Working Paper Sustainability and Innovation
No. S 9/2013

David Dallinger

The contribution of vehicle-to-grid to balance fluctuating generation: Comparing different battery ageing approaches

Fraunhofer ISI

Abstract

Abstract-This paper analyzes how energy throughput and depth of discharge-based battery ageing affects vehicle-to-grid operation of plug-in electric vehicles. Plug-in electric vehicles are discussed as a grid resource to balance the fluctuating electricity generation of renewable energy sources, but their contribution to balance fluctuating generation strongly depends on battery ageing and costs to feed back electricity. Therefore, an electricity system scenario with a very high share of wind and solar generation for Germany 2030 is analyzed focusing on different battery cost scenarios and ageing assumptions for plug- in vehicle batteries. The agent-based approach used renders price-based control with vehicle specific dispatch decision possible. Hence, in dependence of the individual state of charge depth of discharge-based battery discharging costs and expected smart charging revenues can be calculated. The results indicate that depth of discharge- based battery ageing results in a more restrictive vehicle-to-grid operation that is substantially affected by the driving behavior. Overall, vehicle-to-grid allows for increasing the contribution to balance fluctuating generation compared to load shifting only but encounters challenges in terms of costs and battery ageing.[1]

1 To a large extent this paper is, in parts verbatim, based on the doctoral dissertation by David Dallinger submitted to the University of Kassel in Januar 2012.

Table of Contents

Page

1 Introduction

In the European Union, wind and solar are the fastest growing renewable energy sources (RES) for electricity generation. One of the main challenges associated with an electricity system featuring a high share of renewable energy sources is the higher installed capacity and fluctuation in power [1,2]. Currently in Germany, there are 33 GW of installed photovoltaic power with a capacity factor of around 10 % [3]. The simultaneous generation of these power plants reaches a maximum level of 70 % to 80 % and completely rises and declines within a time period of hours. To a lesser extent, the same applies to wind generation in Germany, which has an installed power of 31 GW and an average capacity factor between 20 % and 30 % [3]. If even higher installed capacities of fluctuating generation are assumed, this results in a highly volatile residual load requiring storage, demand response and/or wide distribution options in order to balance the variable electricity output.

Plug-in electric vehicles (PEVs) could provide both storage and demand response. Further, PEVs convert electricity very efficiently and can significantly reduce emissions from passenger transportation if low carbon technologies are used to generate the electricity consumed by electric vehicles. The interaction between fluctuating electricity generation of renewable energy sources (RES-E) and PEVs therefore represents a major research challenge to reach the CO_2 reduction goals of the European Union and to minimize worldwide climate change.

The interaction of PEVs and fluctuating generation from renewable energy sources is analysed in several studies. Studies by Ekman [4] for Denmark and by Fernandes et al. [5] for Spain discuss the PEVs load shifting and storage opportunities. For load shifting only and vehicle-to-grid (V2G) distinct integration benefits have been found. However, both studies do not consider battery degradation and trade the individual vehicle batteries as one large battery. The here used PowerACE model allows investigating the dispatch decision of individual PEVs' agents. This renders vehicle-specific analysis with individual state of charge possible. The main contribution of this paper, therefore, is to extend the available studies for a German case and to analyse two different methods to calculate battery discharging costs. The structure of the paper is as follows. First, an overview of the used methods is provided. Next, the assumptions and results as well as a sensitivity analysis are presented. Finally, a conclusion summarizes the main findings of the paper.

2 Method

For the analysis presented the PowerACE model is used [6,7]. PowerACE is an agent- based electricity market model which is utilised to investigate the effects of fluctuating renewable generation on electricity prices. The simulation period is one year with an hourly time resolution. In a perfectly competitive market assuming bids based on variable costs, fluctuating RES-E affect the resulting clearing prices because of the merit-order- effect [8,9,10]. The merit-order effect describes the phenomenon that RES generation using a bid price of zero replaces bids of thermal power plants with higher variable costs. In the here used simulation approach, the effect of RES-E on the clearing price plays an important role in controlling the charging and discharging of PEVs. The merit-order-effect provides the incentives for PEVs to charge when the supply from fluctuating generation is high.

PEVs are modelled as distributed agents with own objectives controlled by dynamic price signals [11]. In the simulation a single PEVs' agent represents 1000 vehicles. Each PEVs' agent is characterised by individual driving behavior, vehicle specification and battery discharging costs. The vehicle specification includes the battery size, grid connection power and the energy use per km as defined in the section ASSUMPTIONS. Driving behaviour is randomly assigned to a PEVs' agent using deterministic data available from the mobility study German Mobility Panel [12]. The discharging costs are calculated as described in [11]. Thereby two different methods building on the energy throughput and depth of discharge-caused battery ageing are used. The energy throughput-based ageing (Ah) only depends on the ampere hours processed. For the depth of discharge (DoD)´-based wear-out costs depend on the actual battery state of charge. Here, discharging is influenced by the driving behavior and less likely by the time point at which a PEVs' agent returns from a trip.

To quantify the effects of PEVs on the electricity system a method introduced in [13] is applied. Parameters describing the residual load with and without PEVs agents demand and V2G contribution are recorded. Comparing these parameters allows determining the contribution to balance fluctuating generation and comparing different charging and discharging strategies. An overview of the used parameters is given in the Nomenclature. The percentage of surplus fluctuating generation $1\text{-}(cf_{neg(PEVs)}/\ cf_{neg})$ as well as the change of the ramp rate factor *rrf* are used as main evaluation parameters. For comparability reasons with other studies all parameters are normalized by the German peak- load, which is 77,950 MW in the investigated scenario.

3 Assumtions

In order to analyze the effect of fluctuating renewable energy generation from wind power and photovoltaics, as well as the contribution of PEVs to balancing these RES-E a scenario for Germany in 2030 (GER 2030) is used. The scenario equals the GER 2030 scenario used in [13] a study focussing on demand side management describing smart charging only. The DSM results presented in [13] are compared to the here analysed effects of V2G. This allows quantifying the additional benefit including bidirectional charging technology in the PEVs. The following assumptions for the GER 2030 scenario differentiate between the electricity sector and the vehicle sector.

3.1 Electricity sector

In order to investigate the contribution of PEVs integrating RES-E into the grid, a scenario is defined based on surveys available in the literature. This scenario is used to create an environment with very high RES penetration (necessary to reach the CO_2 reduction goal of the German government). The main scenario used GER 2030 refers to the “Lead Scenario 2010”, which was part of a survey investigating high RES penetration in Germany carried out on behalf of the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety [14].

The installed capacity of fluctuating renewable generation is shown in Figure 3-1. Values up to 2012 represent the real installations in Germany. The future assumptions are based on [14]. The total installed capacity from fluctuating generation in 2030 is 125.8 GW which equals 162 % of the 77.8 GW peak-load. The generation share of intermittent RES is 47.6 %, with 87 TWh, 95 TWh and 57 TWh coming from wind onshore, wind offshore and photovoltaics. Total electricity demand is 502.1 TWh per year. The hourly characteristics of RES generation and the load curve are taken from [3,15] with 2008 as reference year. Electricity imports and exports and storage technologies such as hydro-pumped storage are not taken into account because the focus is on how V2G can contribute to balance RES-E.

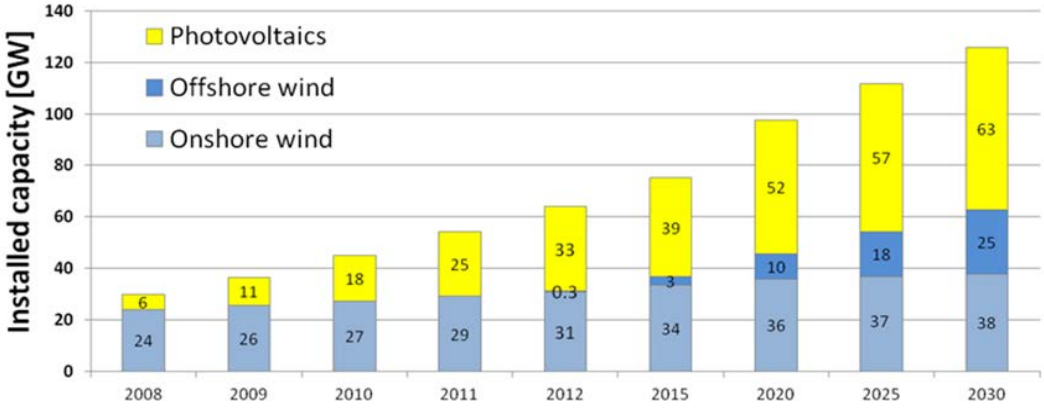

Figure 3-1: Installed capacity of fluctuating generation in Germany

Source: [3] and Lead Scenario 2010 [14]

The power plant park assumed includes power plants >10 MW from [16] that are still available in 2030. New installations are added taking the optimal power plant mix to serve the residual load curve for the assumed load and RES-E scenario [7]. The installed capacities are 749 MW from oil power plants, 32,461 MW from gas turbines, 13,942 MW from combined cycle gas turbines, 14,375 MW from coal power plants, 9,119 MW from lignite power plants and 820 MW from waste power plants. The assumed fuel prices and the resulting merit-order curve of the fossil power plant park are given in Figure 3-2.

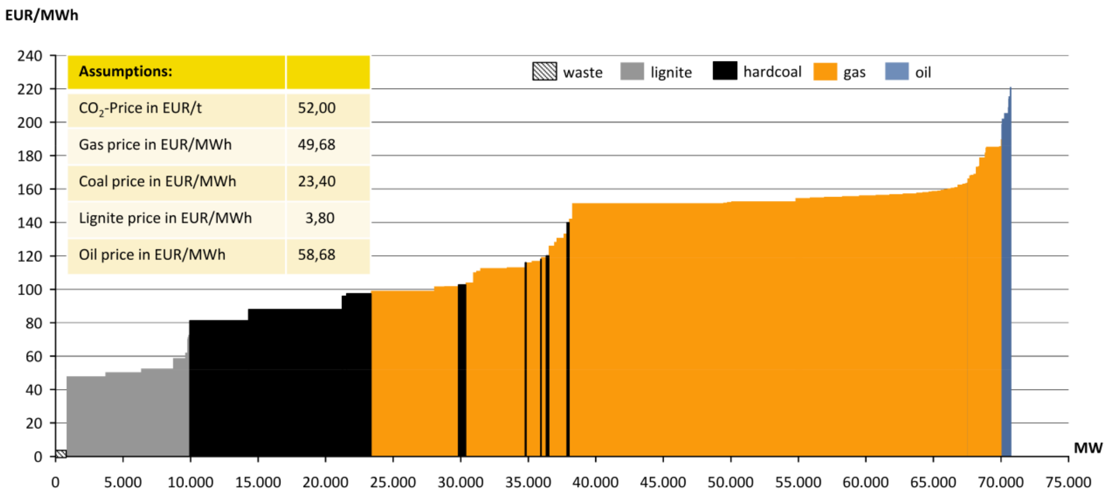

Figure 3-2: Merit-order curve of power plant park in 2030 Germany

Source: Own assumptions based on [7,16]; CO2 and fuel prices [14]; Figure created by David Biere

3.2 Vehicle sector

The penetration scenario for PEVs follows [17], a study investigating a 100 % penetration of alternative vehicles (HEVs, PHEVs, BEVs and fuel cell vehicles) for Japan in 2050. The penetration of PHEVs and BEVs was adapted to the German market by specifying two electric vehicle concepts: PHEVs with 4.5 kWh or 12 kWh and BEVs with 15 kWh or 30 kWh of usable battery storage (see Table 1). The assumptions with regard to the energy use of PEVs imply a reduction in weight as well as in air and rolling resistance compared to today's vehicles. To simulate parking time, trip duration and the trip range of vehicles deterministic driving data from the one week questionnaire survey [18] is used.[2] The equivalent energy used shown in Table 1 includes the charging efficiency. For V2G, an additional efficiency of 94 % is assumed. The battery charging power is assumed to be constant over time. Total PHEV penetration in 2030 is 12 million or 24 % of the total passenger vehicle fleet, with a PHEV share of over 80 %.

Table 3-1: Passenger vehicle types and scenario for Germany 2030

Device	Type (km)*	Usable storage [kWh]	Grid con-nection power [kW]	Equivalent energy use [kWh_{el}/km] **	GER 2030 (12 million PEVs)
1	PHEV (25)	4.5	4	0.18	31.6 %
2	PHEV (57)	12	4	0.21	50.4 %
3	BEV (100)	15	8	0.15	13.9 %
4	BEV (167)	30	8	0.18	4.0 %

Comments: * In brackets: hypothetical driving range in km; ** at grid connection including: charging η = 98.5 %, lithium-based battery: η = 97 % and electric motor η = 95 %

Table 2 summarizes the power and storage capacity of the resulting vehicle fleet. A fleet of PEVs provides high power with a relatively low usable amount of battery storage. In total, 12,000 PEVs are modelled as individual agents for GER 2030, representing 12 million PEVs. Thus, the operation of one vehicle is scaled-up by a factor of 1,000.

2 Survey period: 2002-2008; total participants 17,771; number of trips 77392

Table 3-2: Resulting power and energy values of the vehicle fleet scenarios

	GER 2030		
Type	**Vehicles [thousand]**	**Connection power [GW]**	**Storage capacity [GWh]**
PHEV (25)	3,885	15.54	17.48
PHEV (57)	6,585	26.34	79.02
BEV (100)	1,230	9.84	18.45
BEV (167)	300	2.40	9.00
Sum	**12,000**	**54.12**	**123.95**

In this study, it is assumed that the necessary infrastructure is always available. PEVs are plugged-in after each trip. The battery degradation parameters used are summarized in Table 3. C_{bat} describes the battery costs in euros per kWh. The parameters a and b are used to characterize the battery cyclical life. A detailed description of battery discharging cost calculation is available in [11]. For V2G, the two scenarios, the energy processed and the depth of discharge are distinguished. Both scenarios have optimistic assumptions on battery ageing and cost reduction.

Table 3-3: Battery degradation parameter

	Energy processed (Ah)			Depth of discharge (DoD)		
Type	a	b	C_{bat} [euros/kWh]	a	b	C_{bat} [euros/kWh]
PHEV (25)	7000	-1	281	4000	-1.632	281
PHEV (57)	7000	-1	247	4000	-1.632	247
BEV (100)	7000	-1	247	4000	-1.632	247
BEV (167)	7000	-1	233	4000	-1.632	233

4 Results

The following section presents the results of the PowerACE model for a scenario GER 2030. The section is subdivided into the contribution to balance fluctuating generation, a sensitivity analysis on battery costs and size as well as vehicle to grid revenues.

4.1 Contribution to balance fluctuating generation

To determine the contribution of PEVs to balance fluctuating generation the characterisation parameters introduced in the model section and defined in [13] are used. Further the load duration curve is provided to illustrate the effects of fluctuating generation on the residual load and the PEVs' contribution. The simulation results for the defined scenario without PEVs' contribution is used as reference case for comparison of the V2G results. Further, results for load management only (referred to as demand side management or DSM) and charging after the last trip (LT) published previously in [13] are applied to compare the V2G results.

The load duration curve for the defined scenario GER 2030 is given in Figure 4-1. The x-axis shows the simulation period of one year in percent whereas the y- axis gives the hourly mean power or load once with absolute (right side of Figure 4-1) and normalized (left side of Figure 4-1) values. The whole describes the total system load. The green area represents the electricity generation from fluctuating RES and the gray area the remaining residual load. The red area shows the demand of PEVs. The maximum on the left side of the load duration curve indicates for the demand increase due to PEVs (P_{max}). The minimum value on the right side gives the maximal surplus generation or minimal residual load (P_{min}).

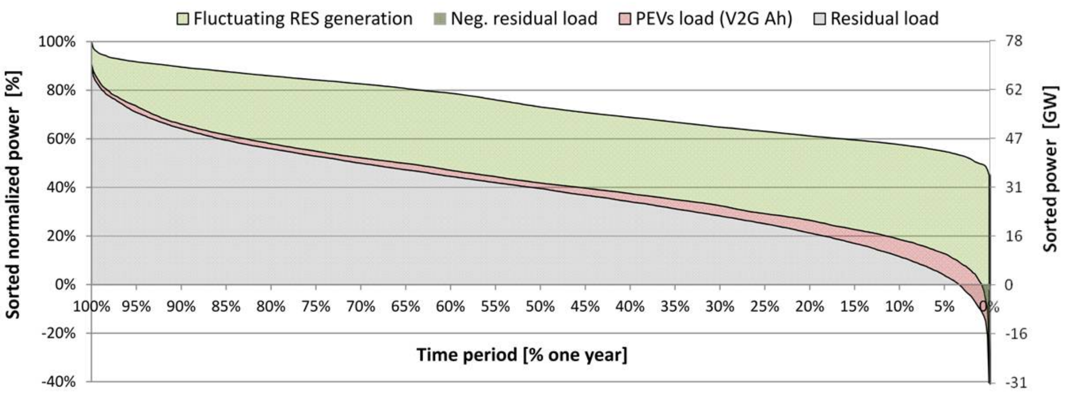

Figure 4-1: Load duration curve for Germany 2030 including V2G

The green and red area under the x- axis gives the total surplus of fluctuating generation. The surplus generation or negative residual load in total is 1.95 TWh (see Table 4). In the case of the V2G Ah, 1.58 TWh of the negative residual load can be consumed by PEVs (read area under the x- axis). 0.37 TWh remain as surplus generation (dark green area under the x- axis).

Comparing the results of the two methods used to calculate the battery discharging costs, depth of discharge-based and energy throughput-based, shows that in the case of V2G Ah electricity fed back into the grid by PEVs is lower (see column V2G in Table 4). Here, especially the dependence of the discharging costs on driving behaviour plays an important role. If a vehicle agent comes back to the grid after a trip the battery state- of- charge (soc) is likely to be low because electricity was used for driving. Therefore, discharging costs are higher than in the case of V2G Ah. To realise low DoD-based discharging costs first the battery needs to be charged. Typically, electricity prices are high when people arrive at home in the early evening and demand therefore is high. During this time period soc tend to be low and DoD discharging costs high. This coherence between soc and electricity prices explains the lower discharged electricity in case of V2G DoD.

Table 4-1: Demand and generation for different charging and V2G scenarios

	Demand			**Generation**			**Surplus**
Scenarios	System load	PEVs	Thereof V2G losses	Power plants	Fluctuating RES-E	V2G	Fluctuating RES-E
Reference	502.1	-		265.1	239	-	1.946
LT	502.1	15.8		280.5	239	-	1.614
DSM	502.1	19.7		283.6	239	-	0.762
V2G DoD	502.1	24.8	0.3	283.6	239	4.7	0.445
V2G Ah	502.1	26.3	0.4	283.6	239	6.2	0.370

Note: The unit of all values is TWh.

Comparing the V2G contribution with load management only - here referred to as DSM – indicate a slightly higher consumption (around 0.3 TWh) of surplus electricity from fluctuating renewable energies (see Table 4 and Table 5 parameter cf_{neg}). Considering the V2G efficiency losses of 0.3 - 0.4 TWh the contribution to consume surplus generation compared to DSM is low. However, analyzing the duration curve parameter P_{min} and the ramping parameter in Table 5 indicates that V2G contributes to reduce the extreme edges of the residual load. This, for example, is indicated by the parameters rr_{max} and rr_{min}, that are strongly reduced compared to the reference and DSM scenario (see Table 5).

Table 4-2: Characterisation parameters comparing V2G and the reference cases

	Duration curve parameter					Ramping parameter				
Scenario	cf_{pos}	cf_{neg}	$1-(cf_{neg(PEVs)}/cf_{neg})$	P_{max}	P_{min}	rrf_{pos}	μ_{pos}	μ_{neg}	rr_{max}	rr_{min}
Reference	38.8%	-0.285%	-	90.4%	-43.5%	2.03%	4.39%	-3.76%	28.21%	-19.23%
LT	41.1%	-0.236%	17.01%	98.3%	-41.9%	2.20%	4.82%	-4.04%	28.5%	-19.2%
DSM	41.5%	-0.112%	60.81%	91.3%	-34.3%	1.52%	2.96%	-3.09%	27.7%	-18.4%
V2G DoD	41.5%	-0.065%	77.09%	88.8%	-27.7%	1.18%	2.37%	-2.35%	22.9%	-15.8%
V2G Ah	41.5%	-0.054%	80.99%	88.8%	-26.2%	1.15%	2.33%	-2.27%	19.9%	-13.4%

Note: Reference: Results for simulation without plug-in electric vehicles; LT: Last trip uncontrolled charging; DSM: Demand side management. V2G: Vehicle-to-grid, depth of discharge (DoD) and energy throughput (Ah) are used to account for battery ageing.

4.2 Sensitivity analysis

The costs for mass-produced automotive lithium batteries are one of the most sensitive parameters for the total costs of ownership calculation (e.g. [19]). Because of the relatively low production volume today and the uncertainty about the precise technology in the future, there is a large bandwidth of cost development assumptions. Therefore, the assumed specific investments in batteries are adapted by plus and minus 20 % and 40 % in the GER 2030 reference case.

Reducing the battery costs increases the share of negative residual load that can be consumed and reduces the ramp rate factor (see Figure 4-2). In terms of the negative residual load consumed, DoD ageing is more sensitive to both cost increases and decreases. The sensitivity to a cost increase is higher for Ah ageing than for DoD ageing with regard to ramping. On the contrary DoD battery ageing is more sensitive than Ah ageing to a cost decrease.

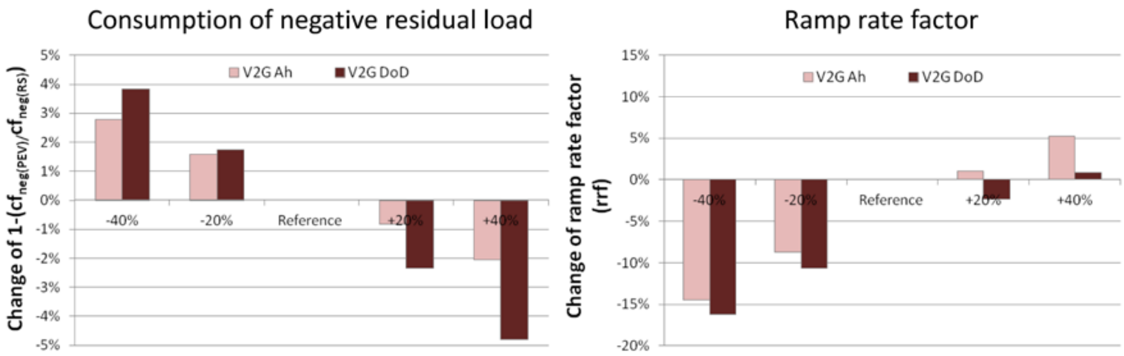

Figure 4-2: Comparing results for varying battery costs

Note: V2G: Vehicle-to-grid; Depth of discharge (DoD) and energy throughput (Ah) are used to account for battery ageing. The reference scenario uses an average battery price of 258 euros/kWh.

For DoD-based battery ageing, the energy fed back into the grid increases from 4.4 TWh in the reference case to 5.6 TWh and 7.1 TWh with a 20 % and 40 % cost reduction, respectively. For Ah with 6 TWh in the reference case, the same cost reduction results in 7.3 TWh and 8.7 TWh of electricity fed back into the grid. The sensitivity regarding the integration of RES-E is not very high but detectable and differs depending on the ageing method used to model PEVs' batteries.

The assumptions about battery size in the GER 2030 scenario are restrictive and small batteries in combination with PHEVs are favored. Nevertheless, vehicle concepts with bigger batteries are also part of the current research discussion on PEVs. Consumer surveys indicate that the electric driving range and therefore the battery size are of great interest [20]. Varying the battery size therefore provides valuable results for this analysis compared to other studies. To analyze the battery size variation, the total fleet is modeled with 15 kWh and additionally with 30 kWh of usable battery storage for all vehicles.

Battery size affects the electric driving share of PEVs. Especially for last trip charging, an increase in battery size increases the electric driving share. Compared to the reference case, the electric driving share of 53.7 % increases to 69.6 % with 15 kWh batteries and to 85.6 % with 30 kWh batteries. For smart charging and a full availability of infrastructure, the share increases from 70.3 % to 79.8 % and to 89.3 %, respectively. This affects the electricity demand of the

PEVs' fleet and, in the case of smart charging, the electricity available for load shifting.[3]

Bigger batteries can increase the negative residual load consumption for all charging strategies. Compared to DSM, V2G DoD charging results in a disproportionately large and V2G Ah in a disproportionately low increase (see Figure 4-3). In terms of DoD ageing, not only the battery size but also the battery cost function is affected by a change in battery size. The negative residual load consumption increases even more for V2G DoD due to the energy available at lower costs.

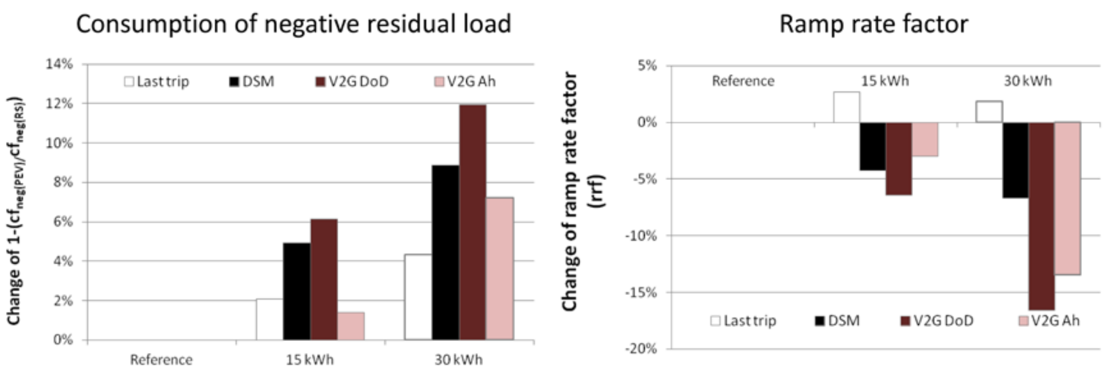

Figure 4-3: Comparing results for different battery sizes

Note: V2G includes the price mark-up; DSM: Demand-side management; V2G: Vehicle-to-grid; Depth of discharge (DoD) and energy throughput (Ah) are used to account for battery ageing. Numbers depict battery size in kWh. The reference scenario uses an average battery size of 10.3 kWh.

The same tendency is observed for the smart charging ramp rate factor. The highest reduction with 17 % is observed for V2G DoD with 30 kWh batteries. For last trip charging, the ramp rate factor rises for both simulated cases. The reduction of the ramp rate factor for a 30 kWh battery compared to a 15 kWh battery could be caused by a higher diversity in the state of charge after the last trip. For a battery of 15 kWh, most batteries are empty after the last trip. Hence, the charging time is the same for many PEV's agents. This causes high simultaneity in stopping the charging process. Overall, differences in the ramp rate factor for last trip charging are only in the range of 2 % compared to the reference values. The sensitivity of the battery size to the integration of RES-E is

3 The PEVs' demand for last trip charging is 19.2 TWh (reference), 24.8 TWh (15 kWh) and 30.5 TWh (30 kWh) and 25.0 TWh (reference), 28.8 TWh (15 kWh) and 32.3 TWh (30kWh) for smart charging.

very high. Nevertheless, from an economic point of view, PEV types with smaller batteries are more likely [19]. Therefore, varying the battery size is considered to be less relevant compared to battery costs.

4.3 Smart charging revenues

The possible profits due to smart charging are mainly affected by the costs for infrastructure, the operation of a smart charging backend control system and battery ageing as well as revenues from system services, energy arbitrage or load shifting. At today's costs and revenues, profits are only small or even negative. Future perspectives are characterized by high uncertainty about revenues and costs. Nevertheless, the following chapter reveals potential revenues on day-ahead energy markets which could act as consumer incentives.

Possible revenues due to smart charging are affected by the price spread between peak- and base-load power plants. In the GER 2030 scenario the marginal costs-based base/peak spread between a gas turbine (152 euros/MWh) and a coal power plant (81.2 euros/MWh) is 71.6 euros/MWh. With the assumption of zero marginal costs for fluctuating generation the maximal spread could theoretically be 152 euros/MWh. From this point of view a high share of fluctuating generating would result in higher price spreads and therefore better market opportunities for demand response or storage applications.

A detailed analysis shows that coherences become more complicated in systems with high share of fluctuating generation (see Figure 4-4). For an electricity system without fluctuating generation typically every day base-load occurs during the night and peak- load during the day. This causes the high frequency of price spreads between 50 and 70 euros/MWh for 2008 data in Figure 4-4. The installation of fluctuating generation units results in highly diverse residual load situation but not necessary in higher price spreads. On the one hand the results indicate that extreme spreads between marginal costs of gas turbines and extreme low residual load situations are more frequent (see right side in Figure 4-4). On the other hand also relatively low price spreads, caused by situations with high generation output from wind turbines reducing the overall residual load are more likely, too. Here, the base peak spread is within the marginal costs of different base-load power plants. In the GER 2030 scenario this is between a coal power plant (marginal costs = 81.2 euros/MWh) and negative residual load (marginal costs = 0 euros/MWh). In case of photovoltaics a reduction of mid day peaks is also likely to result in situations with lower daily price spreads. Therefore, average daily price spreads for the GER 2030 scenario, which result in 81 euros/MWh, are not significantly higher than the average price spreads for the 2008 data (77 euros/MWh).[4]

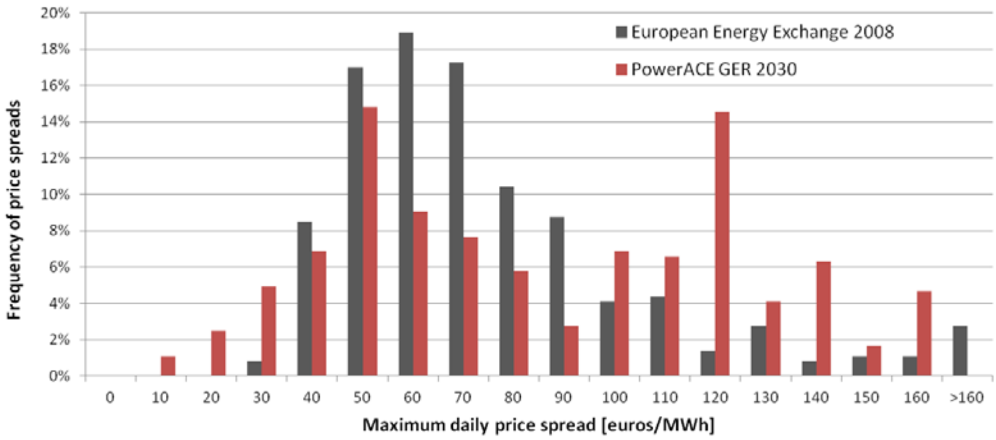

Figure 4-4: Comparing results for different battery sizes

Note: PowerACE simulation results with charging strategy: Demand-side management (DSM); GER: Germany.

Besides the price spread, driving behavior, battery size and electric driving share all influence the savings due to smart charging. A higher yearly electricity demand increases the possible revenues of smart charging. Electricity costs are found to be a linear function of the electricity demand for DSM and last trip charging (for DSM see Figure 4-5). This is intuitive for last trip charging because no dispatch decision is possible. For DSM, a larger battery could facilitate a longer grid management time and therefore the opportunity for additional savings. However, additional DSM savings with a larger battery are not obtained with the batteries implemented and savings remain a function of the demand. For V2G, savings are affected by battery size and electricity demand. A larger battery allows higher energy arbitrage which results in a higher income and reduces the average price paid per kWh. Figure 4-5 shows the savings for smart charging compared to the costs for last trip charging with the same electricity demand.

4 Note that real market behavior tends to result in higher peak prices or even negative base load prices. In the simulation a prices mark-up based on full costs is used to consider the low utilisation of peak-load power plants in electricity systems with high share of fluctuating generation. Nevertheless, market behavior and game theory are not considered.

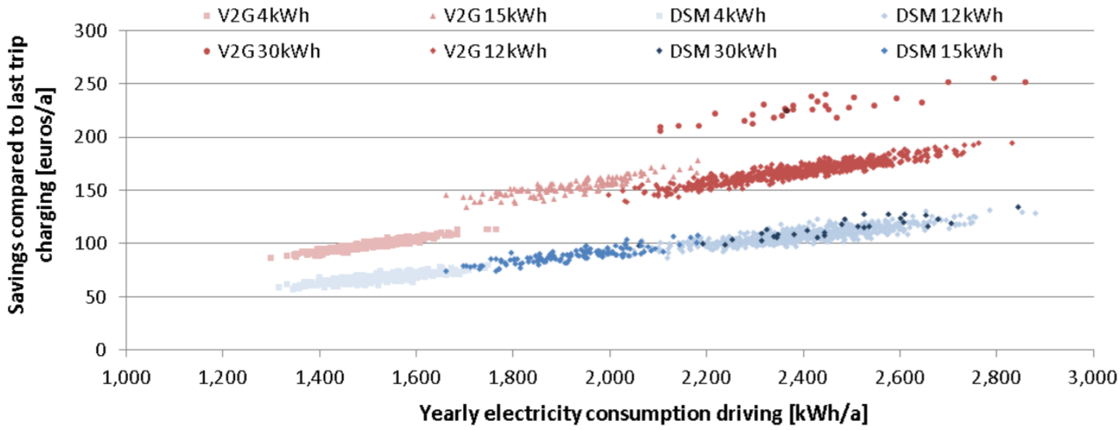

Figure 4-5: Savings for smart charging compared to instant charging after each trip.

For DSM, yearly savings are between 50 and 100 euros for PHEVs (25) with a 4.5 kWh battery. The PHEVs with a 12 kWh battery achieve savings between 100 and 120 euros. For the BEV, a higher efficiency is assumed. Therefore, the demand and savings of the BEV with a 15 kWh battery are lower than PHEVs' (12 kWh) savings and demand. For V2G, savings are between 100 and 250 euros depending on battery size and yearly electricity demand. The costs for battery degradation are considered in this estimation, but additional costs – e.g. for smart charging equipment and the operation of PEVs' pools – are not included and are expected to be disproportionately higher for V2G.

5 Conclusions

The paper investigates how different battery discharging cost calculation methods affect the contribution of plug- in electric vehicles to balance fluctuating generation.

For the investigation an agent-based approach using the PowerACE model is applied. In addition to very valuable research focusing on solving the unit commitment problem including uncertainty on forecaster errors [5] or energy planning tools [21] combined with detailed dynamic system simulations [22] the used approach allows to investigate the perspective of single vehicles including the aging of associated batteries.

The results indicate that depth of discharge-based discharging cost calculation results in a more restrictive discharging behavior compared to energy throughput-based discharging costs. Studies trading vehicle batteries as one large battery therefore are likely to overestimate the vehicle-to-grid performance. Especially, the amount of energy fed back into the grid is significantly lower if depth of discharge-based aging is considered. In terms of balancing fluctuating generations results are within the same range but sensitivities to battery size and costs are higher in case of the depth of discharge-based method. It should also be mentioned that depth of discharge-based ageing cost calculation results in a higher tendency of fully charged batteries which leads to battery wear out in terms of battery calendar life time.

Comparing vehicle-to-grid with load shifting only indicates that the additional V2G benefits are relatively low. This is especially true for the consumption of surplus generation from fluctuating sources. In contrast to this, analyzing the reduction in hourly ramp rates shows that vehicle-to-grid highly contributes to balance fluctuating generation. The increase of the residual load change rate due to renewable generation units is one major challenge for system security. Here, vehicle-to-grid is able to realize significant improvements. In conclusion, analyzing not only surplus generation but also residual load ramping shows that vehicle-to-grid results in an additional contribution balancing fluctuating generation.

For both charging strategies, load shifting only and vehicle-to-grid, expected revenues from day-ahead electricity markets are less than 200 euros per year compared to uncontrolled charging after the last trip. Coherence between a higher share of fluctuating generation in combination with rising prices for primary energy carriers and higher revenues from smart charging did not occur. The merit-order-effect results in increasing price spreads for specific situations when high and low residual loads occur during one day. In terms of smart charging revenues these high price spreads are compensated by low spreads occurring during long base-load periods. Here, prices spreads are only between marginal costs of different power plants in the base-load segment and therefore relatively low. Hence, realizing smart charging business cases will be very challenging even if prices for primary energy carrier are rising and high fluctuating generation output reduces spot market prices. Therefore, it remains particularly important to realize smart charging at low costs e.g. while using available components in vehicles as well as onboard metering.

6 Acknowledgements

This work has been co- financed under grant of the German Federal Ministry of Economics and Technology (BMWi) as part of the project *iZEUS* - intelligent Zero Emission Urban Systen -. I thank Martin Wietschel, David Biere and Gillian Bowman-Köhler for discussions and critical reading of the manuscript.

7 Nomenclature

Symbol	Parameter	Description
$1-(cf_{neg(PEVs)}/\ cf_{neg})$	Consumption of negative residual load	Ratio of negative residual load without PEVs and with PEVs. Gives the percentage of negative residual load that can be consumed by PEVs
a and b	Cycle life parameter	Parameters to determine battery cycle life
C_{bat}	Battery costs	Costs for the battery in euros/kWh
cf_{neg}	Negative residual load characterized by the negative capacity factor	If the fluctuating generation exceeds the load negative residual load occurs. To compare different situations the negative residual load is normalised with the peak- load. The resulting cf_{neg} describes the capacity factor of the negative residual load.
$Cor_{RES\text{-}load+PEV}$	Correlation	Correlation between fluctuating generation and system load and system load including PEVs demand
P_{max}	Maximal power	Maximal hourly system power in one simulation year
P_{min}	Minimal power	Minimal hourly system power in one simulation year
rr	Ramp rate	Change in generation or load between two time steps. Here, the hourly change is used.
rrf	Ramp rate factor	The ramp rate factor *rrf* gives the area under the sorted ramp rate curve for positive rrf_{pos} and negative rrf_{neg} ramp rates. The two areas are equal
rrf_{pos}	Ramp rate factor	The ramp rate factor is defined as the sum of the normalized ramp rates in one simulation year.
RS	Residual load	The residual load is defined as the total system load minus fluctuating renewable energy generation. cf_{pos} describes the capacity factor of the negative residual load.
μ_{neg}	Mean value of all negative ramp rates	A high mean of the negative ramp rate indicates a strong decrease e.g. of the residual load.
μ_{pos}	Mean value of all positive ramp rate	A high mean of the positive ramp rate indicates a strong increase e.g. of the residual load.

8 References

[1] NERC: North American Electric Reliability Corporation, Accommodating High Levels of Variable Generation: Special Report. Accessed May 29, 2013. http://www.nerc.com/files/IVGTF_Report_041609.pdf, 2009.

[2] Parsons, B., Milligan, M., Zavadil, B., Brooks, D., Kirby, B., Dragoon, K. and Caldwell, J., Grid impacts of wind power: a summary of recent studies in the United States. Wind Energy 7 (2): 87-108, 2004.

[3] EEX: European Energy Exchange, Transparency in Energy Markets - Gesetzliche Veröffentlichungspflichten der Übertragungsnetzbetreiber. European Energy Exchange AG -Transparenzplattform. Accessed July 11, 2011. http://www.transparency.eex.com/de/, 2011.

[4] Ekman, C. K., On the synergy between large electric vehicle fleet and high wind penetration – An analysis of the Danish case, Renewable Energy, Volume 36, Issue 2, February 2011, Pages 546-553, ISSN 0960-1481, 2011.

[5] Fernandes, C., Frías, P. and Latorre, J. M., Impact of vehicle-to-grid on power system operation costs: The Spanish case study. Applied Energy, Volume 96: 194-202, 2012.

[6] Sensfuß, F., Assessment of the impact of renewable electricity generation on the German electricity sector - An agent-based simulation approach. Dissertation, Karlsruhe Institute of Technology, Karlsruhe, 2007.

[7] Dallinger, D., Plug-in electric vehicles integrating fluctuating renewable electricity, Dissertation, University Kassel, 2012.

[8] Sensfuß, F., Ragwitz, M. and Genoese, M., The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36 (8): 3086-3094, 2008

[9] Green, R. and Vasilakos, N., Market behaviour with large amounts of intermittent generation. Energy Policy 38 (7): 3211-3220, 2010.

[10] Sáenz de Miera, G., del Río González, P. and Vizcaíno, I., Analysing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain. Energy Policy 36 (9): 3345-3359, 2008.

[11] Dallinger, D., Link, J. and Büttner, M., Smart Grid Agent: Plug-In Electric Vehicle, Submitted to IEEE Transactions on Sustainable Energy

[12] MOP: German Mobility Panel, Project handling: Institute for Transport Studies of the University of Karlsruhe, Accessed July 11, 2011. http://www.dlr.de/cs/en/desktopdefault .aspx / tabid-704/1238_read-2294/, 2002-2008.

[13] Dallinger, D., Gerda, S. and Wietschel, M., Integration of intermittent renewable power supply using grid-connected vehicles – A 2030 case study for California and Germany, Applied Energy, Volume 104, April 2012.

[14] Nitsch, J., Pregger, T., Scholz, Y., Naegler, T., Sterner, M., Gerhardt, N., Von Oehsen, A., Pape, C., Saint-Drenan, Y. and Wenzel, B., Langfristszenarien und Strategien für den Ausbau der erneuerbaren Energien in Deutschland bei Berücksichtigung der Entwicklung in Europa und global. Deutsches Zentrum für Luft- und Raumfahrt, Fraunhofer Institut für Windenergie und Energiesystemtechnik, Ingenieurbüro für neue Energien, vol. BMU - FKZ0, Accessed November 11, 2011. http://www.erneuerbare-energien.de/inhalt/47034/40870/, 2010.

[15] ENTSO-E: European Network of Transmission System Operators for Electricity, Hourly load values of all countries for a specific month, Accessed July 11, 2011. https://www.entsoe.eu/db-query/consumption/mhlv-all-countries-for-a-specific-month/, 2011.

[16] Platts. World Electric Power Plants Database. Accessed March 31, 2012. http://www.platts.com/Products/worldelectricpowerplantsdatabase/Overview, 2010.

[17] METI: Ministry of Economy, Trade and Industry. Strategic Technology Roadmap (Energy Sector) - Energy Technology Vision 2100. Accessed March 31, 2012. http://www.iae.or.jp/2100/main.pdf, 2006.

[18] MOP: German Mobility Panel. 2002-2008. "Project handling: Institute for Transport Studies of the University of Karlsruhe", 1 Accessed July 11, 2011. http://www.dlr.de/cs/en/desktopdefault .aspx / tabid-704/1238_read-2294/.

[19] Kley, F., Ladeinfrastrukturen für Elektrofahrzeuge Entwicklung und Bewertung einer Ausbaustrategie auf Basis des Fahrverhaltens. Dissertation, Karlsruhe Institute of Technology (KIT), Karlsruhe, 2011.

[20] Peters, A. and Dütschke, E., Zur Nutzerakzeptanz von Elektromobilität Analyse aus Expertensicht, Fraunhofer Institute for Systems and Innovation Research. Accessed March 31,2012. http://www.elektromobilitaet.fraunhofer.de/Images/FSEM_Ergebnisbericht_Expert-eninterviews_tcm243-66462.pdf, 2010.

[21] Lund, H. and Kempton, W., Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy, Vol. 36 (9), pp. 3578-3587, 2008.

[22] Pillai, J. R., Heussen, K., Østergaard, P. A., Comparative analysis of hourly and dynamic power balancing models for validating future energy scenarios. Energy, Volume 36, Issue 5, Pages 3233-3243, 2011.

Authors' affiliations

David Dallinger

Fraunhofer Institute for Systems and Innovation Research (Fraunhofer ISI)

Contact: Brigitte Kallfass

Fraunhofer Institute for Systems
and Innovation Research (Fraunhofer ISI)
Competence Center Energy Policy and Energy Markets
Breslauer Strasse 48
76139 Karlsruhe
Germany
Phone: +49 / 721 / 6809-150
Fax: +49 / 721 / 6809-203
E-mail: brigitte.kallfass@isi.fraunhofer.de
URL: www.isi.fraunhofer.de

Karlsruhe 2013