Location-specific Dimensioning of Electric Vehicle Destination Charging Infrastructure

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***Abstract*— The current discussions about the NO_X emissions and the targets of CO_2 reduction will push the transformation of the traffic sector towards e-mobility in the next years. Given the fact that one obstacle for electric vehicle (EV) acceptance still is the visibility of charging points, the expansion and distribution of the charging infrastructure at public spaces suiting the different use cases becomes an important part for the reliability related to the range. To dimension the charging infrastructure at destination charging locations (DCLs), such as supermarkets, shopping centers and cinemas, the consideration of regionalized impacts and factors depending on the particular location, such as the occupancy rate, is required. Additionally, a regionalization of an EV scenario for 2020 to 2050 in steps of five years provides the electrification rate on municipality level. These data are combined with charging profiles, which are based on real mobility statistics as well as data on charging probabilities, to determine the required EV parameters at the DCL. An optimization algorithm filters out the profiles matching best the occupancy of the DCL. By charging the EVs of the chosen profiles a total load profile for the location results, from which the number of required charging points is derived. In order to evaluate the efficiency of the simulated charging infrastructure, the distribution of the resulting states of charge is investigated. This paper carries out a case study by showing the results of the simulation for a supermarket for the year 2035 and a summary for the other years of the time scale.**

Keywords—EV regionalization, charging infrastructure, charging profiles, destination charging

I. Introduction

A. Motivation

In the course of the transformation of the traffic sector towards e-mobility, Germany pursued the goal of one million electric vehicles (EVs) in 2020 [1], which was adjusted to 2022 [2]. To support the development of mastering this transformation, public charging infrastructure is build up in a scale that exceeds the required amount with regard to the current number of EVs. This should lead to a better visibility of charging points and convey the impression of reliability to take away the people‘s range-related anxiety. Currently, there are 17,400 public charging points in Germany [3] and according to the National Platform Electromobility (NPE) 77,000 are required to achieve the goal of one million EVs at least until 2022 [2]. To forecast the impact of this amount of new charging points on the distribution grids, the local dimensioning of the charging infrastructure and the resulting charging profiles are required. In order to generate private charging profiles an approach is existing in [4], that takes real driving behavior based on mobility statistics from a German study [5] into account. Hence, charging profiles for the public space, divided in parking spaces of destination charging locations (DCLs) and residential (overnight) on-street parking, are required. It has to be taken into account that there are dependencies and synergies between the charging behaviors in the different spaces [6]. Charging infrastructure dimensioning should be considered within building processes, i.e. the demand of DCLs such as supermarkets, shopping centers or cinemas as well as the everyday demand for overnight charging in public space is to be mentioned [6]. For dimensioning the charging infrastructure at these DCLs, information about the particular location, especially the occupancy rate and the usual duration of stay are required. In [7], where the charging in a specific car park is optimized for grid support, statistics of this location itself were used to model the occupancy. In order to transfer this to investigation objects with no such statistics available, another source of data is required. An approach in that way is already presented in [8], where the occupancy of the DCL is modelled by the Google Popular Times Data [9], though the authors made the assumption that the number of charging places is given and did not take real driving behavior data into account as a basis to determine the arrival time and the State of Charge (SoC).

B. Objective

The objective of the methodology presented in this paper is to determine charging profiles for different DCLs by combining the usage of the Google Popular Times with the preceding driving and charging behavior. On the one hand this can support the considered location with dimensioning their future charging infrastructure and on the other hand it helps estimating the charging behavior to investigate its impact on the distribution grids.

The results are developed within the research project NOx-Block, in which are also brought out charging points in a higher amount than demanded by EVs currently. A low cost charging infrastructure for residential on-street charging is built up by three local municipalities based on Mobile Metering Technology of ubitricity. The private space is also taken into account, but the focus remains on the public space. By simulating scenarios for the charging infrastructure in all parking spaces the impact on the distribution grids and the exploitation of the charging flexibility is investigated.

II. Methodology

In this section the developed methodology is described. The major part of the simulation process and its input data is summarized in Fig. 1.

A. Regionalization

Currently, the vehicle population in Germany is about 47.1 million cars [10]. The battery and plug-in hybrid EVs amount to 150,000, which equals a share of 0.3 % [10]. In order to get the electrification rate at the considered location for a certain year, a regionalization is carried out for a German EV scenario for the years 2020 until 2050 in five year steps. For this simulation the average of the latest EV scenarios for Germany from twelve studies between 2015 and 2018, which is shown in Fig. 2, is chosen. The absolute number of EVs of any municipality is then determined by an algorithm taking different factors like current EV numbers, population, motorization, funding projects and buildings into account. Assuming that the vehicle population in Germany and in the individual municipalities remains constant, the relative electrification rate can be derived.

Furthermore, in the simulation of the driving profiles described in section II.C it is possible to choose a region typology, so that different data depending on the spatial circumstances are used to generate the profiles. The data of the typologies represent the spatial differences between rural and urban areas and are divided into seven categories from metropolis in urban areas to provincial village in rural areas. For example, the driving distance in rural areas is higher than in urban areas [5].

B. Occupancy of DCLs

The number of EVs can only be determined, if the occupancy of the location is known. Therefore the Google Popular Times Data [9] are used as in [8]. As shown exemplarily in Fig. 3, these data contain only relative numbers of the maximal occupancy. According to that at least one absolute number of people is required to determine the absolute occupancy at every time step. There are several possibilities implemented:

- the total number of people for the whole day,
- the maximum number of people (for an occupancy of 100 %),
- the average number of people per hour over all days.

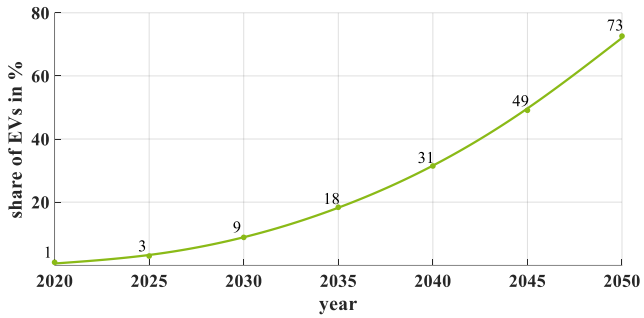

Fig. 2. Electrification rate of a middle EV scenario for Germany over the next 30 years.

For the considered location, an average value per hour $\overline{n_{ph}}$ over all days is given. The average number of EVs per hour then arises from the percentage of people $p_{car,i}$, which use a car to reach the location of the considered purpose i, and the electrification rate $p_{EV,j}$ for the considered year j determined from the regionalization in the section before. By converting this to the percentage of every time step of each day the absolute occupancy of the location is generated. Through a normal distribution with deviations of 15 % from the expected value of the particular hour, the occupancy data is converted from hourly to minutely time resolution. On the one hand the generated driving profiles described in section II.C consists of time steps of one minute and on the other hand it generates a scattering so that the values in every minute of an hour are not always the same. There is no interpolation done, because this would change the daily average and thereby distort the total number of people. Furthermore, it is not necessary for just choosing the profiles, which is explained in the next section.

C. EV Parameters

To determine the EV parameters at the considered location, a simulation of the driving behavior is carried out. It is based on an algorithm presented in [4], but with current data from the study on mobility in Germany from 2017 [5]. The mean duration of stay at the considered location, on the contrary, is taken from the Google Popular Times, if possible. The battery capacity of the EVs is assumed to be 40 kWh and their energy consumption to be 20 kWh per 100 km. The algorithm also generates private charging profiles for the vehicles with an assumed charging power of 11 kW. Since these profiles only take into account charging processes at home, they are extended by charging at public spaces and also consider the case that EV users may not have their own charging point at home. In addition, charging in different

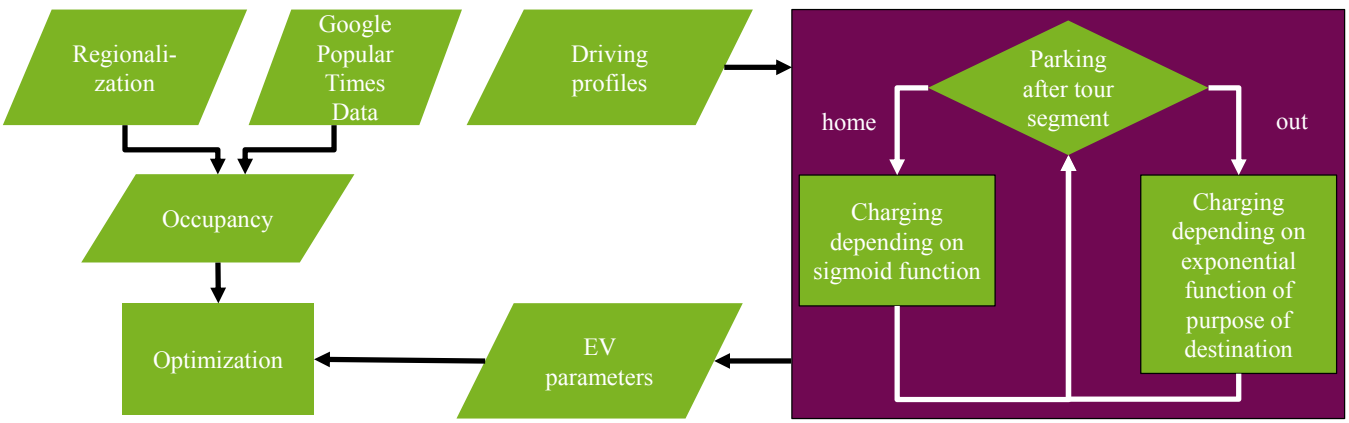

Fig. 1. Part of the methodology process

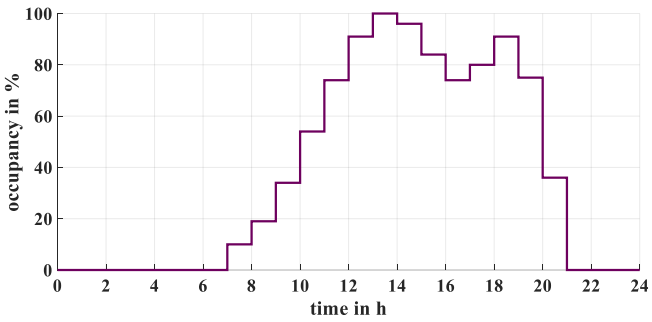

Fig. 3. Occupancy of an exemplary DCL for a Saturday from Google Popular Times Data.

spaces is depending on each other and influencing each other. Based on the generated driving profiles charging profiles are created, which include both private and public charging. Thereby more realistic SoCs at the considered locations are achieved. Besides the percentage of EV owners with a private charging point, probabilities for the existence of charging infrastructure at the DCL and for charging depending on SoC, parking duration and the possession of an own charging point are implemented.

The percentage of EV owners having a private charging point depends on the considered year. In [2] a ratio of 1.125 EVs by one private charging point is assumed for the present, which equals about 89 %. In the future with a trend to an electrification rate of almost 100 % and a developed public charging infrastructure it will reach more and more a value of 75 %, which is nowadays the share of cars whose owners have a parking slot at home [5]. That leads to a distribution over the next years shown in Fig. 4.

For the probabilities of charging at the DCLs and residential on-street charging, the results of a study on EV users [11] are implemented differentiated between residential on-street parking EVs and private parking EVs. The probabilities for charging at the DCLs are already containing the probabilities for the existence of charging points at the DCLs, but it is assumed that they are also depending on the SoC. Especially the residential on-street parkers would likely park at a DCL that has charging points, if possible, for example when driving to a supermarket. The existence of charging infrastructure (i.e. the possibility to charge the EV's battery) is assumed whenever an EV user visits a DCL with his car, since otherwise he would not have taken the journey.

The probabilities for charging at DCLs and at work are implemented as exponential functions, based on the hypothesis that the lower the SoC the higher the need of charging and the more likely it is that a location with charging points is served. For these functions the lower limit is computed by the share of the considered charging place as

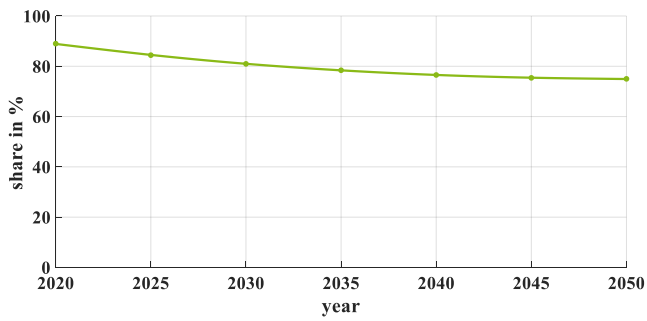

Fig. 4. Share of private charging points at home over the next 30 years.

well as the current frequency of infrastructure usage given in [11]. Furthermore, it is assumed that no one wants his SoC to fall under the low battery level of 20 % and that the consumption of the daily average distance of 20 % can nevertheless still be reached, so that at 40 % SoC the charging probability of 100 % is reached.

The SoC-dependent probability of charging when coming home is modelled by a sigmoid function, which is defined as follows:

$$f(t) = \frac{G}{1 + e^{-kGt}\left(\frac{G}{f(0)} - 1\right)}. \tag{1}$$

The upper limit is G = 100, the lower limit f (0) = 10 and the logistic growth rate k = 0.00107203. The lower limit is given by [11], which says, that 10 % of EV users with a private charging point are charging more than once a day. It is assumed that this is equal to charging after every tour, so that these 10 % are already charging at a SoC of 99 %. In [11] it is said that 36 % of EV users are charging once a day. With the average distance per day of 40 km and the assumed consumption of 20 kWh per 100 km the SoC limit for charging results in 80 %. Hence, the value of k can be determined. Fig. 5 shows the resulting function. The chosen function also reflects the higher probability at lower SoCs but simultaneously the gradient is getting smaller again, because some people are charging only when their EV has a low SoC.

Based on the implemented functions a pool of 10,000 week profiles is generated. Based on the created profiles the parameters after every tour segment of every tour [12], i.e. purpose, arrival time, departure time, parking duration, SoC and day, are determined taking the intermediate recharging into account. The tour segments with the purpose of the considered location are filtered out.

D. Optimization

A mixed integer linear optimization problem solved in YALMIP, which is a toolbox for modelling and optimization in MATLAB [13], filters out the parking profiles which best fit the occupancy. This is achieved by minimizing the deviation between the approximation and the occupancy as well as the deviation to the average duration of stay. It has to be ensured that the total amount of chosen profiles approximately matches with the total number of visitors per day.

1) Variables and Constants

Parking profiles D_t are derived from the determined arrival and departure times. They show if the particular EV is parking at the location or not for every time step $t \in \{1 \ldots T\}$. The occupancy O_t represents the transferred Google Popular

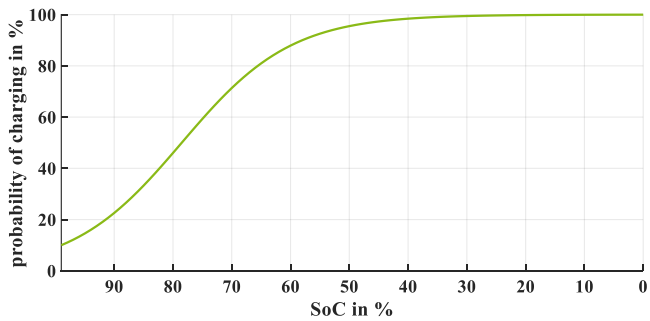

Fig. 5. The probability for private charging at home depending on the SoC.

Times Data described in section II.B for every time step t. The approximation to the occupancy A_t for every time step t and a binary decision variable $b_n \in \{0;1\}$ which indicates for every parking profile $n \in \{1 \ldots N\}$ if it is chosen, are defined. The average parking duration for the location is described by $\overline{t_{park}}$ and the number of chosen profiles by k_D for which equation (2) applies.

$$0 \leq k_D \leq N \tag{2}$$

2) Constraints

In order to get the approximations for every time step t all parking profiles D_t, for which b_n is one, are summarized to get the total profile as shown in (3).

$$A_t = \sum_{n=1}^{N} b_n \cdot D_t \ , \forall\, t \tag{3}$$

3) Objectives

There are two optimization objectives, which are weighted equally. The first objective is to minimize the sum of the percentage deviation between the occupancy O_t and the approximation A_t of every time step t, see equation (4).

$$\min \left\{ \sum_{t=1}^{T} \frac{|\, O_t - A_t \,|}{O_t} \right\} \tag{4}$$

In (5) the second objective is shown, which minimizes the deviation between $\overline{t_{park}}$ and the average parking duration of the chosen profiles.

$$\min \left\{ \left| \overline{t_{park}} - \frac{1}{k_D} \cdot \sum_{n=1}^{N} (b_n \cdot \sum_{t=1}^{T} D_t) \right| \right\} \tag{5}$$

The result determines the combination of profiles which best reflects the occupancy and represents the total parking profile.

E. Restrictions

To avoid a discrimination of conventional vehicles when the parking area with the number of parking spaces N_{ps} is overfilled, a limit for the maximum number of EVs is determined by using the electrified percentage on the number of available parking spaces. If the total parking profile exceeds this limit, it has to be restricted to the maximum at the considered time step. In that case, the calculated limit also indicates the number of charging points that are required maximally, but not every parked EV in the total profile is certainly charging. It depends on the parking duration and the SoC whether the owner plugs in his car or not. To set up assumptions for these parameters, the functions of section II.C. cannot be used, because they contain the probability of the existence of charging points at this location. This means the probability for charging must be higher here, because people who want to charge their car's battery are more likely to visit such a location. Additionally, it is very likely that the energy will be cheaper than at home or even free in certain circumstances. So, there is an incentive to also charge with a higher SoC than at home and a low duration of stay. Furthermore, for cost reasons the DCLs goal is probably not to be able to serve every EV at every time step, especially in the future. In this case, discrete limits are assumed instead of a probability function, because it mainly depends on if it is worth to plug in the cable or not. For the SoC a limit of SOC_{max} = 95 % is assumed, over which no car and under which every car is charging. The parking duration is limited to $t_{park,min}$ = 10 minutes, under which no car and over which every car is charging in this case.

F. Charging profile

After the number of vehicles demanding energy is known at every time step, the EVs have to be charged. It is assumed that every charging point has the same charging power and that DCLs are trying to avoid fast charging due to high costs for high power fast charging infrastructure. Accordingly, the maximum charging power is set to 22 kW. The actual charging power is DCL-dependent, though it cannot be assured, that every EV is fully charged when leaving, especially for short parking durations.

Starting with the arrival time of the particular EV, it is checked in every time step if the battery is full. Otherwise the EV is charged with the chosen charging power until either the SoC of 100 % or the departure time is reached. If the time step is reached, where the amount of energy to be charged due to the charging power exceeds the battery capacity, the power is reduced proportionally to the remaining energy in this minute. The resulting individual charging profiles are merged to a total charging profile presenting the obtained power at every time step. Additionally, a profile with the number of charging EVs at every time step is created.

III. Case Study Results

An exemplary simulation is carried out for a supermarket in the German city Dortmund for 2035. For the electrification rate the regionalization has determined $p_{EV,2035}$ = 16 % for the considered year. The input data for the considered case study are shown in Table 1.

TABLE I. INPUT DATA FOR THE CONSIDERED SUPERMARKET

Input data				
$p_{car,i}$	$\overline{n_{ph}}$	N_{ps}	$\overline{t_{park}}$	P_{cp}
42 %	102	100	0.4 h	22 kW

The probability for covering a distance with the purpose "purchase" by car $p_{car,i}$ is given in [5], while $\overline{t_{park}}$ is picked from the Google Popular Times. Because of the comparatively short duration of stay the charging power is assumed to be 22 kW. In the following results a Saturday is considered because of the maximal occupancy. The relative occupancy of the location for this day is already shown in Fig. 3. The optimization determined 300 parking profiles that are merged to represent the occupancy. For a comparison between the approximation and the normal distributed occupancy, see Fig. 6. In this case a maximum of 15 EVs are parking at the same time. After the restrictions for the parking space as well as the SoC and the parking duration filtered out the EVs that are not charging, 13 simultaneously parking EVs and a total amount of 191 EVs for the whole day are remaining. In this case the limit of the parking area does not restrict the number of charging EVs, because it is big enough to offer a parking space for every car, even at the time of highest occupancy. Hence, for 2035 an amount of 13 charging points is recommended for this DCL. By charging the remaining EVs, the total load profile is derived, which is shown in Fig. 7. So, for the year 2035 a maximum simultaneous charging power of 220 kW is reached. The variation of the charging power, which is

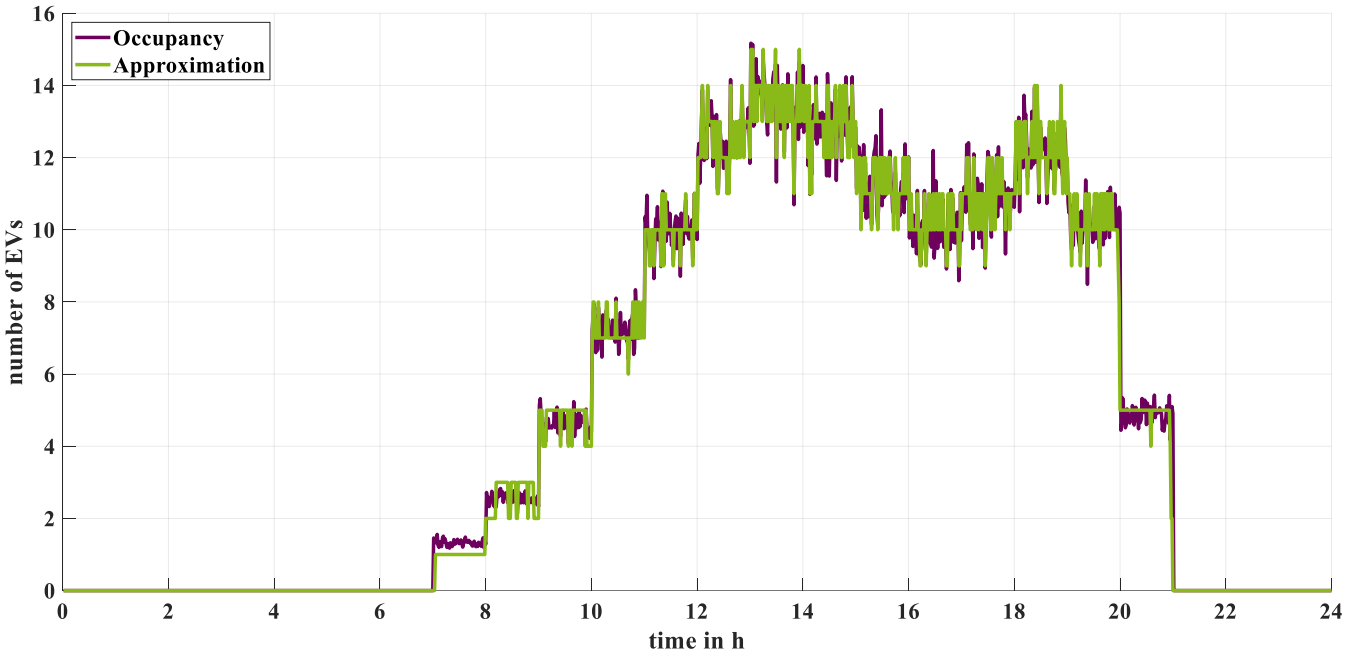

Fig. 6. The occupancy in minute time steps in purple and the approximated sum of parking profiles in green.

partially at 0 kW, is due to the fact that some EVs arrive with a high SoC, so that it does not take much time to fully charge them. As long as no new EV arrives, there can be time steps where no charging power is required. This is also shown in Fig. 8, where the number of charging EVs in every time step are presented. The maximum of simultaneously charging EVs is 10. It has to be taken into account that these results are not containing a charging management system, which could reduce the charging power as well as the necessary amount of charging points. However, a charging management system may be difficult to utilize effectively at a supermarket due to rather short parking durations and the missing information about these durations in advance. Additionally, the results are

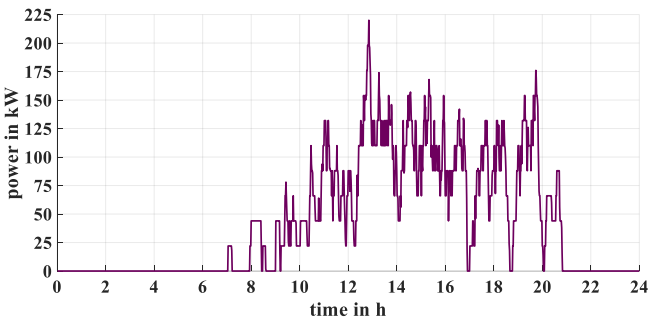

Fig. 7. The resulting total charging profile of the DCL for the whole day.

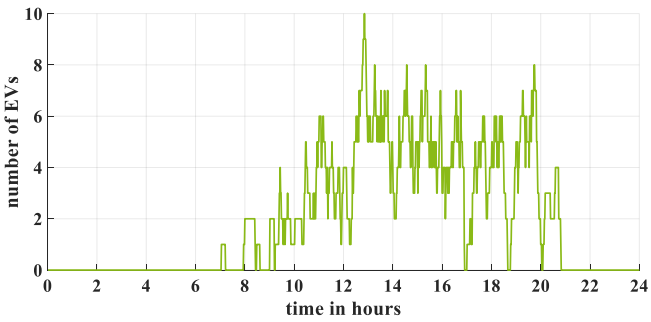

Fig. 8. The number of simultaneously charging EVs at every time step.

depending significantly on the assumptions made for the charging probabilities, both for other locations as well as this DCL. To evaluate if a replacement of the transformer or the supplying cable is necessary or even to specify the timing for grid enhancement, the data of the electrical equipment is obligatory.

The SoC distribution at departure is shown in Fig. 9. About 80 % of the SoCs at departure are reaching 100 %. Only a few exceptions have a SoC under 60 %. To consider the development of the results over the entire time horizon, Table 2 gives an overview of charged EVs, charging points and maximum charging power for all years under investigation. With a rising share of EVs the maximum charging power as well as the number of charging points increases. While in 2020 one EV is occasionally arriving, considering the results in 2050 an amount of 37 charging points is required. It seems a little too much for such a parking area depending on the particular cost limit of the DCL and considering that the charging points are not utilized to capacity most of the time. The assumptions for the SoC, at which the users start to charge, can change over the years, because the infrastructure will be expanded significantly towards the year 2050. In addition, the trend to build up more charging points than demanded from EVs will change in the future, so that the claim of the DCLs will not be to serve every EV anymore while at the same time visitors will no longer assume that they

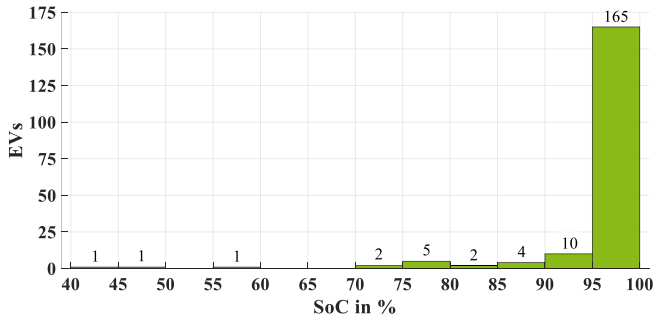

Fig. 9. Distribution of the SoCs of the EVs at departure.

can certainly charge their EV. The share of full batteries at departure varies between 69 and 90 %, which is due to the varying distribution of the SoCs of the profiles chosen by the optimization.

TABLE II. RESULTS FOR THE DIFFERENT YEARS

Results	Year						
	2020	*2025*	*2030*	*2035*	*2040*	*2045*	*2050*
Total Number of charging EVs	16	31	97	191	341	570	878
Share of full batteries in %	69	90	82	79	77	82	83
Number of charging points	1	2	7	13	19	33	55
Maximum charging power in kW	22	44	110	220	286	466	804

IV. CONCLUSION AND OUTLOOK

This paper presents a methodology to dimension the charging infrastructure of DCLs and to determine the resulting total charging profile. As shown in section III, the forecasted charging powers in the case study are showing that a high increase of load comes along over the years, if the assumptions made for the factors influencing the decision of charging are applied and the claim of the DCLs is to serve every demanding EV. With an average share of 80 % a majority of the EVs have a SoC of 100 % at departure, which should be sufficient for a DCL with such rather short parking durations.

For the purpose of efficiency improvement the charging power that is required for every individual EV to get a full battery within its parking duration could be determined. This would lead to some higher powers, but also to some charging points with a lower power. So, this would especially be reasonable at locations with a higher parking duration. Otherwise the consequence could be that EVs with a comparatively high SoC are getting parked at charging points with a higher power than required. Another way to reduce the number of charging points and especially the charging power is to implement a charging management system. This approach will be the focus on future investigations. Possible objectives could besides peak shaving be an increase of self-consumption, if a photovoltaic system exists at the DCL. Though the flexibility is assumed to be moderate due to rather short parking durations at supermarkets, but its exploitation could rather be aimed by other kinds of DCLs like cinemas or shopping centers.

Part of the presented methodolgy could be transferred to determine charging profiles for the private charging infrastructure of an employee parking area of industry or companies. To complete the required information for expansion scenarios charging profiles for public residential on-street charging should be the next step. Therfore a concept could be to expand the regionalization from municipality to street level and take into account if there are single-family houses with a parking slot or apartment buildings.

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