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A Model for Public Fast Charging Infrastructure Needs

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Abstract

Plug-in electric vehicles can reduce GHG emissions although the low availability of public charging infrastructure combined with short driving ranges prevents potential users from adoption. The rollout and operation, especially of public fast charging infrastructure, is very costly. Therefore, policy makers, car manufacturers and charging infrastructure providers are interested in determining a number of charging stations that is sufficient. Since most studies focus on the placement and not on the determination of the number of charging stations, this paper proposes a model for the quantification of public fast charging points.

We first analyze a large database of German driving profiles to obtain the viable share of plug-in electric vehicles in 2030 and determine the corresponding demand for fast charging events. Special focus lies on a general formalism of a queuing system for charging points. This approach allows us to quantify the capacity provided per charging point and the required quantity. Furthermore, we take a closer look on the stochastic occupancy rate of charging points for a certain service level and the distribution of the time users have to wait in the queue. When applying this model to Germany, we find about 15,000 fast charging points with 50 kW necessary in 2030 or ten fast charging point per 1,000 BEVs. When compared with existing charging data from Sweden, this is lower than the currently existing 36 fast charging points per 1,000 BEVs. Furthermore, we compare the models output of charging event distribution over the day with that of the real data and find a qualitatively similar load of the charging network, though with a small shift towards later in the day for the model.

Keywords: Charging infrastructure, queuing model, stochastic occupancy rate of charging points, electric vehicle

1 Introduction

Plug-in electric vehicles (PEV) can reduce GHG emissions if powered with renewable energy. A barrier to the market diffusion is the low range given by current batteries. Though it is possible to find user groups who fulfill their driving needs while remaining economical without public charging (see e.g. [1]), a broader introduction of battery electric vehicles would require an improvement of battery technology or a more extensive charging infrastructure. This is also postulated by potential vehicle buyers [2]. Yet, existing models for public charging infrastructure focus on their placement and not on the quantification of public charging points [3-5]. With more PEVs on the roads, consideration of queuing and charger capacity is an important issue that needs to be addressed [6].

Hence, the aim of this paper is to propose a model that is able to quantify the need for public charging infrastructure and apply it to Germany and its need until 2030. Here, we focus on public fast charging points (with at least 50 kW power), since first calculations on slow charging points showed no effect on PEV market diffusion [6, 7]. We compare some of the model outputs with real world data from charging infrastructure in Sweden. Using the model, we answer the following research question: How many charging points are needed in Germany in 2030? In the following sections, the methods and data are described, followed by initial results, a discussion and conclusions.

2 Methods and Data

2.1 Methods

First, we determine the number of PEVs and their charging behaviour by using the simulation model ALADIN (Alternative Automobiles Diffusion and Infrastructure, described in detail in [7]). The model works as follows: Every driving profile is simulated individually with four types of drive trains: BEVs, plug-in hybrid electric vehicles (PHEVs), gasoline and diesel vehicles. Based on the simulation, the best drive train option is determined in a utility function which includes the total cost of ownership for the vehicle, but also the cost for individual charging infrastructure as obstructing factor and a willingness-to-pay-more as favouring factor (see [7] for details).

The vehicle TCO are slightly adapted compared to [7], so that the operating expenditure (a^{opex}) for each vehicle is calculated as:

$$\alpha_i^{opex} = VKT_i \cdot \left(c_{e/c} \cdot k_{e/c} + k_{OM}\right) + k_{tax} + k_{fast\ charging_i} \cdot D(L)_i$$

It comprises driving dependent and driving independent costs. The cost for driving consists of the specific consumption for electric or conventional driving ($c_{e/c}$) in kWh/km or l/km and the specific cost for electricity or fuel ($k_{e/c}$) in EUR/kWh or EUR/l. By adding the cost for operations and maintenance (k_{OM}) we obtain the specific costs per kilometer which are multiplied by the annual vehicle kilometres travelled (VKT_i) for the driving dependent cost.

Driving independent costs consist of annual vehicle tax (k_{tax}) and the cost for the occasional use of fast charging infrastructure ($k_{fast\ charging_i}$) multiplied by the number of days that exceed the electrical range of a BEV ($D(L)_i$). Note that PHEVs are not assumed to use fast charging since they can refuel their vehicle with conventional fuel.

To include this calculation in ALADIN, the number of days on which the BEV range is exceeded has to be determined. Therefore, a method proposed in [9] is used that allows us to calculate the number of days that exceed the BEV range. As a result of using ALADIN, we obtain driving profiles from a large data set, for which the best drive train option is a BEV. Furthermore, we can determine the BEV stock until 2030 (see [7] for a discussion).

An understanding of the distribution of daily vehicle kilometers traveled allows us to estimate the probability of rare long-distance travel and in order to that the need for fast charging events [9]. Based on the assumption that fast charging infrastructure is needed when the driving distance exceeds the electric range, we need to quantify the number of trips longer than the given electric range of 200 km. Therefore, we calculate the number of days $D(L)$ per year for which the driving distance r is larger than the electrical range L to determine the need for fast charging events. In other words, $D(L)$ are the number of days per year that would require fast charging infrastructure to cover the full driving distance with a BEV.

We obtain the number of days D per year with a daily driving of more than L kilometres as

$$D(L) = 365\ \alpha \left[\frac{1}{2} - erf\left(\frac{\ln L - \mu}{\eta\sqrt{2}}\right)\right] \approx \frac{365\ \alpha}{1+(\frac{L}{e^{\mu}})^{\pi/(\eta\sqrt{3})}}.$$

Based on the finite number of driving and observation days, we can estimate the number of days $D(L)$ with vehicle kilometers travelled larger than the electrical range L which represents the need for fast charging events per year (see [9] for a discussion).

Secondly, we determine the number of fast charging points based on the fast charging events in 2030 in a queuing model. Naturally, users want to find a vacant charging point when they arrive at a charging station. On the other hand, charging infrastructure operators are dependent on an economic operation of their charging stations and aim a high occupancy rate. Hence, we developed a queueing model to quantify the need for fast charging events as a stochastic process of arriving users at fast charging points. This allows us to investigate the possible capacity of fast charging points for a given service level. Furthermore, we examine the possible occupancy rates of charging points fulfilling these restrictions with different charging power.

The inter-arrival times between two users needing fast charging events are assumed to follow an exponential distribution. Furthermore, we assume that the service time is exponentially distributed. With these assumptions, we obtain

$$E[interarrival\ time] = \frac{1}{\lambda} = \frac{1}{arrival\ rate}$$

and

$$E[service\ time] = \frac{1}{\mu} = \frac{1}{service\ rate}.$$

The queuing model comprises one charging point. Moreover, the waiting room is limited to a maximum of two users in the system – one charging and one waiting. If the charging point is occupied and another user is already waiting in the queue, further arriving users are rejected. The operating sequence is based on the "first come, first serve" principle. According to the notation of Kendall, the queuing model can be denoted as $M/M/1/2$ [17]. Figure 1 shows the transition graph with the possible states for the system.

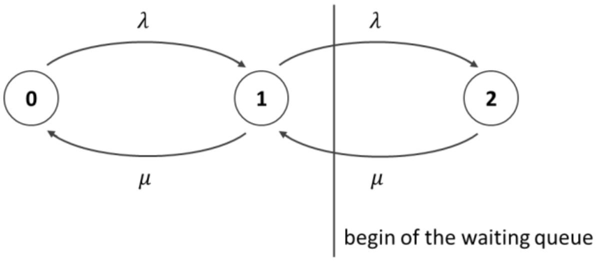

Figure 1: Transition graph of the queuing model.

The circles show the number of users in the system, which arrive with arrival rate λ and recharge the battery of their BEV with the service rate μ.

Formulas for the calculation of the characterising operating numbers for the queueing model are summarized in Table 1.

Table 1: Overview of the operating numbers for the queuing model following [17].

Parameter	**Formula**
Occupancy rate	$\rho = \frac{\lambda}{\mu}$
Probability for i users in the system	$\pi_i = \frac{(1-\rho)\rho^i}{1-\rho^{K+1}}\ f\ddot{u}r\ \rho \neq 1$
Average number of users in the system	$U = \sum_{i=0}^{K} i\pi_i = \frac{\rho}{1-\rho} - \frac{(K+1)\rho^{K+1}}{1-\rho^{K+1}}\ f\ddot{u}r\ \rho \neq 1$
Average number of waiting users	$U_q = \sum_{i=1}^{K}(i-1)\pi_i = L - (1-\pi_0)$
Average time spent by a user in the system	$W = U/\tilde{\lambda}$
Average user waiting time	$W_q = U_q/\tilde{\lambda}$

For a comprehensive evaluation of the waiting times and the resulting service quality for the users, the distribution of waiting times and the expected waiting times W_q are of interest. According to [17], the time user spend in the queue is Erlang distributed with

$$F_q(t) = 1 - \frac{1-\rho}{1-\rho^K} \sum_{n=1}^{K-1} \rho^n \sum_{r=0}^{n-1} e^{-\mu t} \frac{(\mu t)^r}{r!}$$
$$for\ \rho \neq 1.$$

Since we require a service level, which ensures that the waiting time for users remains limited, the occupancy rate has to be $\rho < 1$ at any time. Whereby $\rho \neq 1$ is always fulfilled. Consequently, the $F_q(t)$ is considered as always valid in the following.

The service rate μ is the reciprocal value of the average charging time t_b. Therefore t_b is determined by the expected value for the demanded energy, the nominal load to the power grid and the efficiency of the power electronics and the battery which is assumed with $\eta_{charge} = 86\%$ [20,21]. In order to analyze the influence of the charging power to the required number of fast charging points and characterising parameters, a charging power of 50, 100 and 150 kW is considered.

For limiting the waiting time until the charging process can be started, a certain number of charging points is required. In other words, the arrival rate for a given charging point must be sufficiently small so that a required service level can be achieved. Thus, we determine an arrival rate which ensures that the tolerable waiting time t_W in the queue of a charging point is not exceeded with a certain probability. According to [17], the probability that arriving users have to wait not more than t_W minutes is given by

$$P(W \leq t_W) = 1 - \frac{\lambda\mu^2 - \lambda^2\mu}{\mu^3 - \lambda^3} e^{-\mu t_W}.$$

This equation can be solved algebraically to λ. As a result, we obtain the minimum arrival rate λ per charging point, depending on the service rate μ, the tolerated waiting time t_W and probability, that a user do not have to wait longer than t_W. We assume that 80% of the arriving users are willing to wait no longer than 5 minutes. With this assumption, we may determine a solution for λ which will be referred as λ_{tW} in the following.

The reciprocal value of λ_{tW} represents the mean inter-arrival time which can be processed by a charging point for a certain service level. For single-server systems with limited waiting room ($M/M/1/2$), the entry rate $\tilde{\lambda}_{tW}$ into the system is different from the arrival rate λ_{tW}. This distinction is required since arriving users can be rejected due to the limited capacity of the queue. Formally, the entry rate $\tilde{\lambda}_{tW}$ for a certain charging point is given by $\tilde{\lambda}_{tW} = \lambda_{tW}\,(1 - \pi_K)$ [18] and represents the capacity of a charging point.

This relates to the average arrival rate of the user source, which is given by the need for fast charging events over a certain time period. However, the intensity of the demand varies in during the day. Furthermore, the number of long distance trips fluctuates during the week and thus the need for fast charging events. To determine the required number of charging points, a compromise between short waiting times for users and a high occupancy rate of charging points is obtained. This ensures that the battery can be recharged within a reasonable waiting time, even during a peak demand. For this purpose, we analyse the BEV profiles to determine the driving day with the highest amount of driving distances exceeding the electric range L as the bottleneck day for which the system has to be designed. To consider the intensity of the need for fast charging events, we assume that it depends on the arrival rates in the course of the day. This is taken into account with the relative distribution of arrival times of trips on the bottleneck day from [18]. Thereby, we receive the required number of fast charging points by the ratio of the arrival rate from the user source on the bottleneck day λ_{max}^D and the enter rate into the system $\tilde{\lambda}_{tW}$. Formally this results in

$$n_{FC} = \frac{\lambda_{max}^D}{\tilde{\lambda}_{tW}}$$

measured in charging points per 1,000 BEV.

An overview of all model steps is provided in Figure 2.

2.2 Data and further assumptions

For this paper, we use driving profile data from Germany: the German Mobility Panel for private users and the REM2030 profiles for commercial users [10, 11]. Both have been described in detail in [12, 7]. These data sets contain information about all trips performed with vehicles for at least one week and can be considered representative for the vehicle size and driving distances in the German vehicle registrations [7].

All cost assumptions are taken from [7]. Furthermore, we use data from [13] to validate results. The following additional assumptions have been made: The usage of fast charging infrastructure is only possible for private battery electric vehicles. For the calculations in 2030, we assume a BEV with a gross battery capacity of 40 kWh and 90%

usable net capacity. An energy consumption of 0.18 kWh/km enables a electrical range of 200 km. Moreover, it is assumed that fast charging infrastrutrue is only used when the eletrical range is exceeded on long distance trips. Then, BEVs are assumed to be able to recharge at a fast charging station. We assume that vehicles recharge from an average state of charge (SOC) of about 20% and until a SOC of 80%. This leads to an expected value for the energy need of 21,6 kWh at fast charging stations.

For every day on which the electric range of a BEV is exceeded, a potential BEV buyer has to pay 10 EUR (for 21,6 kWh of public fast charging, i. e. a public charging price of about 0.50 EUR/kWh) to cover his mobility need. An additional range from recharging of about 100 km is sufficient for most profiles [7].

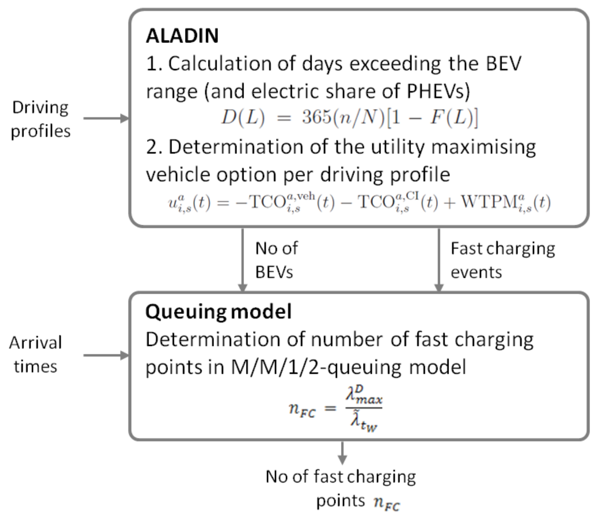

Figure 2: Overview of modelling steps.

3 Results

3.1 Simulation results

The simulation results contain two parts: the market diffusion results of ALADIN and those of the queuing model. Results for market diffusion are only briefly described, since their detailed description can be found in [7] and we will put more emphasis on results of the queuing model.

In 2030, for 765 out of 6,339 vehicle driving profiles, a BEV is the utility maximizing drive train. In the following these will be referenced as “BEV profiles”. Table 2 contains a brief summary of all vehicle driving profiles and the BEV profiles.

For BEVs, we observe a slightly higher average of days with driving within the observation period and a much higher amount of average daily vehicle kilometres travelled (VKT) than for the full sample. This results from the high amount of VKT necessary to amortize the higher investment for an alternative fuel vehicle compared to a conventional one.

Following [9], we further receive an average annual need of 30 fast charging events per year per BEV. The stock of plug-in electric vehicles sums up to 4.8 million PEVs in 2030 without public fast charging and to 5.6 million PEVs if it is possible to fast charge for private and company cars. The number of BEVs increases with 1.2 million instead of 500,000 private BEVs and 300,000 instead of 100,000 BEVs as company cars. For these vehicles fast charging with the abovementioned price of 10 EUR per charging event is considered. If these BEVs recharge 30 times per year at public fast charging stations on average, about 45 million fast charging events would take place throughout the year or about 120,000 per day on average.

Table 2: Summary statistics of driving behaviour based on [10].

BEV driving profiles (N = 765)	*0.25*	*Median*	*Mean*	*0.75*
Share of driving days	0.86	1	0.94	1
Average daily VKT [km]	42.6	71.7	86.0	112.1
All driving profiles (n=6,339)	*0.25*	*Median*	*Mean*	*0.75*
Share of driving days	0.86	1	0.93	1
Average daily VKT	22.0	38.3	50.6	65.0

Let us now turn to results from the queuing model. According to [18], about 96.7% of all arrivals occur in the time period from 5 am to 10 pm. Thus, we assume that the system has to handle the average arrival rate from the user source in the time period from 5 am to 22 pm on the bottleneck day, referred to as λ_{max}^{D}.

The analysis of the BEV profiles shows that on Fridays, the bottleneck day, about 36% more long distance trips occur than on the weekly average. According to the assumption, that the temporal distribution of long distance trips relies on the arrival rate during the day, about 96.7% of all fast charging events will be conducted between 5 am and 10 pm. This time period will be referred as “main time” in the following. As a result, we can determine an average λ_{max}^{D} = 6.3 fast charging events/(hour*1,000 BEV) during the main time.

For determining the capacity of fast charging points the following requirements have to be fulfilled: To ensure a swift charging process and provide planning certainty for the users, 80% of the arriving users shall not have to wait longer than 5 minutes until they can start their charging procedure. Thus we obtain the minimum arrival rate, which can be processed from a fast charging point for the described requirements on the service level. For 50 kW chargers the minimal arrival rate amounts to $\tilde{\lambda}_{tW}^{50\,kW}$ = 0.011, 100 kW chargers to $\tilde{\lambda}_{tW}^{100\,kW}$ = 0.027 and for 150 kW chargers to $\tilde{\lambda}_{tW}^{150\,kW}$ = 0.059.

The determination of the required number of fast charging points is based on the assumption that fast charging events are equally distributed over the year and between all charging stations. Hence, for a 50 kW infrastructure 10.0 fast charging points are needed per 1,000 BEV, respectively 3.9 100 kW charging points or 1.8 charging points with 150 kW per 1,000 BEV.

Table 3 shows different operating numbers for the determined fast charging infrastructure need on the bottleneck day for the period of time from 5 am to 10 pm. It is noteworthy that the ratio of the number of required charging points per 1,000 BEV decreases unproportionately with increasing charging power for the same service level. For example, by doubling of charging power from 50 to 100 kW, the required number of charging points is reduced more than half. In consequence, the average occupancy rate of the charging points increases with increasing charging power. Thus, higher charging power enables to serve more vehicles per day for a given service level and average waiting time. For a comprehensive evaluation of the described fast charging infrastructure need from a user and operator perspective, we take a closer look at the distribution of the average waiting times in Figure 3 and the stochastic occupancy rate in Figure 4 during the main time on the bottleneck day.

Figure 3 shows the cumulative distribution function of the average waiting time at a public fast charging station. We show the different power rated with different colours (50 kW in blue, 100 kW in yellow and 150 kW in red. We observe short waiting times for a high number of users for all three power levels, yet waiting times below five minutes are more common for lower power rates as here their numbers are higher (cf. Table 3). The intersection of all three curves is at the service level of 80 % with a tolerated waiting time of five minutes which was the presumption. However, a waiting time far above five minutes is more rare with higher power rates, since users can recharge more quickly.

Table 3: Operating numbers of the queuing model for the bottleneck day
(for the period of time from 5 am to 10 pm)

Operating numbers			**Charging power [kW]**		
			50	**100**	**150**
Fast charging points per 1.000 BEV	LP	[#/1.000 BEV]	10.0	3.9	1.8
Tolerated waiting time	t_W	[min]	5	5	5
Mean charging time	t_b	[min]	30.3	15.2	10.1
Mean inter-arrival time	t_a	[min]	95.5	37.1	17.1
Average waiting time	W_q	[min]	7.78	4.85	4.50
Average occupancy rate	ρ	[%]	32	41	59
Average served vehicles/charging point/day	F	[#]	8	21	46

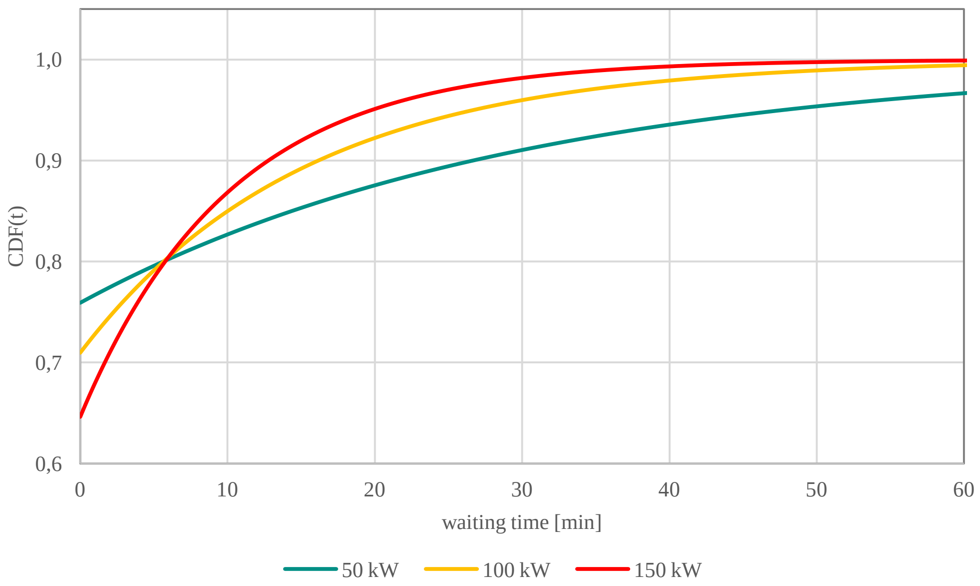

Figure 3: Distribution of the average waiting times in the queue of a fast charging point for the period of time from 5 am to 10 pm on the bottleneck day for 50, 100 and 150 kW charging points.

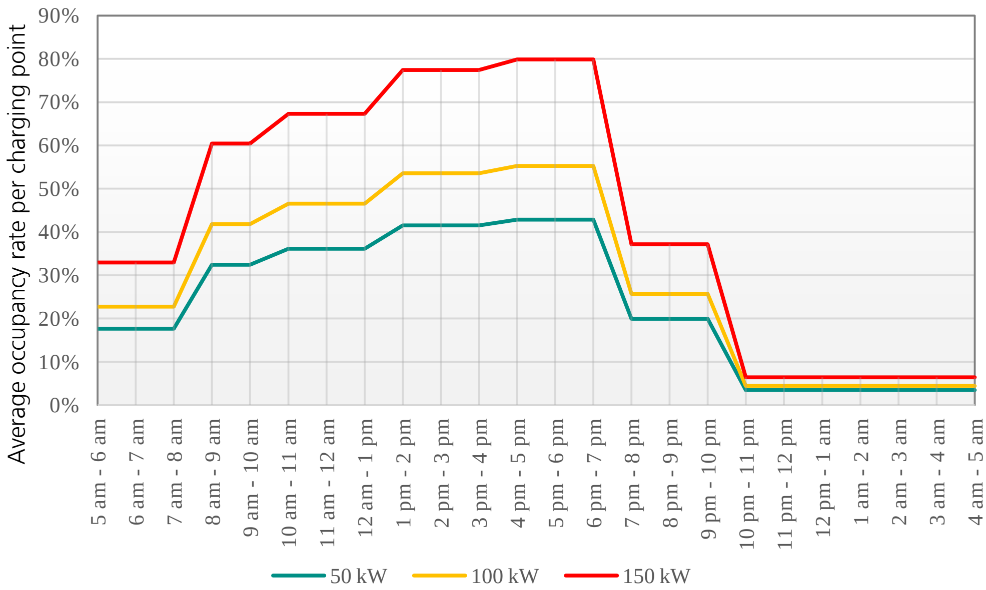

Figure 4: Stochastic occupancy rate of 50, 100 and 150 kW charging points on the bottleneck day.

Turning to Figure 4, we see the average occupancy rate of charging points during the day using the same colors for power levels as in Figure 3. For charging points with 50 kW charging power, it is much more likely to start a charging process without waiting than for charging points with higher charging power. This results from the coherence, that the lower the charging power, the more charging points are required to fulfill a certain service level. However, the regime of the distribution of waiting times shows that higher charging power reduces the time users have to wait in the queue, since ongoing charging procedures can be completed faster. Thus, it can be concluded that higher charging power can provide higher service quality with respect to waiting times in the queue and planning certainty for the overall time which should be calculated for fast charging.

The time period from 4 pm to 7 pm on the bottleneck day represents the overall demand peak. For this reason, it is interesting to investigate which occupancy rate can be achieved as a maximum for a given service level. Figure 4 shows that 50 kW charging points just achieve a maximum occupancy rate of 43% if the service level has to be fulfilled on the bottleneck day. The average occupancy rate during the mean time on the bottleneck day is about 32%. In contrast, charging points with 150 kW are able to reach up to 80% during the peak time and about 59% during the main time.

3.2 Comparison to real charging infrastructure usage

Some of the results obtained can be compared to the usage of currently existing charging infrastructure. Here, we utilise charging data from Sweden [13] which consists of 43 fast chargers with a power of 50 kW (Chademo and CCS). The data has been gathered over 14 months from 2014-12-30 to 2016-03-09 and consists of 136,878 charging events (both fast and slow chargers).

The total number of fast chargers in Sweden amounts to 121 Chademo chargers and 117 CCS chargers (some at the same charging site) [23] for a BEV fleet of 6600 cars [22], yielding 36 chargers per 1000 BEV, though less charging sites per BEV. This is much higher than the calculated values in the previous section. However, charging infrastructure in Sweden is either provided by the municipalities and is free of charge, or by one of the big power utilities where a user have to pay a fixed per-minute price for charging.

In this analysis, we only include charging events from the 50 kW chargers. The data has been cleaned by removing registered charging events that are shorter than 3 minutes or longer than 3 hours, yielding ca 34,934 remaining charging events. Probability densities have been calculated by kernel density estimates and cumulative densities via the Meier-Kaplan estimator.

In Figure 5 we show the distribution of charging events over the hours of the day, these specifically refer to the start of a charging event. Compared to Figure 4 above we obtain the same plateau-like behaviour, though the plateau is shifted approximately two hours earlier in the day. Yet, note that since we refer to the start time of the charging event, some of these events could be extended up to an hour later.

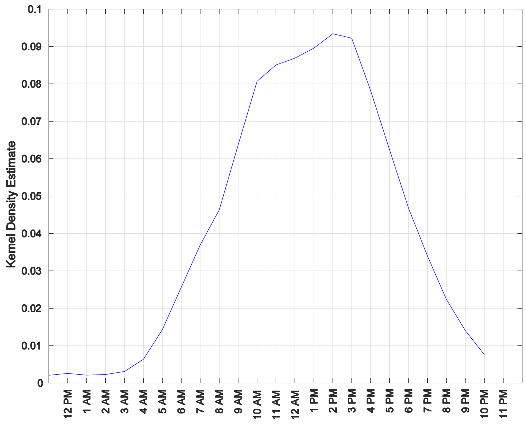

Figure 5 Distribution of charging events during the day. Note that the times displayed refer to the start times of charging events.

As a proxy comparison to the waiting time displayed in Figure 3 above, we have calculated both the duration of charging events in Figure 6 and the vacancy time of the chargers in Figure 7, that is, the length of time the chargers are not used in-between charging events. Figure 6 alone would be identical to the waiting time in Figure 3 if a car arrives just at the start of a charging event for one previous car. This may not often be the case (see Figure 7), the interpretation of Figure 6 is then that it shows the maximum waiting time for a user. But a better understanding of the real waiting time requires consideration of Figure 6 and 7 in tandem. Here, it should be noted that the vacancy times in Figure 7 are much longer than the charging times in Figure 6, thus the availability of the charging infrastructure is high, and the occupancy rate low. However, we have to keep in mind that the ratio of charging points per 1,000 BEVs with 36 in this data is much higher compared to 10 charging points per 1,000 BEVs in the simulations.

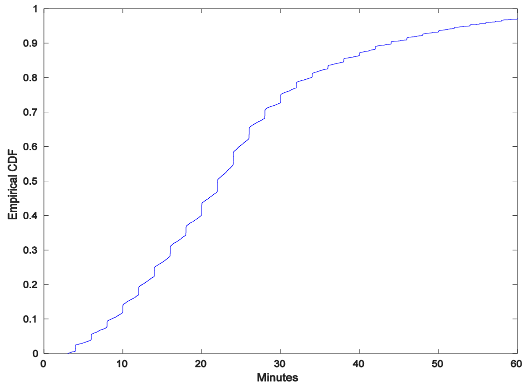

Figure 6 CDF of the duration of charging events.

Furthermore, Figure 7 can be interpreted as the utilization of the charging infrastructure in Sweden, which is low at the moment. This could stem from the high number of charging stations per BEV.

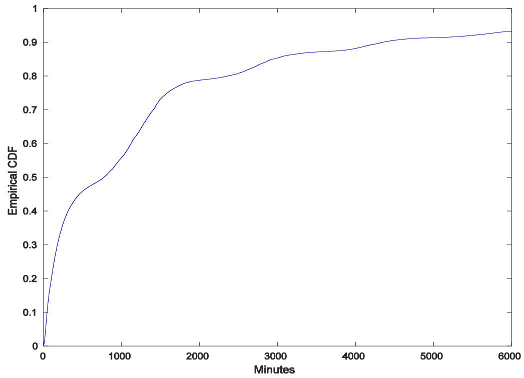

Figure 7 CDF of vacancy times of charging points.

Furthermore, the charging times are exponentially distributed after ca 25 min of charging in the data of actual charging, which is approximately the time needed to reach 80% SoC if you arrive with 10-20% SoC. This is in line with the assumptions in section 2.2. However, it is not exponentially distributed if the charging times are lower than 25 minutes which might influence results. This subject needs attention in further research.

Thus, although the data of the previous section was on German driving and the charging behaviour stems from Sweden, we could confirm several assumptions and simulation results with measured data.

4 Discussion and Conclusion

This analysis proposes a model to estimate the number of fast charging points. It can be applied to other countries if driving profile data with an observation period of at least one week is available. This model does not reflect geographical correlation of PEVs and charging points nor differentiate between urban or rural areas. Furthermore, the driving and refuelling behaviour of conventional vehicles is considered for PEVs which might differ as well. We calculated a need of 82 fast charging events per day and 1,000 BEV. Based on the results of the ALADIN model, the selected driving profiles for which the best drive train option is a pure BEV comprise a higher mileage in comparison to the overall data set. In reality the daily VKT of BEVs may be lower and thus also the need for fast charging events. For simplification, the model assumes that fast charging events are equally distributed over the year and between all charging points. It might be useful to set up charging points in areas with a low occupancy, e.g. to fulfil a public supply mandate, while other charging stations may be frequented much more. This could have an impact on results for the lower number of fast charging points with a higher power, since they might not be sufficient from a user's point of view. This geographical distribution could be an enhancement for further research.

It is also necessary to mention the effect of fast charging on batteries. Due to high powers a lot of heat is produced inside the battery which could increase battery degradation. However, until 2030, we assume that this current technical restraint should be solved.

Another frequently discussed issue is the high risk of grid overload due to parallel fast charging events during the demand peak. The highest load profile can be found on the bottleneck day between 4 pm and 7 pm. According to the determined charging infrastructure and stochastic occupancy rate a power supply of 2.58 MW would be required. Alternatively, about 2.57 MW for 100 kW charging points or 2.59 MW for 150 kW of power supply are necessary. Compared to the installed power of 185 GW, this seems to be a minor issue on a national level, while it might affect electricity grids locally.

We find some robust results which should be retained:

(1) The model shows that there is a nonlinear coherence between charging power and the needed number of charging stations for a certain service level. For higher charging power there are unproportionately less charging points required. For example, there are 10.0 50 kW charging points needed per 1.000 BEV and just 3.9 100 kW charging points needed per 1.000 BEV.

(2) For the 1.5 million private and company car BEVs in sock in 2030, about 15,000 50 kW charging points are necessary to cover the demand for fast charging events. Alternatively, about 5,850 100 kW charging points or 2,700 150 kW charging points are required. Consequently, the same need for fast charging events can be served with less charging points which leads to a higher occupancy rate.

(3) The Swedish charging data shows 36 50 kW chargers per 1,000 BEVs, which is much higher than the model output, yet verifies the distribution of charging times over the day given by the model and the assumption of exponentially distributed inter-arrival times for users.

(4) Yet, there is no conclusion possible if higher charging power is beneficial from an economical perspective as the additional costs for higher charging power are not part of this research. Moreover, with higher charging power occupied charging stations become faster available which reduces the waiting time for the customer, although the same demand has to be covered with disproportionately less charging points.

(5) The cost of an extended charging infrastructure should also be compared to the cost of larger batteries in the vehicles. The interrelation between charging infrastructure, battery size, and driving patterns is complex and requires further research.

Acknowledgments

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