A Stochastic Model for Simulating the Availability of Electric Vehicles for Services to the Power Grid

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Abstract

Since private passenger cars drive on average less than 2 hours per day, each electric vehicle could potentially provide capacities for grid services during more than 22 hours per day. The presented stochastic model, which bases on more than 167,000 data points from a mobility survey, simulates the driving behavior of private passenger cars. The article estimates the availability of electric vehicles for grid balancing services using the generated profiles from a stochastic model. Three basic (“zero-intelligence”) charging strategies were applied.

In conclusion, more than 90% of all vehicles are parked at any given point in time. Thereof, more than 25% are parked at home at any given time. Moreover, the simulation results show the urgent need for intelligent charging strategies in order to avoid additional peak loads during the evening hours and to make the service potential of electric vehicles available to the grid.

1. Introduction

While electric vehicles (EV) are already widespread in particular applications (e.g., fork lifts or baggage carrying) [1], their use as individual motor cars is still limited. E.g., only about 1,400 EV were registered in Germany in 2008. However, advancing battery technology, a peaking oil price in 2008, the current automobile crisis and the hope for ecological advantages are currently drivers towards the electrification of individual motor car traffic all over the world.

Moreover, the combination of two major energy conversion systems, namely the electric utility system and the light vehicle fleet (e.g., individual motor cars), could create considerable synergies [2]. One proposed concept is Vehicle-to-Grid (V2G) realized through “... vehicles with an electric drive motor powered by batteries, a fuel cell or a hybrid drive train, [that] can generate or store electricity when parked, and with appropriate connections can feed power to the grid […]” [3].

EV can be subdivided into hybrid EV (HEV) and battery EV (BEV). The subset of HEV combines the (parallel or serial) electric drive motor with a combustion engine whereas the BEV are EV without any support from a combustion engine. Although the energy to fulfill an EV’s mobility function could be guaranteed alternatively (e.g., by fuel or a battery exchange), EV are assumed to be plug-in vehicles in this article. This means they discharge into and charge from the power grid.

The concept of V2G focuses on how EV can support the power grid by ancillary services. I.e., the power flow, whether to or from the EV, can be partly controlled by the needs of the power grid, e.g., via a real-time control signal [4] or via a price signal. However, even without V2G, the effects of significant numbers of EV that charge from the power grid need to be investigated. Simultaneously, the main function of an EV must not be forgotten – to provide and ensure mobility for its user. Therefore, all usage beyond mobility of an EV must be brought in accord to the mobility needs and preferences of its user. For example, an empty battery at the start of a travel route as a result of V2G would be unacceptable. Charging strategies and V2G management will have to reconcile both the power grid and the EV user’s needs.

Besides the mobility requirements of a car user there are further social, political and cultural impediments to V2G. Sovacool and Hirsh [5] emphasize that these more subtle impediments play an equally important role in addition to the undoubted technical challenges.

This article focuses on an estimation of V2G availability. We define a stochastic model that simulates the driving behavior of potential EV users. The model allows for a variation and evaluation of parameters that are relevant in the emerging domain of electric mobility, such as the number of EV, the available charging infrastructure, and the applied charging strategies. It is based on the data of a large mobility survey on private passenger cars in Germany.

The subsequent sections are structured as follows: Section 2 reviews related scientific work and identifies
requirements and goals of a simulation model. The stochastic model is defined in Section 3. Afterwards, simulation results based on the model’s implementation are summarized in Section 4. Finally, Section 5 gives a conclusion of the findings in this paper and presents an outlook to further research in this area.

2. Related work

The idea of EV that interact with the power grid has been investigated throughout the last decade from different perspectives.

Considering the technical feasibility, a V2G demonstration project [6] proved that a converted VW Beetle with lead-acid batteries can actually provide regulation services. Thereby, temporal availability of the EV was approximated through given (independent) grid connection profiles.

Profitability of V2G was investigated for urban Japan in [7]. In Japan, most car owners commute with public transportation and use private cars primarily on weekends for recreational purposes. Hence, such a scenario offers great potential for grid services. In order to skim potentially high prices in peak power times, EV were assumed to provide power to the grid only in 5 months during a year, at 3 to 10 days per month and 4 hours per day.

Profitability was also examined with respect to power markets in the U.S. by first developing equations to calculate cost and revenue of V2G [3] and then entering data of wholesale power markets in the model [8]. Temporal availability of EV for V2G was assumed to be 18 hours a day on average in these articles.

Since temporal availability of EV fleets is often well known, profitability was exemplified for two fleets in [9]. Temporal availability of 23 hours (for commuter vehicles) and 17 hours (for meter reading vehicles) were assumed.

The problem of grid optimal dispatching of PHEV was examined for six regions in the U.S., concluding that under optimal dispatch rules, no additional electric generation capacity is necessary [10]. Yet, the authors emphasized that “further analysis of consumer driving patterns may allow a more detailed analysis of potential benefits of midday charging”.

Lund and Kempton [4] analyze the effects of a large-scale V2G system based on a model of the Danish energy system (EnergyPLAN). They analyze the integration of power from renewable energy sources (especially wind) and combined heat and power (CHP) sources. Both source types pose significant integration difficulties to the power system.

While most renewable sources are intermittent, CHP plants (especially distributed micro-CHP plants) are typically heat-led and disregard to the needs of the power grid. Their paper shows that V2G can significantly support the integration of larger shares of such non-conventional resources.

Finally, a recent study in Germany investigated the effects for the grid considering different numbers of charging EV [11]. In particular, the charging place was considered based on data of a survey of personal “Mobility in Germany” (MiG) [12].

To summarize, many investigations of V2G and charging strategies need to work with assumptions and mean values with respect to the temporal availability. Local availability was hardly a subject. However, we expect more precise statements about the potential of V2G with a simulation model that allows for adequate disaggregation in all dimensions (Figure 1). Such a model needs to be based on data of actual driving behavior,

![Figure 1. Dimensions of V2G availability](image)

3. Stochastic model

3.1. Data source

The survey "Mobility in Germany" (MiG) [12] provides data for the simulation model. These data are structured in four tables of which the ‘travel segment table’ (list of travel segments with attributes such as distance, duration, purpose, etc.) is most relevant. The travel segment table includes more than 167,000 data points from about 25,000 households. Therein, a ‘travel segment’ is complete when a person reaches a destination with a certain purpose. The travel segment for the way back is collected separately.

The survey focuses on private passenger traffic and provides detailed information about travel segments that are driven by car, e.g., information about time, distance, and the destination type (purpose, e.g., shopping or work) of a car ride. This allows for time- and place-disaggregated considerations. The survey was conducted between December 2001 and December 2002. More than 60,000 data points on car rides were gathered through structured interviews asking for the driving profile of the previous day. Since MiG focuses
on private everyday life mobility, information about voyages and business trips is included on a very rudimentary level only, and therefore not used for the model [13].

Besides MiG, two more surveys have been reviewed, but not included as data sources: (1) "Traffic of motorized vehicles" includes about 98,500 data points, but it focuses on commercial transport instead of private passenger cars [14]. (2) "Mobility panel" provides a one-week driving profile for about 1,000 households [15]. Due to the small sample size, this survey was less appropriate than MiG.

3.2. Choice of the simulation method

The data points of the MiG survey represent one-day excerpts of driving behavior. In particular, no person or car has been traced over a whole week. Hence, simply retracing each travel path (sequence of travel segments) would result in a day-oriented simulation. However, testing even rudimentary load-shifting charging strategies requires the consideration of overnight charging. In order to get realistic driving profiles that are consistent over a whole week, the simulation model derives probability distributions of driven travel paths. The stochastic model finally generates driving profiles of EV. Based on the generated driving profiles, the V2G potential of three scenarios (see Section 3.4) using Monte-Carlo simulations was analyzed.

The stochastic model and the Monte-Carlo simulations are based on the assumption that driving profiles in future will be similar to those in 2001. I.e., EV will be used for the same rides as today's conventional cars and the overall demand for mobility with respect to passenger car usage remains the same.

3.3. Model definition

The outputs of the stochastic model are two matrices describing the driven kilometers \((D)\) and the location of vehicles \((L)\). The columns of both matrices describe the time dimension, i.e., each column stands for a time slot in the simulation period. Each row of the matrices represents an EV. The matrices provide the data basis for analyses of different charging strategies and their impact on the grid.

The stochastic model consists of three phases: The first phase initiates the basic variables. The second phase generates a driving profile for each simulated EV by determining detailed travel paths. Paths base on the stochastic distributions derived from the survey. In the third phase, the determined matrices are "driven" by the EV during the defined simulation period and V2G relevant data are evaluated (e.g., the battery state of charge).

Figure 2 depicts the control flow of the first two phases of the simulation model with \(n\) being the index of an EV within a fleet of \(N\) vehicles and \(t\) being a time slot of the simulation period \((1 \leq t \leq T)\). The following paragraphs will describe the basic parameters of the model and subsequently explain the detailed calculation steps of the second phase.

![Figure 2. Control flow of the simulation model](image)

3.3.1. Basic parameters. The basic parameters of the stochastic model are derived from the survey data. Table 1 defines the symbols for the relevant data attributes from the survey. The set of all considered records in the 'travel segment table' of the survey is defined as \(W = \{w_1, ..., w_i\}\), the set of all records in the 'vehicle table' is \(V = \{v_1, ..., v_j\}\).

The original survey data contains only a generic location type indicating the destination and the purpose of each travel segment. In a data preprocessing step, the generic location type and the purpose were
replaced by one of the four location types home, work, leisure, or shopping.

A central element of the model is a travel path. It describes a chronological sequence of travel segments.

\[ \tilde{w}_k = \{w_1, \ldots, w_i\} \]

All travel segments within the travel path are driven by the same vehicle on the same date. The travel path starts and ends at home (location type) and must be consistent and complete, i.e., a travel segment starts where the previous travel segment ended (same location types) and two consecutive travel segments must not lead to the same location type:

\[ \tilde{w}_k = \{w_1, w_2, \ldots, w_i\} \]

\[ w_i = w_i^F \land w_i^D = w_i^D \land w_i^T = w_i^T \land 1 \leq s < S - 1 \]

### Table 1. Symbols of survey attributes

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(w_i^F)</td>
<td>ID of the Vehicle that drove travel segment (w_i)</td>
</tr>
<tr>
<td>(w_i^T)</td>
<td>Location type From where travel segment (w_i) started</td>
</tr>
<tr>
<td>(w_i^D)</td>
<td>Date when travel segment (w_i) was driven</td>
</tr>
<tr>
<td>(w_i^S)</td>
<td>Starting time of travel segment (w_i)</td>
</tr>
<tr>
<td>(w_i^E)</td>
<td>Ending time of travel segment (w_i)</td>
</tr>
<tr>
<td>(w_i^W)</td>
<td>Weight of travel segment (w_i)</td>
</tr>
<tr>
<td>(w_i^L)</td>
<td>Length of travel segment (w_i) [km]</td>
</tr>
<tr>
<td>(v_j)</td>
<td>ID of the vehicle (v_j)</td>
</tr>
</tbody>
</table>

The sampling in MiG was stratified with weights in different dimensions. The weight enters in the probability calculations.

Table 2 defines the attributes of a travel path that are inherited from the contained travel segments. The set of travel paths is symbolized by \(\tilde{W} = \{\tilde{w}_1, \ldots, \tilde{w}_k\}\).

### Table 2. Attributes of travel paths

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\tilde{w}_k)</td>
<td>ID of the Vehicle that drove (\tilde{w}_k)</td>
</tr>
<tr>
<td>(\tilde{w}_k^D)</td>
<td>Date when (\tilde{w}_k) was driven</td>
</tr>
<tr>
<td>(\tilde{w}_k^L)</td>
<td>Length of travel path (\tilde{w}_k) [km] (sum of lengths of all contained travel segments)</td>
</tr>
<tr>
<td>(\tilde{w}_k^S)</td>
<td>Start time of travel segment (w_i) of travel path (\tilde{w}_k)</td>
</tr>
</tbody>
</table>

#### 3.3.2. Start of a travel path.**

The discrete probability of a travel path start in time slot \(t\) is calculated through the number of travel paths starting at a daytime \(t'\) on a weekday \(d\) normalized by the total number of travel paths \(\tilde{W}\).

\[ f_1(d, t') = \frac{\tilde{W}_{\text{weekday} d \cdot \text{daytime} t'}}{\tilde{W}} \]

with

\[ \tilde{W}_{\text{weekday} d \cdot \text{daytime} t'} = \{\tilde{w}_k | \text{weekday}(\tilde{w}_k) = d \land \text{daytime}(\tilde{w}_k) = t'\} \]

The start of a travel path (Boolean variable) in time slot \(t\) is then derived using a uniformly distributed random variable \(\omega \sim U(\Omega, \Omega = [0, 1])\).

\[ \omega \leq f_1(\text{weekday}(t), \text{daytime}(t)) \]

#### 3.3.3. Travel path type.

If a travel path starts in time slot \(t\), the type of the travel path is to be determined. The type of a travel path defines the number of travel segments within the travel path as well as the destination of each travel segment. In other words, the travel path type is like an archetype of a round trip. Based on the four location types (home, work, leisure, shopping) and the travel path properties (see Section 3.3.1.), there are 19 disjoint travel path types (the maximum length of a travel path in the survey data were five consecutive travel segments). The function \(\text{type}(\tilde{w}_k)\) returns the type of a travel path.

The discrete probability that a given travel path type starts in time slot \(t\) is calculated similarly to the start of a travel path in \(t\).

\[ f_2(d, t', y) = \frac{\tilde{W}_{\text{weekday} d \cdot \text{daytime} t' \cdot \text{type} y}}{\tilde{W}_{\text{weekday} d \cdot \text{daytime} t'}} \]

with

\[ \tilde{W}_{\text{weekday} d \cdot \text{daytime} t' \cdot \text{type} y} = \{\tilde{w}_k | \text{weekday}(\tilde{w}_k) = d \land \text{daytime}(\tilde{w}_k) = t' \land \text{type}(\tilde{w}_k) = y\} \]

The cumulative probability function \(F_3\) is defined as

\[ F_3(d, t', y) = \sum_{y=1}^{19} f_2(d, t', y') \]

The type of a travel path in time slot \(t\) is derived using a uniformly distributed random variable \(\omega\).
If the value of $\omega$ is between the cumulative probabilities of $y$ and $y+1$, the travel path is of type $y$.

### 3.3.4. Travel path duration.

The duration $\tilde{w}_k$ is the time between the start of the first travel segment and the end of the last travel segment. The travel path duration primarily depends on its type and is defined as a normally distributed variable $\mu_{y}$ with an expected value $\mu_{y}^\omega$ and a standard deviation $\sigma_{y}$. 

$$\mu_{y}^\omega = \frac{1}{\hat{W}_y^\omega} \cdot \sum_{q \in \omega^\omega} \tilde{w}_k^q$$

$$\sigma_{y} = \text{stddev}(\tilde{w}_k^q)$$

### 3.3.5. Internal structure of a travel path.

As a last step, the internal structure of a travel path of type $y$ must be defined. This is done by determining the start times of each travel segment within the travel path and their lengths in minutes and kilometers (except for the start time of the first and the end time of the last travel segment, which are already defined through the start and the end time of the travel path). The result of this step is written in the output matrices $D$ (driving distances) and $L$ (locations) and is determined as follows: Similarly to the travel path length, the length of each travel segment to a location $to$ is derived by using a normally distributed variable $\ell_{to}^\delta$ respectively $\ell_{to}^\delta$.

$$W_{y,t}^\omega = \{w_j | w_j^T = to\}$$

After the length in minutes and kilometers has been determined for each travel segment of the travel path, the start times for all travel segments (except for the first and the last travel segment) are uniformly distributed within the duration of the travel path (without overlapping).

Finally, for each time slot $t$ the driven distance is calculated and written into the driving distance matrix $D$ (driving speed is assumed constant within a single travel segment). If an EV is driving (value in the driving distance matrix is different from zero), $1-$ is entered in the location matrix $L$, since the car is not parked at any location. If the car is parked, the destination (location type) of the last travel segment is entered in the location matrix.

### 3.4. Simulation scenarios

The simulations are based on different replacement scenarios and charging strategies. Table 3 contains the key parameters of the replacement scenarios and Table 4 presents further details on how these parameters have been derived. The scenarios refer to cases defined in [18] and represent optimistic replacement assumptions for EV.

#### Table 3. Simulation scenarios

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Short-term</th>
<th>Middle-term</th>
<th>Long-term</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of EV [# mn.]</td>
<td>1.7</td>
<td>9.1</td>
<td>30.3</td>
</tr>
<tr>
<td>Share of EV [%]</td>
<td>5</td>
<td>26</td>
<td>87</td>
</tr>
<tr>
<td>Average battery capacity [kWh]</td>
<td>17.6</td>
<td>20.0</td>
<td>25.8</td>
</tr>
<tr>
<td>Average consumption [km/kWh]</td>
<td>3.9</td>
<td>4.0</td>
<td>4.1</td>
</tr>
<tr>
<td>Full cycle efficiency [%]$^a$</td>
<td>81</td>
<td>81</td>
<td>81</td>
</tr>
<tr>
<td>Charging power (max.) [kW]</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
</tr>
<tr>
<td>Plug-in ratio [%]$^b$</td>
<td>80</td>
<td>80</td>
<td>80</td>
</tr>
</tbody>
</table>

$^a$ 90% efficiency for charge and discharge cycles.

$^b$ Probability of an actually plugged-in EV at a plug-in parking.

Three conditions must be fulfilled before an EV actually charges: (1) availability of charging
infrastructure, (2) the EV user must physically plug-in the EV, (3) the charging strategy of the EV commands ‘charging’. When an EV parks at a place where charging infrastructure is available, the EV user can plug-in. However, the user could decide not to plug-in, e.g., if he realizes that the charging volume during a short parking time is small. This discount in availability for V2G is reflected by the plug-in ratio (cf. Table 3). Only when an EV is plugged in, it might charge, but it can be plugged in without charging. The charging strategy defines for each time slot whether a plugged-in EV charges or not.

Three very basic strategies are investigated:

- \textit{asfap}: Charging "As soon and as fast as possible", represents a zero-intelligence strategy. The EV charges whenever it is plugged in and charging stops not before the battery is fully charged.
- \textit{cheap}: Minimizing the costs for charging (heuristic). The strategy assumes that electricity prices are lower during the night and schedules charging between 22 pm and 6 am if no charging is needed during the day to maintain mobility. If mobility needs require a charging, this is done \textit{asfap},
- \textit{rand}: An EV charges with a probability of 50% if the EV can drive the next travel segment without charging. If charging is needed for the next travel segment, this is done by \textit{asfap}.

To average out the stochastic effects in the Monte-Carlo simulation, each simulation was repeated 1,000 times. The number of simulation runs was set as the number of vehicles $N$ of a defined car segment in the simulation (see Figure 2). In order to scale the simulation correctly for each scenario, the results were multiplied by the number of EV in the specified car segment and then divided by $N$. If a scenario contained multiple car segments, the above described simulation runs have been performed for each scenario and then weighted by the relative weight of the car segment within the scenario.

### 4. Simulation results

To validate the simulation results, Section 4.1 presents three external validation points that were compared with the generated driving profiles. Section 4.2 analyzes the share of parked EV on different weekday types, which is the basis for the comparison of different scenarios of EV dispersion in Section 4.3. Section 4.4 estimates the V2G potential of the simulated scenarios.

#### 4.1. Model validation

Three validation figures were calculated throughout the simulations in order to verify the coherence with the underlying data source.

According to [19], drivers use a car on average for two travel paths per day. With about 56.5 million Germans having a license and 34.8 million private passenger cars, approximately 3.25 paths are driven on average per day and car (simulation: 3.2).

Comparing the on average driven kilometers as well as the average duration per travel path and day, [13] lists 14.1 km (simulation: 15.0) and 20.7 min (simulation: 21.5). Both figures indicate a slight overestimation of total traffic volume by the simulation model. Yet, with respect of the V2G potential, this leads to more conservative results.

#### 4.2. Parking and charging on different weekday types

In Figure 3, the hours of an average day on the x-axis are plotted against the share of EV that park in the corresponding hour. Since the underlying distributions are derived from seven time blocks, it is necessary to average out hourly parking to values per time block.

![Figure 3. Share of parking EV in dependence on weekday types (asfap strategy in short-term scenario)](image)

Apparently, EV park most of the time with peak parking throughout the night. In the morning hours, parking varies between weekday types. Thereby, Monday shows the lowest share of parking EV and Sunday the highest. In the evening of a workday, people return from work, do errands or go to leisure activities. This accumulation of mobility causes an absolute minimum of parking shares between 4 and 9 p.m. Despite the differences with respect to the weekday type, considering the high shares on the x-axis (always >90%), parking largely dominates driving (analyses in [20] confirm these results).

Furthermore, the consideration of different parking locations enabled further insights. For example, even at workdays between 11 a.m. and 3 p.m., i.e., when least
people are at home, still more than one quarter of all EV is parking at home. No other location type offers these high shares of permanent parking EV. Hence, business models for V2G that considers the location type home (e.g., through special charging tariffs) promise to benefit most of EV availability.

However, not all parking EV are available for charging or grid services. Only those parking EV can charge that are (a) at a place with the required charging infrastructure (at least an outlet), and (b) whose users actually plugged-in the EV. Simulations showed that varying the charging infrastructure parameter (between “only-home” and “home-and-work” as possible charging places), as well as the probability that a user actually decides to plug-in (plug-in ratio), lead to very different results. As an example, the average plug-in duration on a workday in simulations where charging was possible at home and work was at around 25% higher than when charging was possible only at home (cf. Table 5).

Table 5. Average plug-in duration per EV *

<table>
<thead>
<tr>
<th>Charging Infrastructure</th>
<th>Workday</th>
<th>Saturday</th>
<th>Sunday</th>
</tr>
</thead>
<tbody>
<tr>
<td>only-home</td>
<td>11h45</td>
<td>13h00</td>
<td>15h10</td>
</tr>
<tr>
<td>home-and-work</td>
<td>14h40</td>
<td>14h00</td>
<td>15h20</td>
</tr>
</tbody>
</table>

* Based on a plug-in ratio of 80%.

Figure 4 reflects the share of charging EV that can charge at home and at work with a plug-in probability of 80% and the charging strategy asfap (cf. 4.3). Since charging curves are influenced by the EV behavior in each time slot, they are plotted on an hourly basis. The continuous line reflecting a workday reveals that if EV can additionally charge at work, most of them would start charging between 7 and 9 a.m. and would be fully charged before lunch. Yet, driving throughout the afternoon causes significant charging at a workday evening as well – at a time when power grids often already bear a high load due to typical load profiles of private households. This underlines the need for intelligent charging strategies in order to prevent a deterioration of load curves by higher shares of EV.

4.3. Comparison of charging strategies

When an EV is plugged in, its charging strategy determines the actual power flow. However, the flexibility of the charging strategy is limited by the capacity of the charging connection.

Assuming an absolute number of 1.7 million EV and charging infrastructure (with 3.6 kW) available only at home, the resulting total grid load is presented in Figure 5. The charging strategy asfap leads to peak loads in the evening, whereas rand is able to significantly reduce load in these hours. The charging strategy cheap shows that there are means to postpone charging into the night. Yet, the steep nightly increase leading to a midnight peak of over 3 GW might be critical for components of the power grid (e.g., substations) and urges for more intelligent charging strategies.

The maximum power all EV in the short-term scenario could provide for V2G services is high as well: While the biggest pump hydro storage power plant in Germany (“Goldisthal”) can provide 1,060 MW [21], the maximum power of (only those) EV parking at any time at home can provide 1,152 MW (with a plug-in ratio of 80%, i.e., 400,000 * 0.8 * 3.6 kW = 1,152 MW). As the overall German power demand does never exceed 80 GW [22], more than 1% of total German power could be provided by EV for a short time (technical restrictions such as grid capacities can limit this potential).

The duration that EV could provide these services is determined by the aggregated volume of energy (in Watt hours) stored in EV over the course of a day.

Apart from the already presented parameters, this volume also depends on the battery capacities. Battery capacities were assumed depending on the vehicle
segment and the scenario (cf. Table 4). Figure 6 shows the aggregated energy volume for the three different charging strategies. Apparently, overall stored energy volumes are significant, however little dependent on the defined charging strategies. This is due to the fact that on average, EV use only a fraction of stored energy for mobility purpose, since the average daily driving distance is short.

Finally, the counter-perspective, i.e., the battery storage capacity of EV, is important for many grid services. Figure 7 depicts this volume for each of the three charging strategies. Independent of the charging strategy, nearly all cars are charged in the early morning hours. Consequently, around 6 a.m., there is no free battery capacity available at all. Since at present only daily but no hourly bands can be traded on the German market for grid regulation services, V2G could not be offered under these conditions.

4.4. Charging in different scenarios

Up to now, the results were based on a dispersion of EV in the short-term scenario. To evaluate the impact of the underlying scenario, two further scenarios (cf. Table 3 and 4) with a higher overall penetration of EV, a shift from HEV to BEV, increasing battery sizes and decreasing power consumption per kilometer were analyzed.

Figure 8 compares the three scenarios with respect to the share of charging EV. Despite an assumed decreasing consumption (cf. Table 4) from the short to the long term scenario, the share of charging EV in the early morning is higher in the long term scenario than in the short term scenario. The reason is the higher share of BEV in the long term scenario. While HEV can continue driving even when the battery is discharged, BEV only drive electrically. This effect is amplified by the fact that BEV dispose of larger batteries. Together, it leads to more electrically driven kilometers and, thus, increases charging shares from the short-term to the long-term scenario.

5. Conclusion and further research

This paper motivated the need for a more precise look at the behavior of EV, in particular with respect to location and time. For that purpose, a stochastic model simulating the driving behavior of private passenger cars was developed and its key elements were presented.

Simulations of that model with various parameterisations allowed for an estimation of different levels of EV penetration on (a) the load for the power grid as well as (b) the potential availability of EV for grid services.

First results show that more than 90% of all vehicles are parked at any given point in time. Thereof, more than one quarter are parked at home. I.e., investments are most beneficial for charging infrastructure at home.

Moreover, the simulation results show that charging strategies require at least some sophistication to effectively balance the load of charging EV. Basic (“zero-intelligence”) charging strategies cause
significant peaks and do not appropriately provide the V2G potential.

Nevertheless, there is a huge potential for V2G. For example, overall energy volumes stored in EV batteries in a short-term scenario is significant. However, while the time of the day plays an important role, the investigated charging strategies had little effect on stored energy volumes.

The maximum of load caused by EV might reach over 3 GW in a short-term scenario, when charging hours are intentionally postponed, for example into the night. At the same time, even under conservative assumptions, more than 1 GW power is available for V2G at any time. This corresponds to the capacity which Germany’s biggest pump hydro storage power plant could provide at maximum and reflects more than 1% of the overall German grid load at any time of a year.

The simulation model allows for enhancement in various dimensions. On a macro level, the model might be extended to include future variations of driving behavior. On a micro level, the integration and specification of more detailed location types promise further insights. For example, parking at home in cities can be roadside, in garages, or in multi-storey car parks. Such information is of value when evaluating the profitability of business models for EV that require high infrastructure investments.

Moreover, the current model can be used to develop and investigate more sophisticated charging strategies. Since charging strategies are the key for the reconciliation of users’ mobility and power grid needs, further research is to be done on this subject as well.

Beyond the scope of the presented simulation model, further aspects are relevant with respect to V2G. Although some commercial solutions already exist [23], technical issues remain to be investigated further. Examples are rules for bidirectional grid connections of EV and standardizations of communication technologies and protocols. Moreover, it is equally important to overcome social, political and cultural challenges (see [4]) as well as to guarantee a high level of V2G usability (e.g., through user-friendly interfaces [2]).

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References


