E-Mobility in car parks – Guidelines for charging infrastructure expansion planning and operation based on stochastic simulations

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Abstract
In this contribution we tackle questions of optimal charging infrastructure dimensioning and operation in car parks with the help of Monte Carlo simulations. First we present an approach for determining vehicles’ arrival and departure times using a first order Markov chain model with car park occupancy and staying time distribution as input parameters. Assigning additional electric vehicle parameters, namely battery capacity, state of charge at arrival and rated charging power, we generate representative results for different types of car parks. After clustering evaluated car parks depending on the share of short-term parkers and the occupancy volatility we state on overload risk, load shift potential, stationary storage sizing and finally on charging infrastructure demand for different cluster groups. Additionally we present an approach for creating load profile forecasts based on electric vehicles’ arrival times and average energy demand.

Keywords: car park, e-mobility, charging infrastructure, Monte Carlo simulation

1 Introduction
To achieve a stock target of 20 million green cars until 2020, countries worldwide are promoting green mobility using several policy initiatives. These measures are namely subsidizing electric vehicle acquisition, tax exemptions, but also granting exceptions for electric vehicle (EV) owners like free parking, bus line usage and exemption from city road charges [1], [2]. Another way of promoting electric mobility is the CO₂ emission target of the EU for new cars up until 2020 [3]. The high international standardization activities also reflect the growing importance of EVs [4], [5]. To successfully integrate the traffic sector into the energy system, a lot of efforts are undertaken especially in cities [6]. The impact of integrating EVs into the power system was already studied in 1973 [7]. In this respect the technology is not entirely new and first EV prototypes were built in the early 19ᵗʰ century [1]. New business areas for operating charging infrastructures are growing up [8] and Europe’s biggest parking facility operator titles that the service station of the future is located in the car park [9]. Car parks are well established systems and a lot of data about usage like occupancy and power supply is available for operators. Since cost efficiency of EV charging infrastructure is not yet expected [10], it should be dimensioned wisely, especially when the installation is not financially supported. For preferably cost effective charging infrastructure dimensioning, historical information of car parks can be used. In this investigation we model stationary traffic of car parks and derive guidelines for expansion planning and operation, utilizing both, specially provided and freely available information.
2 Modelling

The simulation program models all relevant parameters of a representative day depending on the EV share. Therefore information about the user behavior and the EVs as well as the car parks’ power characteristic is necessary. For modelling the user behavior we assume that EV-owners’ parking behavior does not differ from conventional vehicle owners’. This guess can be supported on studies presented in [11]. Since no direct information about vehicles’ arrival- and departure-times is available for data privacy reasons, those times are approximated based on overall occupancy data of the car park and the distribution of staying times.

2.1 Car park occupancy database

The parking behavior of individual vehicles is modeled based on original car park data from the Parkraumgesellschaft Baden-Württemberg (PBW) mbH. For modeling and investigating further car parks, data from different parking guidance systems freely available on the internet ([12]-[14]) was logged with Matlab in intervals of 5 min and saved in a database. For subsequent simulations we analyzed 12 car parks from the cities of Basel, Karlsruhe and Constance. In the statistical evaluation, we focused on time periods where continuously actionable data was available. The daily course of the car park occupancies differ strongly depending on their location and is important for the clustering in Chapter 4.1 (Figure 1).

\[ w(t) = (1 - k) \left( \frac{\beta_1 / \alpha_1}{1 + (\tau / \alpha_1)^{\beta_1}} \right) \]
\[ + k \cdot \left( \frac{\beta_2 / \alpha_2}{1 + (\tau / \alpha_2)^{\beta_2}} \right) \]

fits the staying time distribution very well (Figure 2). In (1) \( \alpha_i \) with \( i \in [1, 2] \) are scale parameters and describe the expected value of the log-logistic distribution functions. The shape parameters \( \beta_i \) with \( i \in [1, 2] \) affect the standard deviation of the distribution functions. We introduced factor \( k \) for weighting the share of long-term parkers. For example on weekends in inner-cities short-term parking predominates, therefore we can set \( k = 0 \).

As the original frequency distribution is not as steady as (1) we superposed a noise on the fitting function and normalized it to one. Thus we get the non-steady and more realistic staying time distribution \( (1 \times T_{stay,max}) \)-vector \( \mathbf{w} \) with the maximum staying time \( T_{stay,max} \). Vector \( \mathbf{w} \) is decisive for determining the number of parking vehicles in the following.

2.2 Vehicles’ staying time distribution

For subdividing different car park types, all objects within a basin-radius of 300 m are relevant [15]. Thus individual user groups can be defined by their specific staying times at the car parks. Objects in inner city districts near pedestrian zones or supermarkets have a higher proportion of short-term parking (average staying time: 1 h - 4 h) than objects close to residential areas. In contrast, employee- or park-and-ride car parks classically have a high proportion of long-term parkers (average staying time: 10 h). Analyzing the original data from PBW we found that the superposed log-logistic distribution function

Figure 1: Exemplary occupancy profiles of different car park types on an average working day

Figure 2: Original frequency distribution of vehicles’ staying time provided by PBW and fitting function (1)
2.3 Estimating the number of parking vehicles

We estimate the number of parking vehicles \( n_{\text{vehicle}} \) knowing the overall car park occupancy vector \( o \) and the relative frequency distribution function vector \( w \). Therefore we firstly calculate the traffic volume \( V \), using the overall car park occupancy \( o(t_{\text{acq}}) \) in every point in time of data acquisition \( t_{\text{acq}} \) and the equidistant acquisition interval \( \tau_{\text{acq}} \) for the observed time period \( T_{\text{max}} \).

\[
V = \sum_{t_{\text{acq}}=1}^{T_{\text{max}}/\tau_{\text{acq}}} o(t_{\text{acq}}) \cdot \tau_{\text{acq}}
\]

(2)

Alternatively the traffic volume can be calculated with the knowledge about vehicles’ staying time \( t_{\text{stay},j} \) with \( j \in [1,n_{\text{vehicle}}] \), which is equivalent to the vector multiplication of absolute frequency distribution \( h \) and vehicles staying times \( T_{\text{stay}} \).

\[
V = \sum_{j=1}^{n_{\text{vehicle}}} t_{\text{stay},j} = h \cdot T_{\text{stay}}
\]

(3)

In our case we have to substitute the absolute frequency distribution vector \( h \) with the estimated relative frequency distribution \( w \) to determine the number of vehicles \( n_{\text{vehicle}} \). With (2), equation (3) can be solved for the unknown number of vehicles

\[
n_{\text{vehicle}} = \frac{V}{w \cdot T_{\text{stay}}}
\]

(4)

\[
= \frac{\sum_{t_{\text{acq}}=1}^{T_{\text{max}}/\tau_{\text{acq}}} o(t_{\text{acq}}) \cdot \tau_{\text{acq}}}{w \circ T_{\text{stay}}}.
\]

Multiplying the relative frequency distribution \( w \) with the factor \( n_{\text{vehicle}} \) and rounding the vector entries, we receive an absolute frequency distribution vector of staying times \( h \). This is used for the determination of vehicles’ individual arrival and departure times.

2.4 Individual arrival and departure times of parking vehicles

Analyzing the provided original data, the parking behavior of different user groups became obvious. For example long-term parkers arrive predominantly in the morning, whereas short-term parkers arrive uniformly distributed over the whole day. In car parks close to theaters and cinemas we observed a rush on parking spaces shortly before show time for the latter group (Figure 1 and Figure 3).

To derive individual arrival and departure times we use a first order Markov chain model. With a given car park occupancy \((1 \times T_{\text{max}})\)-vector \( o_{\text{given}} \) for the observed period (e.g. one day) and an initial guess for the \((1 \times T_{\text{stay, max}})\)-vector \( h_{\text{init}} \) of the staying time distribution, we adjust an occupancy vector \( o_{\text{new}} \) iteratively by placing cars stochastically due to their probability starting in the morning. In the beginning \( o_{\text{new}} \) is defined as zero vector of the same size as \( o_{\text{given}} \).

For one point in time \( t_{i} \) with \( i \leq T_{\text{max}} \) we determine the number of remaining parking spaces \( n_{\text{available},t_{i}} \) for parking vehicles

\[
n_{\text{available},t_{i}} = o_{\text{given}}(t_{i}) - o_{\text{new}}(t_{i})
\]

(5)

and the number of free spaces (maximum traffic volume) \( v_{t_{i}}(c) \) for each group of cars \( c \in [1,T_{\text{stay,max}}] \) from \( h_{\text{init}} \) with same staying time \( T_{\text{stay}} \):

\[
v_{t_{i}}(c) = \sum_{t=t_{i}}^{t_{i}+T_{\text{stay}}} o_{\text{given}}(t) - o_{\text{new}}(t).
\]

(6)

Next we determine a certain priority for each group of cars \( c \) with the same staying time to park at the actual point in time and we get the \((1 \times T_{\text{stay, max}})\) probability vector

\[
p_{t_{i}}(c) = \frac{h_{t_{i}}(c)}{v_{t_{i}}(c)}.
\]

(7)

High probability values \( p_{t_{i}}(c) \) can be reached either if there is a large number \( h_{t_{i}}(c) \) of cars of one group to be placed, or if \( v_{t_{i}}(c) \) is very small, which means that there are not too much vacant
parking spaces. To ensure the preferential selection of cars with high priority, we introduce a probability threshold $p_{\text{thresh}}$ and receive the new frequency distribution vector $h_{\text{pref}, t}$ with the preferred groups of cars:

$$h_{\text{pref}, t}(c) = \begin{cases} h_{t}(c) & \forall p_{t}(c) \geq p_{\text{thresh}} \\ 0 & \text{otherwise.} \end{cases}$$  

Eqs. (8)

Anyhow, to avoid a too specific selection of cars the threshold may be set to zero. By introducing this limit, long-term parkers for example have a higher probability to arrive in the morning than other cars, as far as there are no available parking spaces in the night due to closing times.

Finally we select $n_{\text{available}, t}$ cars out of $h_{\text{pref}, t}$ randomly and adjust $o_{\text{new}}$, so that every arriving car occupies one parking space in $o_{\text{new}}$ according to its staying time. Coincidentally we adjust the frequency distribution vector of staying times for the next point in time $h_{t+1}$, by subtracting before selected vehicles.

As the occupancy curve is adjusted stochastically, over-occupancies may occur, especially in the end of the observed time period ($t \rightarrow T_{\text{max}}$). On the one hand one could repeat the simulation until a good solution is found. We decided to adjust the results as long as any degrees of freedom are given. We start the adjustment at the end of the observed time period, by reducing the staying time of suitable cars that fulfill following points:

1. The distance between the time of over-occupancy and the departure time of the car must be short enough (e.g. 15 min).
2. Too short staying times may not be shortened (e.g. 30 min).
3. After reducing, the vehicle’s staying time must be longer than a given minimum (e.g. 15 min).

If cars with too short staying times do exist, in a last step neighboring staying times of cars can be added together. That leads to a reduced number of cars and a higher share of cars with longer staying times. Therewith we get a light deviation from the initial distribution $h_{t0}$. As the simulation is not too time consuming, this procedure can be repeated manually with variable parameters, until the result is satisfactorily.

### 2.5 Electric vehicle charging parameters

The modelled charging profiles base on measurements on Lithium-Ion-accumulators [16] and were verified with measurements of an EV [17]. We adjusted the model to consider different capacity values and charging rates. The charging profile starts with the pre-charge phase until a state of charge (SOC) of 20 % is reached. The following constant charging current phase reaches up to a SOC of 80 %. The final constant voltage phase stops when the battery is fully charged at SOC = 100 % (Figure 4).

![Figure 4: Modelled and measured charging profile (minimum SOC: 4 %)](image)

The SOC at arrival and departure are uniformly distributed on the [25 %, 65 %] interval and the [90 %, 95 %] interval respectively. The charging power of EVs is assumed to be 11 kW or 22 kW, also uniformly distributed. The frequency distribution of the EV capacities bases on a market analysis and includes 77 vehicles with capacity values from 4.8 kWh up to 85 kWh. To avoid inappropriate combinations of high capacity values and low charging currents, we limited the maximum charging duration to $T_{\text{charge,max}} = 5$ h. In case of exceeding this threshold, the charging rate is adjusted, so that the charging process can be finished within $T_{\text{charge,max}}$. Apart from that, if the charging time exceeds the staying time, the desired SOC won’t be reached and charging will be interrupted at departure.

### 2.6 Charging strategies

One of the biggest potential EV user groups are commuters. But simultaneous charging EVs e.g. due to concentrated arrival times in the morning can lead to high load peaks and overloads [16]. Concurrently long staying times of more than six hours can easily be used for load shifting. Several approaches do exist for intelligent management of charging processes [16], [18], [19]. In this paper we focus on two basic optimization strategies, because Monte Carlo simulations are very time consuming with complex charging strategies. The strategies only optimize the time of charging but
do not vary the shape of the EVs’ charging profile. Thus profiles are subdivided or shifted but not scaled.

In detail, the first charging strategy optimizes the overall charging profile of all EVs, by shifting charging processes of arriving cars within their staying time to points in time of minimal overall load. To ensure a fast charging and to avoid surplus accumulation of charging processes at late hours, earlier minima are preferred. Once the charging profile is determined, it won’t be changed at an arrival of new EVs. As far as charging profiles are only adjusted once, this strategy is the best to minimize the overall load profile of the car park (Figure 5).

Another optimization approach focuses on battery lifetime of EVs and depicts the effect of self-optimization neglecting the global overall load profile of the car park. In particular high cell voltages reduce the battery lifetime [20]. The lifetime can be extended by dwelling the SOC at 30 % to 70 % and reaching a SOC higher than 90 % shortly before usage. In the simulation the battery will be immediately discharged to a SOC of 50 %, if staying time suffices and the SOC at arrival is ≥ 65 %. The adjacent charging process is delayed, so that the battery is fully charged shortly before departure.

By optimizing battery lifetime the peak at about 11:00 a.m. in Figure 5 can be reduced, because discharging of some EVs partially compensates charging processes of other EVs. This effect strongly depends on parking behavior of the customers. Generally battery discharging leads to higher energy demand in the evening and thus the load profile is higher than without optimization. In the morning the energy of battery discharging might be fed into the grid.

3 Monte Carlo Simulation

For car park expansion planning using Monte Carlo simulations, we define by chance, depending on the desired EV share, a selection out of the basic population of all vehicles with staying times > 30 min in every simulation step. We assume equal parking behavior of electric and conventional vehicle owners [11]. Selected vehicles are assigned with EV characteristics (Chapter 2.5). After initializing we simulate relevant time periods (one day) and save results like load profiles with and without optimization, charging infrastructure occupancy etc. We perform 10,000 simulations for every scenario accepting a relative error of maximal 1.54 % on the 1-α confidence level of 95 % (Table 1).

<table>
<thead>
<tr>
<th>Result</th>
<th>Central limit theorem</th>
<th>Chebyshev's inequality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging load profile</td>
<td>0.107 %</td>
<td>0.245 %</td>
</tr>
<tr>
<td>Overload duration</td>
<td>0.675 %</td>
<td>1.540 %</td>
</tr>
<tr>
<td>Simultaneous charging EV</td>
<td>0.244 %</td>
<td>0.556 %</td>
</tr>
</tbody>
</table>

4 Results

4.1 Car park clustering

To define different car park clusters we analyzed correlations for all 12 car parks with 176 to 1716 parking vehicles per day based on several results. It showed that a two dimensional clustering is reasonable (Table 2). One dimension distinguishes volatility of the occupancy profile (O). For example, the volatility influences the expected number of simultaneously parking vehicles (Figure 6 (a)): The higher the volatility of the occupancy profile the higher the maximum number of simultaneously parking and charging vehicles. Comparing the groups with high (O1) and slight (O3) volatility at 50 EV per day, it can be seen, that the maximum number of simultaneously charging EV is twice as high at same EV emergence. On the long term the maximum number of simultaneously charging EV convergences for group O1 against about 25 % of the daily EV emergence (e.g. state theater: most customers at show time) for O2 against 16 % and for O3 against 11 %, neglecting charging point constraints (Figure 6 (b)).
Second cluster dimension subdivides the staying time distribution (S). The difference between the groups appears looking at the average of simultaneously parking EVs: The higher the share of long-term parkers, the higher the number of simultaneously parking EV (Figure 7). Equivalent to Figure 6 it can be seen in Figure 7 (a) that the share of maximal simultaneously charging EV decreases for higher EV emergence.

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Staying time</th>
<th>S1: 50 % – 60 % short term parking</th>
<th>S2: 40 % short term parking</th>
<th>S3: 10 % short term parking</th>
</tr>
</thead>
<tbody>
<tr>
<td>O2: Moderate volatility</td>
<td>C21: Pedestrian zone, office building, inner city</td>
<td>C22: Inner city, public parks, pedestrian zone, museum</td>
<td>C23: Museum, office building</td>
<td></td>
</tr>
<tr>
<td>O3: Slight volatility</td>
<td>C31: University, inner city, municipal facilities, supermarket</td>
<td>C32: Fair, congress center, public park</td>
<td>C33: Company with shift operation</td>
<td></td>
</tr>
</tbody>
</table>

Looking at simultaneity mean values in Figure 7 (b), the dependence on staying time distributions gets obvious. Also the influence of the occupancy profile volatility can be seen. Clustering car parks into certain groups (Table 2) is not too easy, because every car park has its own characteristic surrounding which affects the user group and therewith the occupancy profile. Intersections between groups cannot be avoided.
4.2 Electric vehicles’ energy demand
Especially for forecasting the overall load profile of charging EVs, information about individual EV energy demand (Table 3) is crucial. It depends on EV characteristics given in Chapter 2.5. Distribution parameters of the maximal energy demand given in Table 3 refer to the 0.99 quantile of all iteration steps from the Monte Carlo simulation.

Table 3: Distribution parameter for EV energy demand

<table>
<thead>
<tr>
<th>Parameter in kWh</th>
<th>25 % - 65 % SOC at arrival</th>
<th>25 % - 35 % SOC at arrival</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean energy</td>
<td>9.96</td>
<td>14.20</td>
</tr>
<tr>
<td>Max. energy</td>
<td>12.95</td>
<td>17.89</td>
</tr>
<tr>
<td>Variance</td>
<td>0.27</td>
<td>6.67</td>
</tr>
<tr>
<td>Median</td>
<td>10.03</td>
<td>13.26</td>
</tr>
<tr>
<td>0.99 Quantile</td>
<td>10.29</td>
<td>24.05</td>
</tr>
</tbody>
</table>

4.3 Forecasting the overall load profile
First approaches for forecasting EV charging profiles on higher grid levels do exist [21]. We proofed possibilities for forecasting load profiles caused by EV charging on distribution grid level, especially in car parks.

We analyzed correlations of occupancy curves as well as its first derivative and the resulting overall charging profiles. It showed that forecasting load profiles using the arrival times of parking EVs, the average charging duration (here: 50 min) and the distribution parameters in Table 3 is most accurately. The approach based on mean and maximum EVs energy demand strongly correlates with simulated profiles of individual simulation steps and gives a precise corridor for expected load profiles (Figure 8 (a)). In times of steeply increasing occupancy (e.g. theater at show time), the number of arriving vehicles can be derived from the occupancy profile’s first derivative, if simultaneously leaving vehicles are negligible.

Load profiles are scalable for different EV shares (Figure 8 (b)). This allows forecasting loads for higher EV shares as it is necessary for expansion planning. Load profiles’ mean and standard deviation depend linearly on the EV share. From about 40 EV/d the load profile can be approximated by a normal distribution function for each time step, accepting correlation coefficients \( \rho > 0.9 \) (Figure 9 (a)). By modelling load profiles with normal distribution functions, we benefit from interdependencies of standard deviation and mean values (Figure 9 (b)). Therewith one can state on uncertainties.
4.4 Overload risk
Most of the analyzed car parks are connected to the medium voltage grid with their own transformer. The rated power of supply reaches from 132 kVA to 800 kVA. Due to safety reasons (e.g., denitrification) most transformers are over dimensioned and can provide sufficient power for charging EVs. That’s why we do not expect overloading by integrating a charging infrastructure in the near future for most car parks. Nevertheless in the following we vary the car parks’ power supply to quantify an overload risk dependent on the EV emergence.

We found that the overload risk strongly depends on the occupancy curves’ volatility (Figure 10): The higher the volatility, the higher the overload risk for same EV emergence. The spread of overload risk between cluster groups increases with rising rated power of the grid connection. At same overload risk, the benefit of supply extension is much higher for car parks with slight volatility than for those with high volatility. To exemplarily give an idea of supply extension’s effectivity: Increasing the power supply by 50 kVA, in group O1 18 EVs can be charged additionally at same overload risk. For group O2 the number of additionally chargeable EVs increases by 30 and for group O3 by 45.

4.5 Measures for avoiding overloads

4.5.1 Load shifting
Instead of extending the grid connection one can avoid overloads by optimizing the charging process of the EVs (Chapter 2.6). In car parks with a high share of long-term parkers smart charging is very effective for avoiding overloads, whereas power supply expansion is more effective in car parks with a high share of short term-parking. The benefit of optimizing charging processes increases with higher power supply, as far as the overall load profile is optimized. Individual optimization of battery lifetime reduces the overload risk slightly (Figure 11).

4.5.2 Energy storage
Especially when energy storage systems (ESS) can be charged during closing times, they can cover the EV load demand during the day. For estimating necessary ESS capacities we analyzed the energy turnover in times of overloading. Capacity values are proportional to the square of the EV emergence (Figure 12). Compensating overloads using ESS is most effective in car parks with a high share of short term parkers and a slightly volatile occupancy profile. Due to high
simultaneity of long term parkers’ arrival times, ESS are not advisable for avoiding overloads. The benefit of charge control is much higher.

Figure 12: Mean of overload energy for group O1 (a), O2 (b) and O3 (c) for deriving ESS capacities

4.6 Optimal number of charging points

For optimal charging infrastructure dimensioning, we limit the number of available charging points depending on the daily EV emergence for different groups according to their characteristic staying times (Table 4). For cost effective dimensioning not only the energy turnover per charging point is relevant, but also the occupancy of the charging infrastructure as well as the share of lost customers (Figure 13).

Table 4: Estimating charging point demand depending on daily number of parking EV (x) (before rounding) using different Quantiles Q_i for limitation

<table>
<thead>
<tr>
<th>Group Limit</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1: Mean</td>
<td>0.21x</td>
<td>0.37x</td>
<td>0.50x</td>
</tr>
<tr>
<td>L2: Q_{0.75}</td>
<td>0.27x+1</td>
<td>0.46x</td>
<td>0.67x</td>
</tr>
<tr>
<td>L3: Q_{0.85}</td>
<td>0.28x+1</td>
<td>0.48x</td>
<td>0.70x</td>
</tr>
<tr>
<td>L4: Q_{0.95}</td>
<td>0.35x+2</td>
<td>0.50x+1</td>
<td>0.74x</td>
</tr>
<tr>
<td>L5: Q_{0.99}</td>
<td>0.43x+2</td>
<td>0.52x+2</td>
<td>0.78x+1</td>
</tr>
</tbody>
</table>

Reducing the number of available charging points, of course leads to higher energy turnover per charging point, but increases the number of lost customers too. The extent of this effect depends also on the car park type. Looking at the number of lost customers (Figure 13 (c)), we see that in the state theater due to the rush on car parks before show time a restrictive dimensioning leads to a high number of lost customers whereas this effect is minor in the fair car park with a higher share of long-term parking and slight volatility. But the energy turnover per charging station in car parks with many long-term parkers (S3) is less than for other groups, because of longer occupation and less fluctuating charging times.

This is one reason to set occupancy time into relation with the energy turnover, to find optimal pricing models. Further accounting energy demand requires cost effective calibration of energy meters. Car park operators may avoid those costs by pricing EV staying times, especially since the required infrastructure does exist. We determine factor \( c \) for deriving a staying time based price \( p_{\text{stay}} \) from energy based price \( p_{\text{energy}} \), by equalizing the turnover of energy based and time based pricing. Therefore we acquire overall energy demand \( E \) and traffic volume \( V \).

\[
p_{\text{stay}} = \frac{E}{V} \cdot \frac{E}{p_{\text{Energy}}} = c \cdot p_{\text{Energy}}
\]

with

\[
[p_{\text{stay}}] = 1 \, \text{€}/\text{h} \quad [E] = 1 \, \text{kWh} \\
[p_{\text{energy}}] = 1 \, \text{€}/\text{kWh} \quad [V] = 1 \, \text{h}^{-1}
\]
Figure 13: Mean and maximum (Q₉₉) of charging point occupancy (a), of energy turnover per charging point (b), of share of not charged EVs (c) and of charged EVs per charging point (d) for 10% EV share and different charging point limitation L₁ – L₅ (Table 4)

On average factor c is for the different groups:
- c₁ = 2.73 (kWh/h)
- c₂ = 2.18 (kWh/h)
- c₃ = 1.62 (kWh/h)

We see that in car parks with many short-term parkers the time based price must be higher to compensate the relative high income from energy based pricing, whereas long staying times allow cheaper time based tariffs.

To exemplarily show the cost efficiency of both tariff models and the influence on the dimensioning strategy, we define a scenario with fees, costs and tariffs given in Table 5 to Table 7.

Table 5: Charging infrastructure costs [9]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-off costs of public charging column including installation</td>
<td>10,000 €</td>
</tr>
<tr>
<td>Life time of charging point</td>
<td>8 a</td>
</tr>
<tr>
<td>Annual charging columns costs</td>
<td>1,250 € p. a.</td>
</tr>
<tr>
<td>Operating costs (property rent, maintenance, repair, hotline, accounting system, taxes, etc.)</td>
<td>600 € p. a.</td>
</tr>
<tr>
<td>Charging points per column</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 6: Grid fees for consumers connected to the medium voltage grid [22]

<table>
<thead>
<tr>
<th>Period of use</th>
<th>Demand rate</th>
<th>Energy rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>T &lt; 2,500 h/a</td>
<td>12.40 €/kWa</td>
<td>2.84 Ct/kWh</td>
</tr>
<tr>
<td>T ≥ 2,500 h/a</td>
<td>54.55 €/kWa</td>
<td>0.79 Ct/kWh</td>
</tr>
</tbody>
</table>

Table 7: Tariff models [23]

<table>
<thead>
<tr>
<th>Tariff model</th>
<th>Monthly basic charge</th>
<th>Variable costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy based</td>
<td>4.95 €</td>
<td>0.30 €/kWh</td>
</tr>
<tr>
<td>Time based</td>
<td>---</td>
<td>3.95 €/h</td>
</tr>
</tbody>
</table>

The overall profit results from subtracting fees and costs in Table 5 and Table 6 from the income of the particular tariff model in Table 7. We exemplarily show the results for one car park from cluster group C12. Because the time based tariff in Table 7 generates a much higher turnover than the energy based tariff, we show the optimal number of charging points and the relative deviation individually (Figure 13). For most car...
parks time based pricing allows a more generous charging infrastructure dimensioning, whereas the energy based tariff advises to a more cautious dimensioning (Figure 14).

![Figure 13: Optimal number of charging points for different tariff models](image1)

![Figure 14: Frequency distribution of optimal charging infrastructure dimensioning limit for two pricing models of all car parks and 1% - 10% EV share](image2)

Figure 13: Optimal number of charging points for different tariff models

Figure 14: Frequency distribution of optimal charging infrastructure dimensioning limit for two pricing models of all car parks and 1% - 10% EV share

5 Conclusion

We presented an approach to derive individual arrival and departure times of vehicles from car park occupancy curves applying a first order Markov chain model. After introducing electric vehicle parameters, we performed Monte Carlo simulations for 12 different car parks and clustered them depending on vehicles' staying times and volatility of the occupancy profile. The clustering allows a more type specific statement on overload risk, as well as optimal charging infrastructure dimensioning depending on the electric vehicle emergence. We further found that load profiles can only be forecasted precisely with knowledge about arrival times. Expected load values can be approximated by the normal distribution function from 40 electric vehicles per day, where standard deviation can be derived from mean of charging load. Those load profiles are scalable for estimating load profiles at higher electric vehicle emergence.

Basically car parks with a high share of long-term parkers require more generous charging infrastructure dimensioning due to higher simultaneity of parking vehicles. For those car parks we recommend time based pricing models. In car parks with higher shares of short-term parkers, we observed a better energy turnover per charging point due to higher customer fluctuation, so that energy based tariffs might be advantageous. Currently available tariff models, allow more generous dimensioning for time based pricing than for energy based pricing.

For avoiding overloads, we suggest intelligent charging control for car parks with higher share of long-term parkers, because of bigger load shift potential. Car parks with predominantly short-term parking benefit more from power supply extension. Compensating overloads by energy storage systems also is more effective for those car park types.

6 Acknowledgement

This contribution is based on results from the project “intelligent Zero Emission Urban System (iZEUS)”, promoted by the Federal Ministry for Economic Affairs and Energy in the framework of “Information and Communication Technologies (ICT) for Electric Mobility II”. The authors would like to thank for the encouragement of the project. Furthermore we thank PBW mbH, Stadtwerke Karlsruhe GmbH and Mainova AG for providing important data for these studies.

References


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