or the actual need for charging, instead they presume a predefined number of vehicles that charge per day. Wang et al. (2013), similarly to Liu et al. (2013), look at the distribution system with the objective to minimize power losses and voltage deviations. Both these studies are not based on actual data. Another common objective is to maximize the amount of electric miles traveled or to reduce the number of unfulfilled trips if all vehicles would be BEVs. Dong et al. (2014) base their analysis on GPS data from the greater Seattle metropolitan area and simulate travel and charging behavior based on this data. They assume a 100-mile battery range for the whole fleet. Alhazmi et al. (2017) use the US national household travel survey to generate virtual travel distances using a Monte Carlo simulation. Their main focus is the location of charging stations.

As described above, some studies use actual driving data, see e.g. (Dong et al., 2014, Shahraki et al., 2015, Yang et al., 2017), but these are limited to a specific city or larger metropolitan area. Sathaye and Kelley (2013) look at highway corridors in Texas and base their calculations on existing traffic volumes. Jochem et al. (2016a, 2016b) calculate the number of fast charging points needed along the German autobahn based on Origin-Destination data. With increased penetration of BEV, queueing at charging station will be an issue. Explicit queueing models have been implemented and analyzed in (Yang et al., 2017). Their data consists of taxi movements and is limited to one city. The objective of their study is to minimize the infrastructure investment.

We aim at contributing to this policy relevant field of research by determining the necessary number of fast charging points per BEV in a queuing model as well as the potential supplement per kilowatt-hour need to economize. Our research is based on large empirical data sets for driving and charging behavior and is thus a new approach for the field. We focus on public fast charging points (with at least 50 kW power), since calculations on slow charging points showed no effect on BEV market diffusion and no business models for slow chargers (Dong et al., 2014, Gnann, 2015). In the model, we analyze the effects of charging behavior, different vehicle ranges, and increasing charging power. A further novelty of our study is the usage of real-world charging data from Swedish and Norwegian fast chargers to calibrate some of the model parameters.

For the sake of clarity, we refer to a charging point as a device suited for charging a BEV that only charges one BEV at a time. For the analysis on charging data, the number of charging sites is important while for all model calculations, we focus on charging points. Accordingly, we will only refer to charging sites and charging points from now on. Furthermore, we will only analyze the demand for fast charging of BEVs since plug-in hybrid electric vehicles can also be refueled with the existing conventional fueling infrastructure.

In the following section, we present both the charging and driving data as well as the methods applied. In Section 3, the results are presented starting with the empirical analysis of fast charging usage in Norway and Sweden, followed by the model development and results from the queuing model. We end with a discussion and conclusions.

2. Data and methods

For the estimation of the specific charging infrastructure need per BEV, we calibrate a queuing model with real world charging and driving data. We use empirical charging data from Norway and Sweden to analyze the variation of charging behavior throughout the day and between different BEV users. Since current charging behavior might not reflect future conditions of charging - due to increased charging power and vehicle ranges – we use driving data of conventional vehicles from Germany and Sweden as a second input to the queuing model to simulate charging behavior under today's and expected future conditions. Finally, we compare our model results against today’s charging behavior as identified before. The structure of our approach is summarized in

Fig. 1.

[1] Fast charging options of the company CHAdeMO with 50 kW, the Combined Charging System (CCS) with 50 kW, and Tesla Superchargers with 90–125 kW. Data from http://www.eafo.eu/electric-vehicle-charging-infrastructure, last accessed: 22.11.2017.

[2] Data of vehicle stock as sum of BEV registrations until 2016 from http://www.eafo.eu/countries, last accessed: 30.11.2017.

[3] https://elbil.no/english/norwegian-eV-market, last accessed: 22.11.2017.

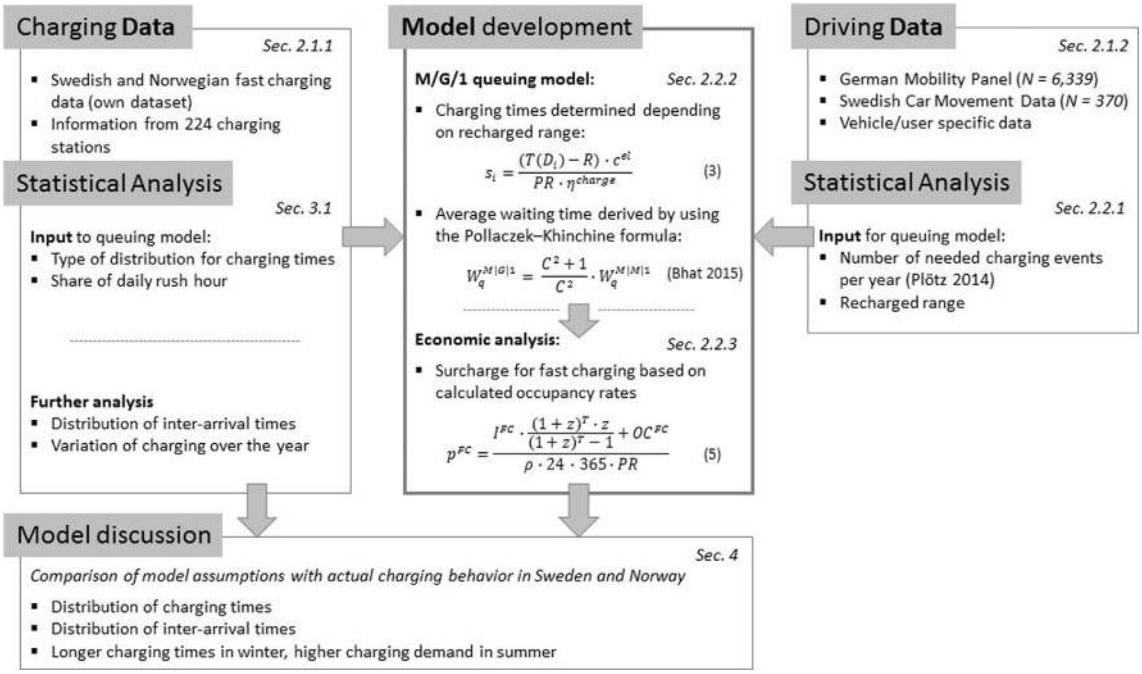

Fig. 1. Flowchart of the approach used in this paper.

2.1. Data

2.1.1. Charging data

We use real world charging data from Swedish and Norwegian fast chargers, first to analyze actual usage of fast chargers and second to deduce realistic parameters for a queuing model (see Fig. 1). The data is provided by Nobil (2016) and contains charging events from both fast and slow chargers, though we only analyze fast chargers here. Specifically, it contains start time of charging events, connection time, and station specifications such as power rating and connector plug type. Concerning fast chargers, the data only contains CHAdeMO and Combined Charging System (CCS) types, Tesla fast chargers are not available. Note that a charging site may contain one or several charging points. The available data allows us to analyze charging events at a charging site but not per charging point.

The raw real-time feed produced by Nobil is converted into charging sessions by observing state-changes per charging point. Some sessions turn out to be very short, indicating either user-error or communication errors. Other sessions last for days indicating users leaving their car plugged in long after having reached full charge, or indicating some other type of communication error with the charging point. Therefore, the data is filtered to only include charging sessions between three minutes and three hours of length, which results in more reasonable charging times.[4] The three minute and three hour cut-off removes 14.7% of the original 36,646 fast charging events in Sweden and 16.6% of the original 779,282 fast charging events in Norway. Further, we wish to analyze a market that is as mature as possible, and thus we only include recent charging events from November 2015 to November 2016. This reduces the number of events further by 41.3% for Sweden and 40.6% for Norway. These restrictions lead to 32 included charging sites and 18,349 charging events for Sweden, while for Norway we use data from 192 chargers with 386,053 charging events. Note that the total number of CCS and CHAdeMO fast chargers in Sweden was about 387 in 2016 and about 835 in Norway (EAFO, 2018); thus, many charging point operators have declined to participate in Nobil's data collection. Descriptive statistics of the data with spread over individual sites is available in Table 1. The empirical charging data has a strong diurnal pattern since today's charging points are rarely used more than once per day.

For our analysis, we make the following assumptions and approximations. Charging times cannot be directly inferred from the data; however, given short enough connection times, we can assume that the connection time is equal to the charging time. Thus, we also use a cut-off of 35 min for connection sessions when forming the probability distribution for charging time. This cut-off would yield full charge for most cars using CCS and CHadeMO chargers today. Furthermore, inter-arrival times cannot be directly inferred either, as we only know when users actually plug-in their vehicles (inter-plugin times). However, the inter-arrival times can be approximated to be the same as the inter-plugin times if there is a negligible queue at the charging site (a person plugs in when arriving at the station without waiting). We can assess how often there is a queue at the measured charging sites by analyzing how often a new plug-in event happens shortly after a plug-out event. In the Swedish data, a plug-in happens within five minutes before a

[4] Note, however, that most batteries will be fully charged in less than three hours. We account for this in Section 3.1 when calculating charging time distributions from the charging data.

Table 1
Summary statistics of charging behavior based on Nobil (2016); *n* is the number of charging sites.

Sweden (n = 32)	*0.25*	*Median*	*Mean*	*0.75*
Average charging sessions per week [#]	3.99	6.33	11.03	10.31
Total number of sessions [#]	208	329	573	536
Average session duration [min]	23.3	24.4	25.3	27.2
Inter-plug-in time [min]	733	1356	1607	2195
Norway (n = 192)	*0.25*	*Median*	*Mean*	*0.75*
Average charging sessions per week [#]	10.8	24.5	38.7	48.1
Total number of sessions [#]	563	1274	2011	2499
Average session duration [min]	19.3	20.9	21.9	23.4
Inter- plug-in time [min]	193.2	386.8	667.5	757.6

Table 2
Summary statistics of driving behavior based on (MOP, 2010, Karlsson, 2013).

MOP (n = 6339)	*0.25*	*Median*	*Mean*	*0.75*
Observation period [days]	7 for all vehicles by design			
Share of driving days	0.86	1	0.93	1
Average daily VKT [km]	22.0	38.3	50.6	65.0
Annual VKT [km]	8000	12,000	13,830	17,000
SCMD (n = 370)	*0.25*	*Median*	*Mean*	*0.75*
Observation period [days]	52	60	58	64
Share of driving days	0.65	0.79	0.76	0.90
Average daily VKT [km]	36.6	48.8	55.0	70.8
Annual VKT [km]	8760	13,944	15,587	20,256

plug-out for only 1.2% of the events, the corresponding number in the Norwegian data is 2.5%, which must be considered low. Thus, there are seldom queues in the actual data, and approximating inter-arrival times by inter-plug-in times is justified.

2.1.2. *Driving data*

For this paper, we use two data sets of private vehicle driving as a second input for the queuing model, one from Germany (the German Mobility Panel, MOP) and one from Sweden (Swedish Car Movement Data, SCMD) to derive fast charging demands of future electric vehicle fleets (see Fig. 1 and next section). Both data sets cover only conventional internal combustion engine vehicles. The data sets have different qualities: the German data has a large sample (n = 6339) with few observation days (7 days), while the Swedish data has a smaller sample (n = 370) but longer observation periods (average 58 days). Their complementary nature in terms of sample size, observation period and their different geographical locations makes our analysis more robust. For a detailed description see MOP (2010), Gnann (2015), Karlsson (2013) as well as Plötz et al. (2017).

The German data set, MOP, is a household travel survey performed since 1994. Here, we use the data from 1994 to 2010 and transfer all trips performed by persons to vehicle trips where unambiguously possible (MOP, 2010, Gnann, 2015). This results in 6339 vehicle driving profiles representative of German driving behavior (Gnann, 2015).

The Swedish data was collected via GPS measurements that were carried out in periods between 2010 and 2012. The measurements are evenly spread over the years, thus capture seasonal variations. Participating cars were randomly sampled from the national vehicle registry of the geographic area of Västra Götaland (Western Sweden). The study area is representative for Sweden in terms of urban and rural areas, city sizes, and demographics. Data pre-processing and filtering has been described in (Björnsson and Karlsson, 2015). For the purpose of this analysis, the Swedish data has been further filtered compared to the description in (Björnsson and Karlsson, 2015), and thus contain 370 cars instead of 429. The additional 59 cars that have been removed for the present analysis had uncertain length of the observation period. Since this paper aims at precision in yearly driving need, or charging need, high precision is needed in the length of the observation period for accurate scaling to yearly basis. Descriptive information about the data sets can be found in Table 2 where summary statistics for length of observation period, share of driving days, and daily and annual vehicle kilometers traveled (VKT) are provided.

The number of driving days is seven for the German vehicles by survey design, while the Swedish data was collected for 58 days on average. in Germany, we find an average annual VKT of 13,830 km which is in line with the national average of 14,015 km (KBA, 2017). For Sweden, the average annual VKT is slightly higher with 15,587 km in the data set and 14,130 km on national average for passenger cars (Myhr, 2017). However, the share of driving days is higher for Germany (93% on average) compared to Sweden (76%). The high driving share in the German data might stem from the short observation period. Both data sets are used to determine the number of charging events per year and day described in the following section.

2.2. Methods

Due to the lack of empirical charging data for vehicle ranges above 100 km as well as for power rates above 50 kW, we simulate charging behavior of future BEV based on driving behavior described in the previous section. In the following, we first show a method to derive the number of charging events per BEV and year as well as the energy to be recharged per charging event (Section 2.2.1). In a second step (Section 2.2.2), we use these parameters to determine the resulting fast charging infrastructure needs applying a M|G|1-queuing model.

2.2.1. Theoretical estimate of the number and duration of fast charging events

The distribution of daily vehicle kilometers traveled allows us to estimate the probability of rare long-distance travel. We follow the methodology described in (Gnann, 2015, Plötz, 2014) which we briefly summarize for better understanding.

Based on the assumption that fast charging infrastructure is needed when the driving distance exceeds the vehicle's electric range, we calculate the number of days $D(R)$ per year for which the daily driving distance r is larger than the vehicle's electrical range R as in (Plötz, 2014)[5]

$$D(R) = 365\alpha\left[\frac{1}{2}-\mathrm{erf}\left(\frac{\ln R-\beta}{\gamma\sqrt{2}}\right)\right] \approx \frac{365\alpha}{1+\left(\frac{R}{e^{\beta}}\right)^{\pi/(\gamma\sqrt{3})}} \tag{1}$$

The parameters in Eq. (1) represent the observed driving behavior: the vehicle specific share of driving days α, the vehicles mean logarithmized driving distance β and the variation between logarithmized daily driving distances γ. For this calculation we use the two above mentioned driving data sets (see Section 2.1.2). The reasoning behind this approach of determining yearly charging events instead of linearly scaling long distance trips from the observation period to one year is that the finite number of observation days of driving data in general and of the used driving data in particular, tends to underestimate the need for long distance trips (Plötz et al., 2017). The underlying assumption is a log-normal distribution of daily driving distances for all vehicles (see (Plötz, 2014) and (Plötz et al., 2017) for a discussion). Though both the Weibull and Gamma distributions perform better at estimating $D(R)$ (Plötz et al., 2017), the log-normal distribution has the best goodness-of-fit (GoF) on the German driving data set for several GoF measures (see Plötz et al., 2017) while at the same time providing a conservative estimate of $D(R)$. As our approach in general provides a conservative estimate of the charging demand, this choice fits well into our methodology.

Table 3 shows the means of the individual parameters $\overline{\beta_i}$ and $\overline{\gamma_i}$ from both data sets, their predicted average daily vehicle kilometers traveled (E(VKT)) as well as the mean number of days requiring fast charging $D(R)$ for battery ranges of 100, 200, and 300 km.

We observe that the mean $\overline{\beta_i}$ and thus the predicted mean daily vehicle kilometers traveled E(VKT) are very similar for both countries. However, the mean variation between driving days $\overline{\gamma_i}$ is larger in the Swedish data. This results in a larger number of days requiring fast charging than in the German data. Even with long electric ranges R of 300 km, the mean number of days with necessary fast charging is still high (11.3 for Sweden and 9.0 for Germany). In our further analysis, we will use the individual β_i and γ_i.Due to the limited range of today's BEV, empirical charging data of vehicle ranges above 100 km is not available. However, higher vehicle ranges will also affect charging times since 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). We assume that BEV users will limit the energy charged publicly to a minimum that is necessary to reach their final destination (see equation 3) since we expect public fast charging to be more expensive than home charging. For this purpose, we extend the methodology of Plötz (2014) and use the mean excess function of the log-normal distribution (c.f. Burnecki et al., 2005) to calculate the user specific average distance driven on a day when the electric range R is exceeded:

$$\begin{aligned} T(D) &= R + \frac{\gamma^2 \cdot R}{\ln(R)-\beta} \quad \text{for} \ln(R) < \beta \\ T(D) &= e^{\beta+\frac{\gamma^2}{2}} \quad \text{for} \ln(R) \geqslant \beta \end{aligned} \tag{2}$$

The recharged range at a fast charging point is the second term of the (first) equation. Results for these estimates can be found in Table A1. Please note that our approach does not assume a proportional increase in recharged range with vehicle range.

Accordingly, individual charging times s_i for every single user i result directly from the recharged range ($T(D_i)-R$), the mean electric consumption c^{el} as well as the power rate and the efficiency η^{charge} of the fast charging points with

$$s_i = \frac{(T(D_i)-R)\cdot c^{el}}{PR\cdot\eta^{charge}}. \tag{3}$$

Finally, the distribution of individual charging times s_i can now be used as a second input for the queuing model (see Fig. 1).

[5] Note, that this approach only considers the amount of charging needed for long-distance trips (so-called interim charging) while occasional charging at public stops with a lower power rate needs to take the driving and charging times during an average driving week into account (see (Gnann, 2015, Plötz et al., 2016) for an approach for slow charging). Furthermore, this approach also neglects other charging options, e.g. at home or at work, that could be used during days when the daily distance exceeds the vehicle range. It can thus be considered as an upper limit for days on which fast charging would be necessary.

Table 3
Means of parameters of individual log-normal estimates and resulting mean number of days for fast charging.

Country	$\overline{\beta_i}$	$\overline{\gamma_i}$	E($\overline{VKT}$)	$D(100)$	$D(200)$	$D(300)$
Sweden	3.35	1.24	28.4 km	43.4	18.5	11.3
Germany	3.34	0.91	28.1 km	43.5	15.9	9.0

2.2.2. Queuing model at charging site

We determine the number of fast charging points necessary to cover demand in a queuing model. Naturally, users want to find a vacant charging point when they arrive at a charging site. On the other hand, charging infrastructure operators are dependent on an economic operation of their charging points and aim at a high occupancy rate. Hence, we develop a queuing model to quantify the need for fast charging points as a stochastic process of arriving users at fast charging points. We determine the number of charging points as the minimum number of charging points needed to limit the average waiting time of arriving users to a pre-defined value. Furthermore, we examine the possible occupancy rates of charging points fulfilling these restrictions with different charging power (see Fig. 1).

The simplest and very common queuing model assumes exponentially distributed inter-arrival times as well as exponentially distributed service times[6] and one spot in the system that can offer service (Bhat, 2015); this system is abbreviated as M|M|1 (Kendall, 1953). While exponential inter-arrival times may be justified by our findings (see also Fig. 3) as well as by the independency of arrivals[7], exponentially distributed charging times mean that the remaining charging time of a vehicle in service does not depend on how long time it has been charging. However, BEV charging times are actually directly determined by the energy recharged and the charging power. Thus, charging times are peaked around a mean and fall off quickly away from the mean. Hence, the assumption of exponentially distributed charging times is not a good description of reality. Due to its long tail, the exponential distribution has a high variance that directly affects waiting times (c.f. Table 4). Therefore, exponentially distributed charging times tend to over-estimate waiting times and we use the more general M|G|1-queuing model instead. From our charging data analysis, we deduce a good fit of a normal distribution for the charging times (cf. Section 3.1 for a discussion on the normal distribution). Queuing models with exponentially distributed service times are often used because they - in contrast to M|G|1 or M|G|c models - allow for closed analytical solutions. Nevertheless, mean waiting times of a M|G|1 queuing system can be deduced from a M|M|1 system by applying the Pollaczek–Khinchine formula (Bhat, 2015): $W_q^{M|G|1} = \frac{C^2+1}{C^2} \cdot W_q^{M|M|1}$ with $C = \frac{E(S^2) - [E(S)]^2}{[E(S)]^2}$.

Two central parameters of a queuing model are the mean arrival rate λ, which is the reciprocal value of the inter-arrival time, and the service rate μ, which is the reciprocal value of the average service time $E(S)$. Given these two parameters and by limiting the average waiting time W_q, we can calculate several characterizing indicators for the queuing model: the occupancy rate ρ, mean number of users waiting in the system L_q, the mean time spent by a user in the system W, and the mean number of users in the system L. These indicators are summarized in Table 4. We further assume that the waiting room is unlimited.[8] If the charging point is occupied and another user is arriving, she just waits in the queue. The operating sequence is based on the "first come, first serve" principle.

Based on the individual charging times that we deduce from individual driving behavior and the charging power rates assumed (see equation (3)), we can determine the expected value $E(S)$ and variance $V(S)$ as input parameters for our queuing model (see Fig. 1 and Table 4). It is important to notice, that the mean occupancy rate ρ of the system only depends on the mean arrival and service rate and is independent from the distribution of arrival and charging times. Accordingly, also mean waiting times only depend on the mean and variance of charging times. Therefore, when selecting an adequate distribution for charging times, the focus should lie on these two parameters as discussed in Section 3.1.

In this paper, we consider queuing models with only one charging point as it allows for a general analysis of charging infrastructure demands, independent from the actual location of a charging site. Alternatively, we could use a queuing model with multiple parallel charging points (M|G|c). This would lead to lower charging infrastructure demand (ceteris paribus) since the capacity of a queuing system increases more than proportionally. For a queuing system with two spot, the capacity can be 2.5-fold.

For the calculation of the number of charging points needed, we further assume the following charging behavior. As we determine average annual charging needs based on the vehicle driving profiles and thus do not know the temporal distribution of these charging events, we assume that they are equally distributed throughout the year. We discuss this in Section 4. Furthermore, based on our empirical analysis in Section 2.1, we assume that 10% of the daily demand occurs in the peak hour (or rush hour, see Fig. 4) which is also confirmed by other studies (Gnann et al. 2016, INL, 2015, infas and DLR, 2008). Thus, in the peak hour, the total demand sets the limit for the total number of charging points and we will calculate these numbers for Sweden and Germany in Section 3.2. In Section 3.3, we show how the dimensioning of the charging infrastructure based on rush hour demand influences average occupancy and consequently profitability.

[6] In our work, the service time is synonym to the charging time of a vehicle.
[7] That means that the probability to wait a certain time until the next arrival is independent from the time passed since the last arrival which is reflected by the memoryless property of the exponential function (see e.g. Bhat, 2015 for details).
[8] For a calculation of charging facilities with multiple charging points and limited waiting rooms, see (Funke, 2018).

Table 4
Overview of characterizing indicators for the queuing model following (Bhat 2015).

Parameter	Formula
Occupancy rate	$\rho = \frac{\lambda}{\mu}$
Mean waiting time[a]	$W_q = \frac{\lambda E(S^2)}{2(1-\rho)}$
Mean number of users waiting	$[L_q = W_q \cdot \lambda]$
Mean time spent by a user in the system	$W = W_q + \mu$
Mean number of users in the system13	$L = \lambda \cdot W = \lambda \cdot (W_q + \mu) = \lambda \cdot E(S) + \frac{\lambda \cdot E(S^2)}{2(1-p)}$

[a] With $E(S^2) = V(S) + E(S)$.

2.2.3. Determining the most cost efficient system

Based on the queuing model, we can determine the price a charging infrastructure operator would have to charge in addition to the electricity price for the financing of the fast charging points. We use the occupancy rates and the amount of energy charged in a year to calculate the price premium per kilowatt-hour at the charging point as

$$p^{FC} = \frac{I^{FC} \cdot \frac{(1+z)^T \cdot z}{(1+z)^T - 1} + OC^{FC}}{\rho \cdot 24 \cdot 365 \cdot PR} \tag{4}$$

The total expenses - the numerator of the equation - consist of the annualized investment I^{FC} for the fast charging points (interest rate z and investment horizon T) as well as of the operating cost OC^{FC} .These total cost are broken down to the price premium p^{FC} per kilowatt-hour when dividing them by the total amount of energy. The total amount of energy is calculated based on the average occupancy of the charging point ρ as well as the power rating PR of the charging point. This allows us to compare the cost efficiency of different power rates and battery ranges.

We use the economic analysis to compare the different charging infrastructure systems and to show the long-term conditions under which fast charging infrastructure could be operated to cover its cost. Here, we determine a necessary price surplus on the electricity price since a time of use pricing scheme for fast charging can generally be considered as efficient (Schroeder, Traber 2012). However, other pricing schemes, such as flat rates, might be advantageous due to their simplicity, but comparing pricing schemes is beyond the scope of this study.

2.3. Techno-economic assumptions

In the calculations, we use net power rates of 50, 100 and 150 kW. Furthermore, we assume net electric ranges of 100, 200 and 300 km and do not differentiate vehicle sizes.[9] The energy consumption of the vehicles is assumed to be 18 kWh/100 km (Helms et al., 2011) and the year of analysis is 2020 to be able to compare results to the German plans for charging infrastructure setup.

The determination of cost estimates for fast charging points is very difficult since only a few studies are available on this topic (cf. Table 5).

In this study, we project the future cost decrease based on the cost component distinction derived from several studies (Funke, 2018). For a charging point, hardware costs were at 25,000 EUR per charging point in 2015 and the cost is expected to decrease by 5% per year to 19,000 EUR in 2020 based on (NPE, 2015). Installation costs are assumed to stay equal at 3500 EUR per charging point. Concession costs do not change either and remain at 1500 EUR. The cost for a substation depends on the maximum power of the charging point and is 10,000 EUR per charging point with 150 kW and 5000 EUR for 50 kW, respectively (Funke, 2018). For a charging point with 100 kW, we assume a cost of 7500 EUR. This cost is not assumed to decrease either, since the technology is already mature. The connection for the power supply line depends on the power and the diameter of the cable. For 50 kW, Funke (2018) suggests 7500 EUR and 25,000 EUR for 150 kW. We assume the cost for a 100 kW charging point to thus be 15,000 EUR and that these costs do not change. Please note that we use average values for grid connection costs as we are interested in the general economic feasibility of a fast charging network. However, especially grid installation costs can vary largely between sites. This results in the investments costs that are shown in Table 5. For operating cost, we use 10% of the investment as suggested by (Schroeder and Traber, 2012). Note that fast charging stations will always contain more than one fast charging point and concession or installation costs cannot be divided, yet for the direct comparison, the assumptions of average cost per charging point are more useful.

3. Results

The presentation of our results is divided into three steps. First, we give an overview of fast charging usage observed at Swedish and Norwegian charging stations. Second, we deduce modeling assumptions of fast charging needs and compare our model to the empirical charging data. Finally, we estimate fast charging needs for Germany and Sweden.

[9] Thus, we do neither discuss the efficiency of the charging station, nor the usable battery capacity. Both, range and power can be considered as usable values.

Table 5
Cost assumptions for fast charging points in various studies.

Power [kW]	Year	Investment and installation [EUR]	Annual cost [EUR/year]	Reference
50[a]	2012	90,000	4000	Schroeder and Traber (2012)
50	2015	35,000	3000	NPE (2015)
50[b]	2015	45,000	3000	Funke (2018)
150[b]	2015	120,000	3000	Funke (2018)
250[a]	2012	125,000	1000 (6000)	Schroeder and Traber (2012)
50	2020	36,500	3650	Assumptions for this study based on (Funke 2018)
100	2020	46,500	4650	
150	2020	59,000	5900	

[a] Number of fast charging points at the fast charging station not mentioned.
[b] Cost for concession and substation not divided by number of possible fast charging points.

3.1. Empirical fast charging station usage

In this section, we compute measures on the charging data that is used as model input (distribution of charging times and share of daily rush hour) and validation of inter-arrival times and some of the model outputs (see Fig. 1).

The validity of the assumption of normally distributed charging times can be assessed by comparing to the empirical kernel density estimates (KDE) and fitted normal distributions of charging times for Sweden and Norway in Fig. 2. The solid lines are the KDE and the crosses mark the fitted normal distributions. Though the KDE have a heavy tail, we have chosen to fit the normal distributions with a cut-off at 35 min (only including data points under 35 min) as longer charge time would not yield any extra energy in the battery given current battery sizes. The parameters of the normal distribution are given in Table 6. As seen in Fig. 2, a normal distribution is not a perfect match to the empirical data, however, the peak of the distribution (the mean), and the spread of the distribution (the variance) are well positioned. These are the two parameters that are relevant for our model, thus the normal distribution predicts these parameters well. In comparison, other distributions, which better account for tail probabilities (such as Weibull and log-normal) do not center the peak of the KDE distribution well. Further, it is more important to have a good fit for the mean and the variance, rather than distribution tails, since long charging times reflect users that let their vehicle remain connected to the charging point well after they have been recharged (given current battery sizes). We also tested the sensitivity of our results for the assumption of a log-normal and a Weibull distribution but found only a limited effect. Therefore, we focus on the normal distribution in the following.

The difference between Sweden and Norway could be explained by differences in payment schemes with the assumption being that payment requirements reduce the time that people charge. Of the fast chargers included in the data set used here, at least 55% require payment in Sweden, and at least 87% require payment in Norway (the database lacks information on payment for some of the chargers in both countries).

The model assumes exponentially distributed inter-arrival times. Fig. 3 shows empirical inter-plug-in times. As is clear from the figure, there is an important day-night influence on arrivals with fewer arrivals to charge at night and more arrivals at daytime. Since no commonly used distributions account for such shifts, inter-arrival times are only practical to calculate over a 24 h period, and the

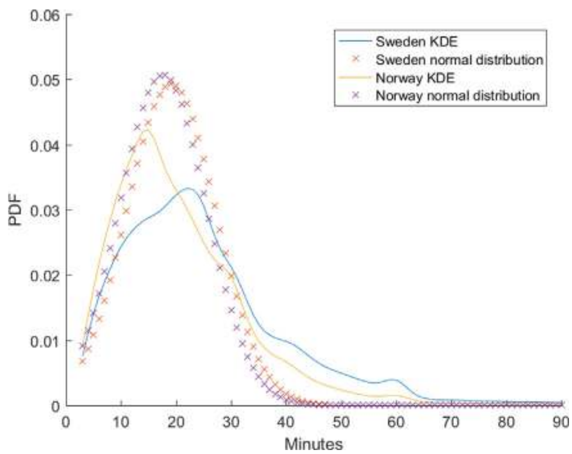

Fig. 2. Charging time distributions for Sweden and Norway. The solid lines are empirical KDEs the crosses are the fitted Normal distribution where only data points below 35 min charging time have been included.

Table 6
Normal distribution parameters including 95% confidence intervals (CI) for charging times for Sweden and Norway.

	Mean [95% CI in brackets]	Standard deviation [95% CI in brackets]
Sweden (min)	19.1 [19.0, 19.2]	8.1 [7.8, 8.2]
Norway (min)	17.6 [17.6, 17.6]	7.9 [7.9, 7.9]

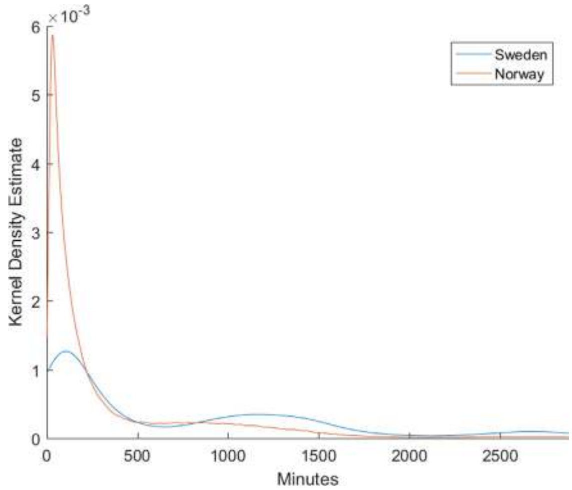

Fig. 3. Kernel density estimate for inter-plug-in times for Sweden and Norway.

data is unfortunately to sparse for this purpose. However, it is clear that Norway has denser arrivals compared to Sweden. The higher density of arrivals in the Norwegian data also leads to more exponentially distributed inter-arrival times, in line with the model assumptions. We interpret this as suggesting that the exponential distribution can be a good choice in a more mature electric vehicle market, especially when focusing on the rush hour demand.

The distribution of charging over the day from the model can be verified by the charging data. In Fig. 4, the start time of charging for Sweden and Norway is displayed. As can be seen, the charging peaks at around 3 PM for Norway, while Sweden has a fairly stable plateau from 11 AM to 5 PM.

A number of features that the model assumes constant have seasonal variations in the data. Most notably the charging times are higher in winter compared to summer, and the frequency of charging events are also higher during vacation periods. In Table 7, these two measures are shown for Norway over 12 months of the year. The charging times vary from the lowest average of 19.1 min in September to the highest of 25.3 min in January, thus possibly affecting queueing times in winter. For the number of events each month, it is clear that July and October are exceptional, with 30% more events compared to the average month. July is a standard summer vacation month, while the autumn school leave occurs in October and November. This increase in charging events would linearly increase queuing at the charging sites during these months.

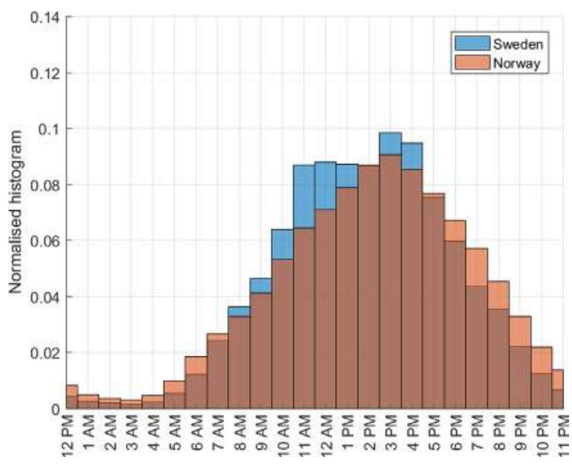

Fig. 4. Distribution of start times of charging in Sweden and Norway.

Table 7
Yearly variations on charging times and number of charging events for the Norwegian charging data.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Deviation of # of events from average.	0.94	0.84	0.63	0.85	0.89	0.99	1.28	1.04	1.04	1.30	1.19	1.02
Charging time [min]	25.3	23.4	22.2	20.8	20.0	19.6	20.1	19.4	19.1	20.2	21.6	22.8

Table 8
Summary statistics of charging times [min] for Sweden (SE) and Germany (DE) differentiated by electric range and power rate.

	Power [kW]	50	50	50	100	100	100	150	150	150
	Range [km]	100	200	300	100	200	300	100	200	300
DE	Mean	14.1	22.8	27.0	7.0	11.4	13.5	4.7	7.6	9.0
DE	Var	5.9	20.6	36.7	1.5	5.1	9.0	0.6	2.3	4.1
SE	Mean	20.9	36.1	41.9	10.5	18.0	20.9	7.0	12.1	14.0
SE	Var	0.4	7.0	54.1	0.1	1.7	13.6	0.04	0.8	5.9

3.2. Model development

For modeling the availability of charging sites we use the queuing model described in Section 2.2.2 based on the empirical charging and driving data (c.f. Fig. 1). In this section, we present the model assumptions of user arrivals and charging times.

Charging times depend on charging power and the amount of energy charged. The energy charged per charging session in turn is influenced by the electric range of the vehicle as well as by individual driving behavior. As we expect users to preferably charge at home due to lower costs, we presume that the amount of energy charged publicly depends on trip distances enabled by the respective charging event (cf. Section 2.2.1). Table 8 shows the projected mean and variances of charging times (in minutes) for the analyzed nine combinations of charging power and battery size. Results are shown for calculations based on German as well as Swedish driving data (MOP, 2010, Karlsson, 2013). Due to the higher share of long distance trips in Sweden, distances that need charging events are higher in Sweden than in Germany. This results in – ceteris paribus – higher charging times. We find charging times for German driving behavior to average 14 min under today's circumstances (electric range of 100 km, charging power 50 kW), while they are higher for Sweden (21 min). The latter are in good agreement with the observed empirical charging times in Fig. 2.

The distribution of calculated Swedish charging times has a higher peak and less variation compared to the empirical data, probably due to the fact that most of the Swedish driving profiles need a complete recharge with an electric vehicle range of 100 km. The variance and length of charging times decreases with higher power rate (see Table 8). With 150 kW, the charging times fall below five minutes. Due to these very short charging times, the direct dependency of charging times from charging energy is disputable. However, we neglect such effects as reliable data on charging behavior with power rates above 100 kW is still lacking.

With longer vehicle ranges, the amount of energy charged increases, leading to higher charging times (see Table 8), while the number of trips needing a recharge decreases (see Table 3). I.e., trips needing a recharging stop with shorter vehicle ranges become feasible and only very long trips still require recharging when vehicle ranges increase[10]. Charging times increase since public fast charging only has to cover these very long distance trips. In addition, for the Swedish driving data we see a larger variance of charging times as a full recharge becomes less relevant with increasing vehicle ranges.

Based on the findings in Section 3.1, we assume that ten percent of daily charging demand happens in the rush hour and scale charging sites accordingly (c.f. Fig. 4). The assumed charging share during rush hour is in accordance with the temporal distribution of empirical charging demand (see Section 3.1 and (Funke 2018)) as well as of the share of long distance trips in Germany (MOP, 2010, Funke, 2018). Results for all indicators mentioned in Section 2.2.2 are shown in the Annex (Tables A2–A5).

3.3. Model results

Let us now turn to the resulting charging infrastructure demand for Germany and Sweden. Keep in mind that for our calculations we use a queuing model with charging times derived from the driving profiles described in Section 2.1 and an average waiting time of at maximum five minutes at rush hour. The results are divided into three parts presented in Table 9 for Germany and Table 10 for Sweden. First, for technical measures we look at the occupancy during rush hour, the occupancy ρ during an average hour as well as the average waiting time W_q during the average hour. Second, we present an economic measure, i.e., the cost premium p^{FC} for each kilowatt-hour charged based on the average occupancy ρ (avg. hour). Last, the main results for infrastructure planners are presented: the number of charging events per charging point and year, and the vehicle to refueling station index (VRI).

For Germany, we find the occupancy rate in the rush hour to decrease with a higher BEV range and to increase with higher power. However, the decrease is lower when the average BEV range increases from 200 km to 300 km than from 100 km to 200 km. Thus, the number of trips that have to be covered by charging at a fast charging point decreases with higher battery size which makes sense as

[10] This results in a decreasing number of trips needing a recharge.

Table 9
Characterizing indicators of queuing model for Germany.

Power [kW]	50	50	50	100	100	100	150	150	150
Range [km]	100	200	300	100	200	300	100	200	300
ρ (rush hour)	41%	30%	28%	58%	46%	43%	68%	56%	53%
ρ (avg. hour)	17%	13%	12%	24%	19%	18%	28%	23%	22%
W_q (avg. hour) [min]	1.48	1.66	1.69	1.15	1.39	1.45	0.94	1.19	1.26
$p^{FC}(T = 10 years)$ [EUR_{2017}/kWh]	0.11	0.15	0.16	0.05	0.06	0.07	0.04	0.04	0.05
Max. no of charging events per point & year	6439	2985	2468	18,256	9076	7492	31,838	16,578	13,871
Fast charging points/1000BEV (VRI)	6.8	5.3	3.7	2.4	1.8	1.2	1.4	1.0	0.7

Table 10
Characterizing indicators of queuing model for Sweden.

Power [kW]	50	50	50	100	100	100	150	150	150
Range [km]	100	200	300	100	200	300	100	200	300
ρ (rush hour)	32%	22%	19%	49%	36%	32%	59%	45%	41%
ρ (avg. hour)	13%	9%	8%	20%	15%	13%	25%	19%	17%
W_q (avg. hour) [min]	1.63	1.80	1.84	1.34	1.58	1.64	1.14	1.41	1.48
$p^{FC}(T = 10)$ [EUR_{2017}/kWh]	0.14	0.21	0.24	0.06	0.08	0.09	0.04	0.05	0.06
Max. no of charging events per point & year	3399	1308	983	10,198	4322	3319	18,438	8221	6415
Fast charging points/1000BEV (VRI)	12.8	14.1	11.5	4.3	4.3	3.4	2.4	2.2	1.8

the daily distances of one/several drivers follow a right-skewed distribution and the trips needing fast charging tend to be longer. Hence, the larger the batteries are, the lower the occupancy of the fast charging point. On the other hand, an increase of charging power always increases the occupancy since charging times are lower and the throughput is higher. This indicates that charging point owners could earn more money when they increase charging power while larger batteries without an increase of charging power could reduce their profitability.

When looking at the average hour, we find similar effects, yet the average occupancy is around 15–30% for almost every combination of charging power and range. E.g. for 50 kW and 100 km range, the charging points will be occupied about four hours per day (0.17·24) while they will be occupied 25 min during the rush hour (0.41·60). Thus, the average waiting times decrease by large to 1–2 min when the whole day is considered. When we use the occupancy of the charging point for the average hour during the day and project this to the whole year, we can calculate the price premium for fast charging points that is enough to cover the cost for the fast charging point.[11] The numbers correspond to the reciprocal of the occupancy and thus decrease with rising charging power and increase with BEV range. However, price premiums are low compared to slow charging points and in line with other studies (Gnann, 2015, Jochem et al., 2016a, 2016b).

Both BEV range and charging power also determine the maximum number of charging events per charging point[12] and thus the ratio between charging points and BEVs. We find the highest number of charging events with BEV ranges of 100 km which are cut to half with a doubling of the battery size, since the larger the battery the longer the distances that have to be recharged. Charging times increase as well and consequently, the charging point is occupied longer. A further increase of range does not really change the number of charging events per charging point and year. With higher power (100 kW), charging times decrease and the number of charging events can be tripled. An increase from 100 kW to 150 kW can almost double the number of charging events with smaller battery sizes (100 or 200 km), but only increase the number of charging events by about 80% when battery sizes are around 300 km.

The vehicle-to-refueling station index (VRI) is a measure that has been used for conventional cars and their refueling stations, but also for natural gas vehicles and their ratio to refueling stations (Janssen et al., 2006, Yeh, 2007). The situation for plug-in electric vehicles is currently more difficult because of lower ranges and higher charging durations of BEVs compared to conventional cars (Gnann and Plötz, 2015). However, at fast charging points with high power the charging times could be acceptable for users. Hence, we believe the VRI to be a good indicator to reflect fast charging infrastructure needs. Based on the earlier made model assumptions, we find a VRI of 6.8 for 100 km BEV range and 50 kW which can be considered today's situation. With increasing range and power, a VRI around 1 is possible, which has been empirically shown to be a good ratio for natural gas vehicles (Yeh, 2007) and a goal for alternative fuel vehicles in general (Gnann and Plötz, 2015). We can thus assume that in addition to home charging points, a fast charging network comparable to the current refueling station network in Germany (VRI = 0.3 for conventional fuels) could be a good complement.

Looking at the Swedish results, we find a slightly lower occupancy of charging points at rush hour and average hour than in Germany. Therefore, the price supplements are a little higher than in Germany. The maximum number of charging events is lower

[11] We show results for a payback time of ten years in Table 9. Results for five years payback time are given in Table A6. Calculation acc. to Eq. (5).
[12] The number of fast charging events per year can be calculated as: $n = 365{\cdot}24{\cdot}60{\cdot}\frac{\rho}{\mu}$

due to the longer charging times because of longer long-distance trips in Sweden (which is confirmed in Section 3.1). This also results in higher VRI's with a range between 12.8 and 1.8.

4. Discussion

Our analysis is based on empirical charging behavior from Sweden and Norway, both countries are major European markets for plug-in electric vehicles (PEV) with regard to PEV share in new vehicle registrations. The employed charging data set contains 18,349 charging events at 32 charging sites for Sweden and 386,053 charging events at 192 charging sites for Norway, respectively (after filtering). By using the described data set, we exclude the charging sites from Tesla, yet this seems reasonable to the authors since they are not publicly accessible to date. With 387 (8 3 5) publicly accessible CCS and CHAdeMO fast charging points installed in Sweden (Norway) at the end of 2016 (EAFO, 2018), our dataset comprises about 8% (23%) of all charging sites geographically evenly distributed in the respective country, thus covering a noteworthy share of all charging events and allowing for a sound analysis of actual PEV charging behavior. Despite the different PEV market shares, Sweden has many more PHEV while the Norwegian PEV stock is characterized by a higher share of BEV, which could result in different fast charging behavior. Yet, the inclusion of both countries in our analysis and the fast charging model makes our findings more robust and easier transferable to other PEV markets.

The design of our queuing model comes with limitations as our results directly depend on the assumptions on charging behavior. While some of our assumptions might lead to an underestimation of charging infrastructure demands, other assumptions might overestimate them.

We assume every charging site to have one charging point. This allows for a general determination of charging infrastructure demand independently from local differences of charging demand as charging sites can be located flexibly, i.e. including the placement of multiple charging points at one charging site. Nevertheless, especially a charging site with multiple charging points (e.g. modeled as $M|G|s$-queuing systems) could reduce the number of charging points needed compared to several charging sites with one charging point (see (Bhat, 2015) for details). Altogether, our model is especially suited for a short- to medium-term analysis. Yet, it might overestimate charging infrastructure needs in the long-term due to the aforementioned reasons.

Our estimates of the required number of charging events per user and year provide an upper limit. Recent analyses of daily driving distributions show that the log-normal distribution provides conservative estimates for the number of days with long-distance travel (Plötz et al., 2017) than estimates based on the Weibull distribution. Thus, the required number of fast charging points could be smaller than stated in the model results.

Furthermore, the calculations have been performed for the expected peak hour demand but a potential operator could be willing to build infrastructure for average demand to reduce investments and accept longer waiting times for users in peak hours. However, the aim of the present paper was to estimate the needed number of fast charging sites to meet general demand irrespective of cost optimization aspects.

With regard to future developments, charging power well above the assumed level of 150 kW could further reduce charging infrastructure demands.

In contrast, the following assumptions might lead to higher charging infrastructure demand than stated by our results. We include the assumption of rush hour demand into our analysis, but neglect for variations during the year. As the analysis of our empirical charging data shows (see also Table 7), in some months, charging demand can be up to 30% higher than average, which would result in a proportional increase of charging infrastructure demand. In addition, a higher energy demand due to heating in winter could lead to higher charging times in winter. Also charging times may change in winter due to cold cables and since charging time is the major parameter influencing waiting times within the queuing model this will also increase the need for fast charging.

We assume charging time to increase less than proportionally with battery size since we do not expect BEV drivers to fully charge at public fast charging sites. The assumption of a proportional increase of energy charged publicly with battery capacity would increase charging infrastructure demand by up to 60%.

The fact that we focus on charging infrastructure demand resulting from actual charging demand and neglect for charging infrastructure demand to guarantee geographical coverage might also underestimate total charging infrastructure needs. Especially in an early market phase, a low number of charging locations might be a barrier to BEV adoption due to psychological effects like range anxiety or a limited acceptance of waiting times. With this regard, our results can be considered as a lower limit of public charging infrastructure demand. For example, our model results hold a vehicle-to-refueling station index (VRI) of 12.8 charging points per 1000 BEV for Sweden (50 kW, 100 km). Under today's Swedish vehicle stock this would result in an average maximum distance of ~20 km to the next charging point. This relates to an actual VRI in Sweden of ~15.3 [charging points/1000 BEV] (EAFO, 2018), resulting in an average maximum distance of ~12 km to the next charging point if they were distributed equally. However, with a higher ratio of charging points to BEV (VRI), the charging infrastructure is economically less attractive. This is indicated by the relatively low usage rate of actual charging infrastructure.

In addition, the driving and charging behavior might change in the future, which could increase or decrease charging infrastructure demand. Yet, no empirical data on these behavioral changes is available at the moment that we could integrate into the analyses.

In summary, however, the presented results of charging infrastructure need are consistent with results from other studies (see e.g. Jochem et al., 2016a, 2016b) and are in line with empirical infrastructure needs of alternative fuel vehicles such as CNG (Yeh 2007).

Altogether, we based our analysis on actual data, however, due to a lack of empirical data for high charging power and long vehicle ranges, we estimate potential future charging demand based on actual driving behavior of conventional vehicles which comes with the aforementioned uncertainties. Consequently, for a better understanding of the influence of charging power and vehicle range on charging times, future research is necessary to provide further empirical data on fast charging behavior. Analogously, the effects of peak demand need further research for a highly used public charging infrastructure.

5. Summary and conclusions

In this paper, we studied the fast charging infrastructure needs in different countries. What can we retain from these results? Queuing models are often designed as M|M|1- or M|M|c-models which means that the inter-arrival times of users in the system as well as the service times are exponentially distributed while the service is provided by one or c service points. Based on real-world charging data, we can say that the charging times (i.e. service times) are not exponentially but rather normally distributed which favors a M|G|1- or M|G|c-model. In this form, the mean and expected value of the distribution play a bigger role. This is an important methodological finding and should be considered in future works.

Our results show that the vehicle-to-refueling-index (VRI), which is the ratio of refueling stations per 1000 vehicles, for fast charging points and battery electric vehicles can be close to conventional cars if charging power and battery sizes keep increasing (VRI for conventional cars at 0.3 for Germany and 1.8 for Sweden). This ratio was assumed to be much higher for estimates given five years ago (cf. Section 1) and may help to readjust expectations from policy makers and the general public. This lower ratio also causes a higher occupation of fast charging points and thus a lower surplus on the electricity price for an economical operation. This is in line with recent publications from the US (US DoE, 2017). Thus, the additional cost for fast chargers is relatively low if a demand driven approach for the setup of public fast charging infrastructure is pursued.

Acknowledgements

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Annex

See Tables A1–A7.

Table A1
Distance to be recharged and ratio to range.

	Range [km]	100	200	300
DE	Distance to be recharged [km]	65	106	125
DE	Percentage of range	65%	53%	42%
SE	Distance to be recharged [km]	97	167	194
SE	Percentage of range	97%	84%	65%

Table A2
Indicators of queuing model for rush hour in Germany.

Power [kW]	50	50	50	100	100	100	150	150	150
Range [km]	100	200	300	100	200	300	100	200	300
E(S) [min]	14.0	22.3	25.1	7.0	11.2	12.6	4.7	7.4	8.4
V(S) [min^2]	5.9	20.6	36.7	1.5	5.1	9.0	0.6	2.3	4.1
μ [1/min]	0.07	0.04	0.04	0.14	0.09	0.08	0.22	0.13	0.12
λ [1/min]	0.03	0.01	0.01	0.08	0.04	0.03	0.15	0.08	0.06
ρ	41%	30%	28%	58%	46%	43%	68%	56%	53%
W_q [min]	5	5	5	5	5	5	5	5	5
L_q	0.15	0.07	0.06	0.42	0.21	0.17	0.73	0.38	0.32
W [min]	19.0	27.3	30.1	12.0	16.2	17.6	9.7	12.4	13.4
L	0.56	0.37	0.34	1.00	0.67	0.60	1.40	0.94	0.85

Table A3
Indicators of queuing model for rush hour in Sweden.

Power [kW] Range [km]	50 100	50 200	50 300	100 100	100 200	100 300	150 100	150 200	150 300
E(S) [min]	20.9	36.1	41.9	10.5	18.0	20.9	7.0	12.0	14.0
V(S) [min^2]	0.4	7.0	54.1	0.1	1.7	13.6	0.0	0.8	5.9
μ [1/min]	0.05	0.03	0.02	0.10	0.06	0.05	0.14	0.08	0.07
λ [1/min]	0.02	0.01	0.00	0.05	0.02	0.02	0.08	0.04	0.03
ρ	32%	22%	19%	49%	36%	32%	59%	45%	41%
W_q [min]	5	5	5	5	5	5	5	5	5
L_q	0.08	0.03	0.02	0.23	0.10	0.08	0.42	0.19	0.15
W [min]	25.9	41.1	46.9	15.5	23.0	25.9	12.0	17.0	19.0
L	0.40	0.25	0.21	0.72	0.45	0.39	1.01	0.64	0.56

Table A4
Characterizing indicators of queuing model for average hour in Germany.

Power [kW] Range [km]	50 100	50 200	50 300	100 100	100 200	100 300	150 100	150 200	150 300
λ [1/min]	0.01	0.01	0.00	0.03	0.02	0.01	0.06	0.03	0.03
ρ	17%	13%	12%	24%	19%	18%	28%	23%	22%
W_q [min]	1.48	1.66	1.69	1.15	1.39	1.45	0.94	1.19	1.26
L_q	0.02	0.01	0.01	0.04	0.02	0.02	0.06	0.04	0.03
W [min]	15.4	24.0	26.8	8.1	12.5	14.0	5.6	8.6	9.6
L	0.19	0.14	0.13	0.28	0.22	0.20	0.34	0.27	0.25

Table A5
Characterizing indicators of queuing model for average hour in Sweden.

Power [kW] Range [km]	50 100	50 200	50 300	100 100	100 200	100 300	150 100	150 200	150 300
λ [1/min]	0.01	0.00	0.00	0.02	0.01	0.01	0.04	0.02	0.01
ρ	13%	9%	8%	20%	15%	13%	25%	19%	17%
W_q [min]	1.63	1.80	1.84	1.34	1.58	1.64	1.14	1.41	1.48
L_q	0.01	0.00	0.00	0.03	0.01	0.01	0.04	0.02	0.02
W [min]	22.5	37.9	43.7	11.8	19.6	22.5	8.1	13.5	15.5
L	0.15	0.09	0.08	0.23	0.16	0.14	0.29	0.21	0.19

Table A6
Resulting price premium to cover cost for charging point (not including price for electricity) in 2020 – based on German model parameters.

Power [kW] Range [km]	50 100	50 200	50 300	100 100	100 200	100 300	150 100	150 200	150 300
$p^{FC}(T = 10)$ [EUR/kWh]	0.11	0.15	0.16	0.05	0.06	0.07	0.04	0.04	0.05
$p^{FC}(T = 5)$ [EUR/kWh]	0.16	0.22	0.23	0.07	0.09	0.10	0.05	0.06	0.07

Table A7
Resulting price premium to cover cost for charging point (not including price for electricity) in 2020 – based on Swedish model parameters.

Power [kW] Range [km]	50 100	50 200	50 300	100 100	100 200	100 300	150 100	150 200	150 300
$p^{FC}(T = 10)$ [EUR/kWh]	0.14	0.21	0.24	0.06	0.08	0.09	0.04	0.05	0.06
$p^{FC}(T = 5)$ [EUR/kWh]	0.20	0.31	0.35	0.09	0.12	0.13	0.06	0.08	0.09

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