E.ON Energy Research Center Series

Plug-in Hybrid Electric Vehicles for CO\textsubscript{2} -Free Mobility and Active Storage Systems for the Grid (Part 2)

André Hackbarth, Benedikt Lunz, Reinhard Madlener, Dirk Uwe Sauer, Rik W. De Doncker

Volume 4, Issue 6
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Executive Summary

Due to its almost exclusive dependence on fossil fuels, the transportation sector accounts for some 32% of the final energy demand in the European Union, and is responsible for about one fifth of the total European Union greenhouse gas (GHG) emissions (EC, 2011a). Consequently, it is one of the focal points of the European sustainability strategies, which among other targets also aim at the mitigation of substantial amounts of GHG emissions in several sectors of the economy. For instance, the European Commission has set the ambitious goal of a 60% reduction of GHG emissions in the transportation sector by 2050 compared to 1990 levels (EC, 2011b). However, the achievement of this objective requires considerable efforts, amongst others the enhancement of the vehicles’ fuel efficiency and the substitution of alternative fuels or electricity for gasoline and diesel. The European Commission adopted several regulations to improve vehicles’ specific GHG emissions in the short term. For instance, emission performance standards for new passenger cars were set to 95 gCO₂/km on average by 2020 (EC, 2009b), with gradually stiffened interim targets. Additionally, the European Commission determined that the share of renewable energy should at least amount to 10% of the final energy consumption in transport by 2020 (EC, 2009a). In Germany, the largest European economy, with its pronounced automotive manufacturing sector, the government has set the goal to get one million electric vehicles on the road by 2020 and to become a leading market for and provider of electric mobility (Bundesregierung, 2009). One reason for this pronounced support of electric mobility in almost all European countries is – besides the reduction of CO₂ emissions by means of reducing oil-based fuel consumption in the transport sector – the possibility to increase electricity generation from volatile renewable energy sources by using electric vehicles as active storage systems in the grid – the so-called vehicle-to-grid (V2G) concept – and thus to reduce the necessity of keeping back-up power plants in reserve (Kempton and Tomic 2005a, 2005b). Furthermore, the usage of PHEVs and electric vehicles as distributed storage systems has the advantage that the storage capacity is available independently of failures or shutdowns in the transmission grid.

In this project, the focus is on major factors which are crucial for a significant market penetration of plug-in hybrid electric vehicles (PHEVs). It is not within the scope of this research project to develop a new vehicle. Rather, besides research questions concerning the vehicle itself, we analyzed major issues concerning a grid connection of PHEVs that allows them to serve as active loads or even active storage systems. The results are expected to support both car manufacturers and electric utilities in their strategic decisions regarding PHEVs.

In Part 1 of the final project report (Hackbarth et al. 2010), several important issues concerning electric mobility were already tackled. Firstly, the analysis of PHEVs began with calculations regarding the optimal size of the vehicle battery investigating both technical as well as economic aspects. Secondly, an analysis of the most important safety aspects and standards was performed. Thirdly, our investigations showed the most important needs in the field of charging equipment and charging infrastructure. Fourthly, potential future revenues for V2G services, for instance generated by the supply of balancing power or peak load, were estimated. Fifthly, business and marketing models, such as (battery) leasing and profit-sharing, which could foster the application of these grid services and the diffusion of PHEVs, were examined, as was the role of the different market actors in the field of electric mobility, such as car owners, electric utilities or telecommunication companies. Finally, the impact of an accelerated diffusion of PHEVs on the power generation portfolio, the energy production costs and the emissions of the power plants, taking different charging scenarios into account, were assessed.
In the present Part 2 of the final project report, we investigated issues regarding battery lifetime, the integration of PHEVs into low-voltage grids, and consumer preferences and their impact on the potential diffusion of electrified vehicles.

The main outcomes of the remaining different work packages can be summarized as follows.

**Battery lifetime and integration into low-voltage grids**

V2G provides the possibility of decreasing the total cost of ownership (TCO) for PHEVs and battery electric vehicles (BEV) by, for example, lowering the costs of electricity consumption. On the other hand, feeding power back into the grid is commonly assumed to have a lifetime-decreasing effect on the vehicle batteries. In order to investigate the effects of different charging algorithms on the battery operating conditions, a simulation setup was introduced aimed to model electric vehicles in a grid segment. The resulting mobility costs (electricity plus battery depreciation costs) and their compatibility with the distribution grid were analyzed. The simulation model used real-world mileage data from mobility statistics and electricity price data from the European Energy Exchange for producing representative results. Comprehensive cyclic aging tests (for Lithium Nickel Manganese Cobalt Oxide, NMC, and Lithium Nickel Cobalt Aluminum Oxide, NCA, batteries) and calendaric aging tests (for NMC batteries) were performed with lithium-ion battery cells. These tests showed an exponential relationship between cell voltage (state of charge, SOC) and lifetime. Considering the fact that high battery SOCs decrease battery lifetime, different charging strategies were implemented: Uncontrolled charging as the reference case, unidirectional price- and SOC-optimized charging as well as bidirectional energy trading with and without SOC constraint.

A first grid simulation showed that price-sensitive charging strategies may lead to an increased grid load due to the coincidence of charging operations. This could be solved, for example, by shifting the price signals in time between different users. The battery simulation results show that by applying intelligent charging algorithms, it is possible to simultaneously increase battery lifetime and reduce charging costs. The economic impact of a longer battery lifetime is approximately twice the revenues that can be gained through energy trading. The results also show that it is difficult to reach the intended battery lifetime of 10 years for vehicle applications without oversizing the battery. By applying intelligent charging strategies, oversizing can be reduced or omitted. This is due to the fact that standstill times are dominating the battery operation and because with uncontrolled charging the battery SOC is above 90 % during more than 80 % of the time. In order to reach the targeted lifetime of the vehicle batteries, it is therefore essential to implement intelligent charging strategies. Oversizing the battery to limit the maximum SOC in order to reach the battery lifetime envisaged can be considered to be a costly alternative, as either the electric driving range is decreased or the battery costs increased.

The rapid introduction of variable electricity tariffs, for example, with a 24-hour prediction of hourly electricity prices and regulations for the power-feedback of electric vehicles would foster the introduction of electric mobility. Intelligent charging algorithms in this case would be able to reduce mobility costs by minimizing electricity consumption costs and decreasing battery depreciation at the same time.

**Business models and consumer needs**

Two approaches were used to model and forecast the adoption and diffusion of alternative fuel vehicles (AFVs) in general, and PHEVs and BEVs in particular, depending on the prevailing framework conditions.
First, the potential demand for privately used AFVs was analyzed by using discrete choice data from a nation-wide survey in Germany and applying discrete choice models (specifically, a standard multinomial logit model and an mixed logit model specification). By expanding earlier studies and additionally taking recharging time, driving range, and governmental incentives as crucial vehicle attributes into account to measure their respective impact on vehicle choice decisions, and, furthermore, considering PHEVs and their unique characteristics as a vehicle alternative, we find that some attributes impact vehicle choice positively, as in the case of driving range, fuel availability, and governmental monetary and non-monetary incentives, or negatively, as in the case of purchase price, fuel cost, CO₂ emissions, and recharging time. Furthermore, we find that German car buyers are currently very reluctant towards the adoption of AFVs, especially concerning electric and hydrogen vehicles, which could be a great barrier in terms of their fast and successful diffusion and to achieving the very ambitious goal of the German government to get one million electric cars on the road by 2020. However, our results also show that PHEVs are far less likely to be rejected than fully electric vehicles and that not all consumers have equally pronounced reservations against AFVs. In other words, especially younger, highly educated, and environmentally conscious consumers, and to some extent also urban drivers of small cars with access to garages or parking lots equipped with electrical wall-plug sockets, are more prone to buy new vehicle technologies in general and plug-in vehicles in particular. Hence, for effectively increasing the adoption rates (or sales figures) of certain AFVs, marketing strategies could be tailored such that they target specifically these consumer groups. On the contrary, and in light of the ongoing demographic change which results in an aging population, our results could also lead to the opposite conclusion that the most relevant target group for policy-makers and car manufacturers should be middle-aged and elderly people, as they still have strong reservations against electric vehicles, and thus could threaten the prospects for individual electric mobility of private vehicle users and, consequently, the ambitious goal of the German government to become a lead market. Therefore, information campaigns or the possibility to test electric vehicles in the field could be especially customized for these consumer groups to reduce their unfamiliarity with, and reservations against, electric mobility.

Additionally, we find that German car buyers are willing to pay considerable amounts for an improvement of the most important vehicle features. However, notable differences in the willingness-to-pay (WTP) can be observed, depending on the consumer group or the respective vehicle alternative. For instance, the marginal WTP for the mitigation of CO₂ emissions is more than twice as large for highly environmentally aware (potential) adopters, compared to adopters with low environmental consciousness. A similar doubling can be observed for the driving range of electric versus other vehicles, and for a reduction in battery recharging time between PHEVs and fully electric cars. This finding indicates that a fast-charging option is not equally important for all plug-in vehicles, and thus could be relevant for the investment strategy concerning recharging infrastructure. Furthermore, households with low stated purchase prices (< €20,000) are only willing to pay about half the amount that households without this budget constraint are willing to expend for the improvement of vehicle features.

The scenario analysis revealed that conventional vehicles remain dominant in terms of market share, and that hybrid and natural gas vehicles are the AFVs most likely to be chosen. As these propulsion technologies are currently the most renowned and available AFVs, and as they also have the farthest-developed refueling infrastructure and do not suffer from short driving ranges or high purchase prices surcharges, this finding is not too surprising. Strikingly, however, our results show that choice probabilities of some AFVs, such as PHEVs and biofuel vehicles, could be increased in a relatively cost-efficient way by granting vehicle tax exemptions, or by allowing the usage of bus lanes and
presenting possibilities for free parking. Thus, to promote AFVs, the German government should think about the introduction of these incentives and not limit these measures to electric vehicles. Contrary to that finding, fully electric and hydrogen vehicles only gain in demand if multiple policy measures are implemented or if at least the subsidization of the vehicle purchase is substantial. Thus financial incentives, as already implemented in some European countries today, and also lobbied for by German car manufacturers, are found to be insufficient to significantly increase adoption rates. Furthermore, our results suggest that an expansion of the refueling/recharging infrastructure density or the acceleration of the recharging process alone is not sufficient for increasing the diffusion of pure BEVs, but that these two measures should rather be implemented jointly. Finally, and also very interestingly, our findings indicate that an increase in the driving range of BEVs to 750 km, leaving all other vehicle attributes unchanged, affects the adopters’ choice probability in the same way as would a market-based multiple policy intervention strategy, comprising a purchase price subsidy, a tax waiver, bus lane usage, free parking, and a widespread fast-charging infrastructure. However, it should be noted that without substantial purchase price or electricity price surcharges these two potential support schemes are not economically viable today and in the near future. Thus, in order to reach the very ambitious electric mobility goal of the German government, the government could increasingly focus on and promote PHEVs (e.g. with subsidies and non-monetary incentives), as they are not burdened by limited cruising ranges and thus could serve as a means to make car drivers familiar with electric mobility, without putting them at risk of being stranded due to an empty battery.

Second, an agent-based model (ABM) was constructed to estimate the future diffusion of alternative drive systems and to review the influence of various parameters on the potential diffusion pathways. We focused on electrified drivetrains, namely hybrid electric vehicles, PHEVs and BEVs, which were described by five attributes (purchase price, fuel consumption, convenience, performance, and emissions). Furthermore, we took four different consumer groups into account (majority, conformists, greens, petrolheads), which differed in their socio-economic characteristics. In a scenario analysis, we assessed the impact of governmental incentives on the diffusion process of the different vehicle technologies. Our results suggest that tax exemptions and convenience improvements can help to promote PHEVs and BEVs. However, different levels of effectiveness among the different promotion strategies occur, which have to be considered when designing successful marketing strategies. The diffusion of electrified vehicles can be promoted by both price cuts and improvements of convenience. However, a simultaneous promotion of both PHEVs and BEVs does not necessarily lead to higher market shares of both drivetrain technologies.

Nevertheless, this study shows that governments are able to promote alternative drivetrains, if the support focuses mainly on the improvement of vehicle convenience, e.g. through the (publicly or privately funded) provision of a comprehensive recharging infrastructure. However, as already mentioned, the cost effectiveness of such an expansion of the recharging infrastructure cannot be assumed today.
1 Introduction

Due to its almost exclusive dependence on fossil fuels, the transportation sector accounts for some 32% of the final energy demand in the European Union, and is responsible for about one fifth of the total European Union greenhouse gas (GHG) emissions (EC, 2011a). Consequently, it is one of the focal points of the European sustainability strategies, which among other targets also aim at the mitigation of substantial amounts of GHG emissions in several sectors of the economy. For instance, the European Commission has set the ambitious goal of a 60% reduction of GHG emissions in the transportation sector by 2050 compared to 1990 levels (EC, 2011b). However, the achievement of this objective requires considerable efforts, amongst others the enhancement of the vehicles’ fuel efficiency and the substitution of alternative fuels or electricity for gasoline and diesel.

The European Commission adopted several regulations to improve vehicles’ specific GHG emissions in the short term. For instance, emission performance standards for new passenger cars were set to 95 gCO2/km on average by 2020 (EC, 2009b), with gradually stiffened interim targets. Additionally, the European Commission determined that the share of renewable energy should at least amount to 10% of the final energy consumption in transport by 2020 (EC, 2009a). Beyond that, most European governments have decided to implement further-reaching programs and regulations to accelerate the diffusion of alternative fuel vehicles (AFVs) in general and electrified cars in particular. For example, purchase and tax incentives for (partially) electric or other ‘environmentally-friendly’ vehicles are granted in Spain, France, the UK, Ireland, Sweden, and Belgium, to name but a few. These inducements to buy amount up to €9,510, as in Belgium, or even up to 70% of the investment, as in Andalusia (for a useful review of electric vehicle promotion strategies, see e.g. ACEA, 2012).

In Germany, the largest European economy, with its pronounced automotive manufacturing sector, the government has set the goal to get one million electric vehicles on the road by 2020 and to become a leading market for and provider of electric mobility (Bundesregierung, 2009). To reach these targets, research on various technical, economic, and behavioral aspects is coordinated centrally and will be funded by more than €1.5 billion in total up to 2013 (Bundesregierung, 2011). In addition, a ten-year motor vehicle tax exemption for electric vehicles was introduced in a first step. Further monetary incentives, such as advantageous taxation rules for commercially used electric vehicles, have been initiated, and several non-monetary buying inducements are under consideration, such as the permission for bus lane usage or special parking areas (BMF, 2012; Bundesregierung, 2011). One further reason for this pronounced support of electric mobility in almost all European countries is – besides the reduction of CO2 emissions by means of reducing oil-based fuel consumption in the transport sector – the possibility to increase electricity generation from volatile renewable energy sources by using electric vehicles as active storage systems in the grid – the so-called vehicle-to-grid (V2G) concept – and thus to reduce the necessity of keeping back-up power plants in reserve (Kempton and Tomic 2005a,b). Furthermore, the usage of PHEVs and electric vehicles as distributed storage systems has the advantage that the storage capacity is available independently of failures or shutdowns in the transmission grid.

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1 Significant parts of this Final Report are directly taken from Hackbarth et al. (2010), Neumann (2011), Hackbarth and Madlener (2011), and Lunz et al. (2012), respectively.

2 AFVs comprise vehicles that run on liquid or gaseous fuels other than gasoline and diesel, or at least partly on electricity, e.g. biofuels, natural gas (liquefied petroleum gas (LPG) or compressed natural gas (CNG)), hydrogen (e.g. fuel cell vehicles), (plug-in) hybrid electric vehicles (PHEVs), and fully (battery) electric vehicles (BEVs).
Even though electric mobility is currently the primary topic of interest of German policy-makers, other alternative fuels are being supported as well. For example, tax reductions for natural gas fuels have been recently prolonged until 2018. Moreover, a minimum quota of 6.25% for biofuels to replace gasoline and diesel has been introduced (BImSchG, 2011), and a public-private partnership, which runs until 2016 and provides €1.4 billion of funding, has been established to boost research on hydrogen and fuel cells (BMVBS/BMWi/BMBF, 2006).

Despite these diversified endeavors by the government and administration, the assortment of AFVs is still limited. Thus, it is hardly surprising that AFVs have not penetrated the market yet to a large extent and so far amount to only about 1.4% of the overall vehicle stock in Germany (KBA, 2012). However, the diffusion of AFVs in general, and electrified vehicles in particular, might rise sharply in the coming years for at least two reasons. First, all major vehicle manufacturers have started to bring mass-produced, and thus affordable, plug-in hybrid or pure electric vehicles to market and have announced that they will do so in the next couple of years with hydrogen-fueled vehicles. Second, consumer prices for gasoline and diesel in 2012 (Q1-Q3) were at an all-time high and expected to increase further (ADAC, 2012a), also due to the eco-tax in place, which makes non-conventional fuels even more attractive. For a fast market penetration of PHEVs and fully electric vehicles, however, it is necessary that their other features also sufficiently match with consumer preferences, which in turn is heavily affected by the cost effectiveness, the driving range and the recharging conditions for these new types of cars, as well as by other technical aspects (e.g. battery lifetime) and legislative framework conditions. Thus, this second part of the final research project report covers a number of issues, which can be expected to have a major effect on the successful diffusion of (plug-in hybrid) electric vehicles.

### 1.1 Goals and expected outcome of project / added value

In this project, the main focus is on factors which are crucial for a significant market penetration of PHEVs. It is not within the scope of this research project to develop a new vehicle. Besides research questions concerning the vehicle itself, we furthermore analyzed major issues concerning the grid connection of PHEVs that allows them to serve as active loads or even active storage systems. The results are expected to support both car manufacturers and electric utilities in their strategic decisions regarding PHEVs.

The project and, thus, the final report consist of two parts. In the first part (Hackbarth et al. 2010) several important issues concerning electric mobility were tackled. Firstly, the analysis of PHEVs began with calculations regarding the optimal size of the vehicle battery, investigating both technical as well as economic aspects. Secondly, as safety and standardization were (and in fact still are) an important field for market introduction of PHEVs, an analysis of the most important safety aspects and standards was performed. Thirdly, charging equipment and charging infrastructure are also (and still are) a controversially discussed topic. Our investigations were based on comprehensive mobility data and did show important issues to be solved in this field. Fourthly, the potential future revenues for V2G services, like the supply of balancing power or peak load, in the future were estimated. Fifthly, business and marketing models, such as (battery) leasing and profit-sharing, which could foster the application of these grid services and the diffusion of PHEVs, were examined as well as the role of the different market actors in the field of electric mobility, such as car owners, electric utilities or telecommunication companies. Finally, the impact of an accelerated diffusion of PHEVs on the power generation portfolio, the energy production costs and the emissions of the power plants, taking different charging scenarios into account, were assessed.
Part 2 of the final report contains the following topics. Firstly, battery lifetime is an important issue, not only for V2G concepts. Therefore, we performed lifetime tests on lithium-ion batteries to identify the influencing factors on the battery lifetime and to predict the possibility of using vehicle batteries for additional grid services. Secondly, in order to investigate the delivery of grid services, a simulation model for PHEVs in a distribution grid segment was developed and possible management algorithms implemented to control the charging behavior. Thirdly, a web-based discrete choice experiment was conducted to assess the preferences of (potential) car buyers regarding AFVs, to estimate the influence of vehicle attributes on vehicle choice, and to calculate the willingness-to-pay for their improvement. After that, in a scenario analysis, the impact of monetary and non-monetary policy measures on vehicle choice probabilities was simulated. Finally, an agent-based simulation model (ABM) was constructed to predict the potential diffusion process of AFVs in the next couple of years, taking the dissimilarities between vehicle alternatives and consumer groups into account.

Note that for all investigations made, the focus was on the German market and the German situation with regard to grid infrastructure, utility needs and players (car manufacturers, suppliers, grid operators etc.), regulatory framework, mobility patterns and consumer behavior and future preferences.

1.2 Positioning of project within E.ON ERC strategy

This interdisciplinary project targets one of the most topical energy research areas of today, electric mobility. Specifically, it helps to integrate and enhance the applied research competences in electrical engineering (esp. PGS and ISEA) and in energy economics (FCN) of the E.ON ERC and associated RWTH institutions in the field of electric mobility. The topics addressed are manifold, ranging from energy storage, consumer behavior, business models, standardization, distribution networks / charging infrastructure to energy efficiency (in an engineering and economic sense!) and specific energy modeling issues. The two parts of the final project report show that the interdisciplinary research undertaken within this project could be integrated almost seamlessly, despite of the fact that this was the first joint report of its kind between the collaborators involved (both on a personal as well as institutional level). The project fostered the co-operation of the Chair of Energy Economics and Management (Prof. Madlener) and those for Power Generation and Storage Systems (Prof. De Doncker, Prof. Sauer) within the E.ON ERC and helped to find a common language and a common understanding of the technical, economic and societal/socio-psychological questions and problems at hand. Furthermore, the project helped to build up knowledge, skills and a track record (publications, contributions to national and international conferences), enabling to successfully bid for follow-up projects and to seek for outside research partners. For instance, FCN and PGS acquired a 4-year research project, funded by the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU; promotional reference: 16EM1032), to be realized jointly with the Deutsche Post Chair of Optimization of Distribution Networks (Prof. Sebastian, RWTH Aachen University), and two industrial partners (Deutsche Post AG, Langmatz GmbH), with the goal to identify the operational suitability of a large-scale fleet of electric delivery vans. Moreover, the project has also allowed to educate several talented students at RWTH Aachen University on how to undertake scientific research and writing in close collaboration with the E.ON ERC staff involved in the project. Last but not least, the positive experience gained could induce at least some of them to follow their professional career later in the field of electric mobility, thus helping to supply skilled workers in a burgeoning and fascinating new market that will bridge the electricity supply industry with the automobile industry and, if emerging successfully, lead to one of the most important paradigm changes of our times – the large-scale use of electricity for individual mobility. Furthermore, the affiliated institute for Power Electronic and Electrical Drives (ISEA, directed by Prof. De Doncker and Prof. Sauer) benefitted from this study, as it stimulated
and provided focus in several large BMBF projects in the area of electric propulsion systems, (bi-directional) battery chargers, and modular battery system concepts.

### 1.3 Definitions

**Hybrid-Electric Vehicle (HEV)**

A Hybrid-Electric Vehicle (HEV) relies on at least two energy sources, usually an internal combustion engine (ICE) and an electric battery together with a motor/generator.

**Plug-in Hybrid Electric Vehicle (PHEV) / Range-Extended Electric Vehicle**

A Plug-in Hybrid Electric Vehicle (PHEV) is an HEV that can be plugged-in and be recharged from the electric grid. PHEVs are distinguished by much larger battery packs when compared to other HEVs. The size of the battery defines the vehicle’s all-electric range (AER). Range-extended electric vehicles, with a significant electric driving range and typically a smaller internal combustion engine as compared to classical PHEVs, are considered as (serial) PHEVs.

**Vehicle-to-Grid (V2G)**

The Vehicle-to-Grid concept uses vehicle batteries to deliver different kinds of grid services, such as balancing power. Normally, V2G is used in the context of a bidirectional power connection between battery and grid, although with a unidirectional connection grid services can be offered as well. V2G services can be supplied with PHEVs, Range-Extended Electric Vehicles, and fully electric vehicles (also referred to as battery electric vehicles, BEV).

**State of Charge (SOC)**

The SOC of a battery describes the charging level of a battery. A fully-charged battery has a SOC of 100%, whereas a fully-discharged battery has a SOC of 0%.

<table>
<thead>
<tr>
<th>Table 1: Exemplary influence factors on study results</th>
</tr>
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<tbody>
<tr>
<td>Influences battery aging by</td>
</tr>
<tr>
<td>Annual mileage</td>
</tr>
<tr>
<td>Vehicle segment</td>
</tr>
<tr>
<td>Availability of charging infrastructure</td>
</tr>
<tr>
<td>Region</td>
</tr>
<tr>
<td>Driving behavior</td>
</tr>
</tbody>
</table>

For analyzing the grid integration of PHEVs (see section 2.2) we focus our investigations on electric vehicles with range extender (for example Chevrolet Volt / Opel Ampera, with ca. 50 km electric driving range) driven from an average German car user with an annual mileage in the range of 10,000 to
15,000 km. This type of vehicle is predominantly placed in the medium-class segment. The conclusions given in this report, therefore, cannot be directly transferred to other vehicle segments like the upper class segment where much higher annual mileages and hence a much higher cyclization of the vehicle batteries occur. Furthermore, we focus our study on Germany, a country where temperature variations have a relatively minor influence only. The influence of different driving behavior (city/rural/highway) on the energy consumption is disregarded. Some exemplary influence factors are summarized in Table 1.

2 Results of work packages

In the following, four main topics will be discussed in detail. In section 2.1, determinants that influence the battery lifetime are assessed and the magnitude of their influence on battery aging is shown. The integration of electric vehicle batteries as active or passive storage system elements into the low-voltage grid, and the influence of different charging strategies on the overall costs of electrically driven kilometers, are analyzed in section 2.2. In section 2.3, we focus on consumer preferences for AFVs in general and electrically propelled vehicles in particular, and derive WTP measures for the improvement of the most important vehicle features. Finally, we forecast the acceptance of AFVs (by their adoption rates or market shares) and their diffusion process in the near future, depending on the development of the governmental policy framework, by applying two different methodological approaches (sections 2.3 and 2.4).

2.1 Battery lifetime

A more detailed description of the following results is given in Lunz et al. (2012).

2.1.1 Introduction

Summarizing the literature (Brousseley et al., 2005; Vetter et al., 2005; Wright et al., 2002; Zhang and Wang, 2009), the state of charge (SOC), which correlates directly to cell voltage (or more precisely electrode potential), represents a significant contributor to battery aging. Influencing both a battery’s calendar life and cycle life, the SOC is an important factor when talking about appropriate charging methods and strategies. Electrochemically, the SOC mainly impacts the stability of electrodes (active materials and binder) and electrolytes. High electrode potentials (high SOC) cause electrolyte decomposition in the surface region of a cell’s anode and cathode, which leads to consumption of active Li+-ions and growth of the solid electrolyte interphase (SEI) on the electrodes’ surfaces, resulting in capacity decline, power fade and impedance rise. Besides electrolyte decomposition, degradation of active masses by dissolution of their substrate or binder decomposition can be observed as well. At low temperatures and high SOCs, aging can be accelerated by limitations of cell kinetics, resulting in lithium metal plating when cycling the battery.

2.1.2 Aging tests setup

For a better understanding of SOC impact on cell degradation, and for parameterization of the simulation models, a set of accelerated aging tests have been carried out both for cyclic (Figure 1, Figure 2, Figure 3) and calendaric (Table 2) stability with Saft’s VL45E lithium-ion cells (45 Ah, Lithium Nickel Cobalt Aluminum Oxide, NCA).
Figure 1: Cycle tests 1 and 2

Figure 2: Cycle test 3

Figure 3: Cycle test 4
Table 2: Storage test matrix

<table>
<thead>
<tr>
<th>SOC</th>
<th>Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>85%</td>
<td>55°C</td>
</tr>
<tr>
<td>60%</td>
<td>55°C</td>
</tr>
<tr>
<td>35%</td>
<td>55°C</td>
</tr>
</tbody>
</table>

2.1.3 Results

Preliminary results\(^3\) of the cycle tests after approximately 3,000 equivalent full cycles are shown in Figure 4 and Figure 5. An increase in capacity at around 2,000 equivalent full cycles can be explained with longer rest periods of the tests between capacity checkups.

At the time of writing this final report, these tests are still ongoing as the end-of-life (actual capacity = 70% of initial capacity) is not reached yet. The relative capacity \(C_r\) was fitted as a function of the equivalent full cycle number \(N\), using the following equation:

\[
C_r(N) = a \cdot \sqrt{N} + b \cdot N + 1
\]  

(1)

This extrapolation shows that more than 7,000 equivalent full cycles can be reached even at an elevated temperature level of 40 °C (see Figure 5). As will be shown later in section 2.2.4.2, this is fully sufficient for PHEV operation.

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\(^3\) The results are preliminary in the sense that the end of life has not been reached in most cases. Concerning the project, the results are final in the sense that the project has ended.
The calendaric aging tests with Saft's VL45E are still ongoing and are not yet showing trends which can be extrapolated to an end-of-life criterion. Therefore, for our analysis we use test data from another cell chemistry (Lithium Nickel Manganese Cobalt Oxide, NMC). These tests employ a state-of-the-art lithium-ion high energy system composed of a graphite-based negative electrode, a LiNi$_{1/3}$Mn$_{1/3}$Co$_{1/3}$O$_2$ (NMC-) based positive electrode and a standard electrolyte (1 molar organic solvent with LiPF$_6$). The cell is designed for BEV and PHEV applications. In a first scenario, accelerated calendar life tests have been carried out at 40 °C and 60 °C test temperature. Each test employs three cells for getting representative data and the cells have been stored at different constant voltages for at least one year.

Figure 5: Preliminary results of cycling test 4 (combined cycle); relative capacity related to initial capacity test of each cell; crosses showing single cell relative capacities

Figure 6: Capacity lifetime vs. SOC for calendar life tests at 25 °C, 40 °C and 60 °C. Lifetimes are calculated by extrapolation to an end-of-life criterion of $C_{\text{act}} = 70\% C_{\text{init}}$
Figure 6 summarizes the results by plotting the calendaric capacity lifetime (end-of-life criterion: 30% capacity loss compared to initial capacity) versus SOC. It clearly illustrates the strong acceleration of aging due to high SOCs.

From a detailed analysis of the tests at 40 °C and at 60 °C, an exponential relationship can be derived for SOC or rather voltage impact on lifetime, showing acceleration of cell aging by a factor of 1.15 and 1.2, respectively, related to a voltage increase of 100 mV. For voltages above 4.04 V (SOC > 90%) the degradation rate shows a stronger non-linearity (factors of 1.6 (40 °C) and 2.5 (60 °C) per +100 mV), which might be caused by a higher rate of the electrolyte decomposition process occurring at more elevated potentials. Considering lifetime issues, longer rest periods at very high SOC should, therefore, be avoided in real operation.

The cycle lifetime is influenced in a similar way by the SOC. For different average SOCs and a cycle depth of 10% ∆SOC, each three cells were operated at 40 °C with a 2C-rate charge / 2C-rate discharge profile. In Figure 7 the relative gain in cycle lifetime compared to cycling with an average SOC of 95% is plotted over the scenario’s average SOC.

Cycling at high average SOC strongly accelerates cell aging, whereas cells cycling at low average SOCs saves lifetime. With respect to charging, lifetime can be saved by reducing the target charge SOC to lower values, or by minimizing the rest periods at high SOCs.

Cars operating in V2G applications have a significantly higher cycle load compared to conventional PHEVs and BEVs. In order to understand how this approximately affects the cells' lifetime, results from cycle and calendar life scenarios are plotted together in Figure 8. It shows the cells’ actual capacity normalized to its initial values versus testing time. In a first test scenario, three cells are cycled, employing current rates of 1C within the cells' voltage limits (4.2 V → 3.0 V) and resulting in 100% full cycles. The second scenario employs the same current rates for charging and discharge but cycles the cell only between 100% and 50% SOC.
The equivalent SOC for the cycled specimen is estimated as the weighted average SOC, where the weights reflect the nonlinear effect of the SOC on aging. The resulting effective state of charge is approx. 73% for the 100% discharge and approx. 85% for the 50% discharge scenario. In order to compare the calendaric aging for cycled specimen based on the average SOC with the calendaric aging of non-cycled ones, Figure 8 contains also capacity data for tests at 100% SOC (fully charged state), 90%, 80% and 50% SOC. The comparison shows that the cycled specimen with lower effective or equivalent SOC exhibit less aging, and that their aging is comparable with that of non-cycled specimen of similar SOC. That shows that the combined aging effect of calendaric aging and aging due to cycling at a rate of 1 C are not significantly larger than the pure calendaric aging at an equivalent SOC. In other words, in this case the calendaric aging is the dominating effect.

An extrapolation of the observed capacity decrease results in a lifetime of at least 10,000 equivalent full cycles. With showing more than 10,000 equivalent full cycles in the tests, the investigated lithium-ion battery technology seems to be ready for fulfilling both driving and power grid operation demands from a technical point of view.

For extrapolating the battery lifetime we use the following assumptions:

- Cycle life is not limiting the battery lifetime in the given application which has a maximum of ca. 2,300 equivalent full cycles (see section 2.2.4.2). This assumption is based on specific lithium-ion battery test data showing a capability of more than 7,000 equivalent full cycles for NCA and more than 10,000 equivalent full cycles for NMC chemistry.
- A first lifetime estimation can be made by only considering calendaric aging. For this extrapolation calendaric lifetime data depending on battery SOC for NMC chemistry is used (based on Figure 6).

### 2.2 Integration into low-voltage grids

The profitability of PHEVs is significantly influenced by battery aging and electricity costs. Therefore, a simulation model for PHEVs in the distribution grid is presented, which allows comparing the influence of different charging strategies on these costs. The simulation is based on real-world mileage data
(BMVBS, 2009) and European Energy Exchange (EEX) intra-day prices in order to obtain representative results. The analysis of comprehensive lithium-ion battery aging test data shows that especially high battery SOCs decrease battery lifetime, whereas cycling batteries at medium SOCs has only a minor contribution to aging. Charging strategies that take into account the previously mentioned effects are introduced, and the SOC distributions and cycle loads of the vehicle battery are investigated. It can be shown that appropriate charging strategies significantly increase battery lifetime and reduce charging costs at the same time. Possible savings due to lifetime extension of the vehicle battery are approximately 2.5 times higher than revenues due to energy trading. The findings of this work indicate that car manufacturers and energy/mobility providers have to make efforts for developing intelligent charging strategies to reduce mobility costs and thus to foster the introduction of electric mobility. A more extensive description of the following results is given in Lunz et al. (2012).

2.2.1 Introduction

PHEVs and BEVs offer the potential to reduce the ecological impact of traffic and the ecological impact of the power sector at the same time. The extent of these benefits has been discussed in the literature. Turton and Moura (2008) state that the technological key element is the capability of vehicles to feed power back to the grid, referred to as the Vehicle-to-Grid (V2G) capability, which may foster the transformation of both sectors. V2G can enhance the integration of renewable energy sources in the power sector by delivering balancing energy (Lund and Kempton, 2008) and improve the efficiency of conventional generation (Sioshansi and Denholm, 2009). Thus the CO₂ emissions can be reduced significantly. As a greener energy mix is beneficial for the overall emissions of PHEVs and BEVs, the emissions of the traffic sector are reduced as well. Furthermore, V2G revenues for the vehicle owner would reduce the vehicle’s total cost of ownership (TCO, which equals purchase price plus all operating expenses like maintenance, recharging etc.; Kempton and Tomic, 2005a,b), so that the price gap of PHEVs and BEVs compared to conventional vehicles can be reduced. A large number of studies investigating V2G technology with different research foci exist in the literature: The studies of Kempton and Tomic (2005a,b) are focused on large-scale ecological and economic benefits of vehicle fleets deployed for V2G services and on business models. They show that V2G generates additional revenues for the vehicle owner and increases overall performance of the electric grid. Galus et al. (2010) introduce a model for power system planning including future V2G vehicle fleets. A simulation of possible profits for the vehicle owner is shown by Andersson et al. (2010). This work focuses on the balancing power markets of Germany and Sweden and concludes that €30-80 per month can be gained in Germany by participating in these markets, whereas apparently no profits are possible in Sweden. Farmer et al. (2010) collected and compared the findings of various studies performed within a North American context. Assuming that the charging patterns of the vehicles are optimized to charge only at off-peak hours, the possible penetration levels of PHEVs without the necessity of expanding the energy system are shown. The majority of the studies considered in Farmer et al. (2010) find that a significant percentage of the total light vehicle fleet can be charged using the surplus generation capacity in low-demand time periods. Furthermore, possible revenues for V2G services from different studies are summarized. The authors conclude that a high uncertainty in the calculated earnings can be found. Sortomme and El-Sharkawi (2011) show charging algorithms which minimize the impact of vehicle charging on the distribution system and maximize aggregator profit. The effect of these algorithms is demonstrated for a hypothetical group of users. Rotering and Ilic (2010) introduce an optimization algorithm for charging electric vehicles in deregulated electricity markets. However, only cyclical aging costs are used and battery aging due to calendaric effects was disregarded in this study.
It is interesting to note that most of the studies about V2G neglect the impacts of V2G services or charging strategies on battery operation conditions at all or only use simplifying assumptions. Therefore, battery degradation costs, which are a main contributor to electric mobility costs, are not dealt with appropriately.

In order to investigate this topic, the following study was performed within our project. Firstly, a simulation model for PHEVs in the distribution grid based on real-world driving behavior is developed. To this end, a low-voltage grid segment is built up in the DigSILENT PowerFactory. The car driving data is taken from a large German mobility survey (BMVBS, 2009), which monitored driving behavior of a representative sample of cars over one week. As data for longer periods are not publicly available, this data set was used and results were extrapolated.

Secondly, price-signal based charging algorithms are introduced with the aim of minimizing charging costs and reducing times at high battery SOC. Strategies for unidirectional and bidirectional charging are presented. Finally, the impacts of the different charging algorithms on the battery operation conditions and on electricity and battery depreciation costs are investigated. The battery SOC dominates battery aging in the PHEV application and is, therefore, analyzed in detail for the different charging strategies.

2.2.2 Model setup

The developed model is able to simulate a fleet of PHEVs in a distribution grid segment. The charging/discharging behavior of the PHEVs can be controlled by different charging algorithms which use price signals and mobility data as their input. For simulating the power flows and the voltage behavior of the distribution grid, household load elements with standard load curves are integrated, too. The PHEV model itself calculates the electricity consumption as well as the battery SOC curves used for calculating battery lifetime. The simulation setup is shown in Figure 9.

![Figure 9: Simulation setup with inputs and outputs](image)
4 hours), which forecasts the electricity price for the next 24 hours. The vehicles then react autonomously and decide when to charge or discharge their on-board battery. This way the communication architecture can be kept manageable. As the energy concept of the German government (BMWi, 2010) commits the energy industry to offer variable prices and smart meters, this concept could in principle be implemented in practice in the future. First field trials are started in Germany using price forecasts to control household loads, for example in the E-Energy project “Smart Watts”.

2.2.2.1 Simulation environment
The grid simulation program PowerFactory from DlgSILENT (DlgSILENT, 2009) is used for enabling power system analysis for the regarded low-voltage grid. As the integrated DlgSILENT Simulation Language (DSL) offers only limited commands and logic functions, a MATLAB interface is utilized to handle complex management algorithms involving database access and matrix manipulation.

2.2.2.2 Simulation components
The main components of the model are the distribution grid segment, household models and the PHEV models.

Distribution grid
The layout of the distribution grid is modeled on the basis of Kerber (2008). It is grouped into two identical lines of 20 households. The medium line-to-line voltage of 20 kV is transformed into the low line-to-line voltage of 0.4 kV by a local network transformer, whose rated power is 160 kVA. The power lines consist of underground cables with four aluminum conductors.

The conductors have a cross section of 150 mm$^2$ and PVC insulation. The distance between two outgoing lines for the households are 17 m, the household connection line is 10 m long. The connection underground cable has four aluminum conductors with 50 mm$^2$ cross section. Figure 10 shows the schematic of the distribution grid.
PHEV model

The PHEV and household modules are implemented as controllable loads. All modules can be enabled or disabled to simulate different PHEV penetration rates. The PHEV model itself consists of a battery model, a charger model and a charging control unit (CCU) to implement the charging strategies. As it is not the goal to implement a dynamic simulation, a simple battery model is used: The model integrates the power input or output to calculate the energy content of the battery. The battery SOC is calculated assuming a linear single-cell voltage behavior from 3.4 V to 4.2 V. It is assumed that the battery has got a constant efficiency of 98% in both power flow directions (Smith and Wang, 2006). Furthermore, the assumed PHEV uses 15 kWh per 100 km (VDE, 2010). Most commercially available electric vehicles limit the SOC range of the battery to increase their lifetime. Our approach uses intelligent charging strategies to reach the lifetime goals and high battery utilization at the same time, which reduces initial battery costs. The electric driving range of the investigated PHEV is approx. 50 km (similar to the Chevrolet Volt; cf. Eberle and von Helmolt, 2010) which equals a usable capacity of 8 kWh. We allow charging up to 100% SOC and discharging down to 20% SOC (to be able to operate in charge-sustaining driving mode) so that the installed battery capacity is 10 kWh. The modeled battery charger can handle bidirectional power flow. It is assumed that the efficiency of the charger is 95% in both directions (Eltek Valere, 2011). The charging power is limited to 3.7 kW, which is the power of the standard German single phase power outlet with 230 V and 16 A. The recent VDE study about electric drive vehicles (VDE, 2010) proves that the 3.7 kW single phase connection is sufficient for common driving purpose especially for PHEVs. The charging control unit is the main intelligence of the vehicle system. Here the MATLAB interface is integrated to implement different vehicle management strategies. The MATLAB file integrated in the control unit accesses the mobility data given in section 2.2.2.3 and calculates whether the vehicle is at the home connection or not, the length of the stay and the charging and discharging program for this stay. Every vehicle reacts independently.

2.2.2.3 Simulation data

The simulation model integrates recent driving and electricity market data to produce realistic results. For the load of the households the BDEW standard profile H0 was assumed (Energienetze Bayern, 2012).

Mobility data

The German Mobility Panel 2008 (BMVBS, 2009) couples a larger-scale cross-sectional mobility survey with a smaller sample panel. For this work, the weekly driving patterns of 1,221 different vehicles are taken from the panel to build the car pool for the simulation. The survey contains information about the time of each departure and arrival of the vehicle in addition to its destination and driving distance of each trip. For the simulation thecomings and outgoingsof vehicles (time of departure and arrival) in the considered suburban distribution grid (pure residential neighborhood) and the respective driven distances are extracted. The vehicles are only recharged at the home plug, which should be the prevalent case in the near future (VDE, 2010).

Price data

It is assumed that the grid operator calculates a day-ahead price signal based on generation schedules, anticipated weather conditions and expected loads. The price signal is updated every four hours for the next 24 hours. As these dynamic price forecasts are not implemented in the market yet, we model the price data using EEX (European Energy Exchange) intra-day prices as the variable cost of electricity generation. The electricity price in Germany consists of the cost for generation and
transportation of the electricity, concession fees and various taxes or levies, such as the contribution to the EEG (Renewable Energies Act) and KWK-G (Combined Heat and Power Act), electricity taxes and sales tax (EnWG, 2005). Grid fees, concession fees and taxes are assumed to be invariant. The average end-user electricity price without sales tax in 2009 was around €0.195/kWh and the average EEX intra-day price was at €0.039/kWh.

The invariant part of the electricity price without sales tax is therefore assumed to be €0.156/kWh. Figure 11 shows the price data of the simulation model consisting of an invariant part, taxes and the EEX intra-day price. The week from January 5 until January 12 of 2009 is chosen as a reference. This price data was chosen for the simulation model because of its high volatility compared to other price intervals. This choice is based on the anticipation of frequently fluctuating power generation due to the increased portion of renewable energy sources in the future.

![Figure 11: EEX price signal for January 2009](image)

### 2.2.3 Charging strategies

The management objectives of PHEVs in the distribution grid can be ordered in three different levels:

1. The first priority should be the interest of the vehicle owner, for example to have a fully recharged battery before the next trip.

2. Vehicles must maintain the functionality of local distribution grids and not cause instabilities.

3. Finally, with least priority, the PHEVs can be used for grid support in the context of V2G.

The management strategies must satisfy the vehicle owner’s interest as a first priority. It is assumed that the owner wants the vehicle to be fully charged at the start of the next trip. For the algorithms to have a certain management time frame, the charging control unit knows the departure time, either by input of the owner or by an intelligent adaptive system that calculates an approximate driving behavior based on prior collected data. Furthermore, an economically rational vehicle owner would want to charge the vehicle at the lowest costs possible. To maintain the quality and stability of the local distribution grid, the supply voltage at the household connections must not deviate by more than ± 10% of the rated voltage, and the local network transformer should not be overloaded. If both prior conditions are fulfilled, the vehicle can offer ancillary services to the grid or take part in energy trading.
2.2.3.1 Uncontrolled charging

The first step of this work is the implementation of uncontrolled charging as the reference case. In this case the battery is charged immediately after arrival of the car. At the time the vehicle has arrived at the home plug (vehicle status changes from 0 to 1), the SOC is upgraded by the energy consumed during the trip (at around 12 h in Figure 13). Then the battery is charged with 3.7 kW until SOC reaches 100%.

2.2.3.2 Unidirectional management

This work proposes two management strategies for PHEVs in case the battery charger is unidirectional or if power flow from vehicle to grid is undesirable: First, the optimization of the battery SOC is shown and, second, the optimization of charging costs (as described by Rotering and Illic, 2010, Chapter IV.B) is implemented.

Battery lifespan optimization

One strategy to increase the battery lifespan is to keep the battery potential as low as possible to decelerate aging mechanisms (see section 2.1). Therefore, battery charging is delayed to the time period immediately before departure. The departure time must be known either by user input or by intelligent self-adapting algorithms. As this work is focused on PHEVs, this algorithm can even be used in the case of uncertainties about the departure time, as the internal combustion engine of a PHEV guarantees a certain driving range also with low battery SOCs at the starting time of a trip.

Cost optimization

As the electricity price is high at high-level-demand time periods and low during low-level-demand time periods, cost optimization for vehicle owners implies load shifting for the grid operator. The vehicles would shift their charging time to the periods with the lowest demands, in order to improve capacity utilization of generators during that time and to reduce peak power demands. For unidirectional cost optimization, the CCU needs to additionally get day-ahead price signals from the grid operator (see section 2.2.2.3). The price data is grouped in 15-minute intervals, the algorithm searches and saves the cheapest charging periods of 15 minutes or portions of 15 minutes as long as the calculated SOC at a charging power of 3.7 kW has not reached 100%. If the parking time exceeds 24 h, the algorithm is reiterated after four hours, which is the assumed duration of a signal update from the grid operator.

2.2.3.3 Bidirectional management

Bidirectional power flow enables PHEVs to act as generation resources. Vehicles can participate in the power markets to buy and sell energy. For that purpose, a trading algorithm has been implemented to calculate the ideal charging and discharging program.

Trading

To ensure a full battery charge at departure, the CCU first calculates and reserves a time window for charging before the anticipated departure. After that, the remaining time before charging has to start is used to calculate a trading plan. The algorithm searches for the optimal selling and buying periods during the stay, under the condition that the necessary amount of energy is recharged before departure. The trading algorithm first searches for the maximum price period starting at $t_{\text{max}}$ in the parking phase that is not saved in a charging or discharging program. It then compares the maximum price $P_{r_{\text{max}}}$ with the minimum price $P_{r_{\text{min}}}$ in the interval starting at $t_{\text{min}}$. If the price difference is bigger than a margin of €0.05 (arbitrary value, including additional costs for bidirectional power flow), the
algorithm will calculate a discharge period at $t_{\text{max}}$ and a recharge period at $t_{\text{min}}$ complying with the given SOC boundary. The algorithm reiterates until all periods have been compared and a completed charging program has been calculated (see Figure 12). The given margin represents the energy losses in the battery system and the cost of battery wear through additional charging cycles. The margin in the simulation model is assumed to be a fixed value of €0.05. This can be made variable in future work, depending on efficiency characteristics, battery aging costs and fixed costs for taking part in the energy market. Figure 13 shows the simulated vehicle status, charging power from grid to vehicle, price signal, and SOC of vehicle no. 5 for bidirectional price-optimized charging.

The SOC of the vehicle is constant during times spent away from the home connection (vehicle status = 0) because the model only considers management of the vehicles at the distribution grid and does not upgrade the SOC while the vehicles are being driven.

**Trading with SOC constraint**

The trading algorithm can also be used with a SOC constraint to increase battery lifetime. In this case, the SOC of the on-board battery will stay below the level at the time of arrival during the trading phase. Figure 14 shows simulation results for bidirectional trading with SOC constraint. In both Figure 13 and Figure 14, $t_1$ is the charging time calculated by the charging algorithm, $t_2$ is the discharge period at peak price, and $t_3$ is the recharge period to refill the battery.
Using trading with SOC constraint, $t_1$ is at the end of the stay. For pure cost-optimized charging $t_1$ is at the lowest price.

2.2.4 Simulation results

Load flow calculations were performed for the proposed charging algorithms. It is assumed that each of the 40 households in the distribution grid is equipped with a PHEV. The analysis of the simulation data is focused on the battery SOC during the standstill periods and the cycle numbers, as these parameters are the main contributions to battery aging. Furthermore, the household supply voltages are analyzed to show the suitability of the proposed simulation model for grid investigations. To obtain a better statistical base, all simulations are run with five sets of 40 arbitrarily selected vehicles from the mobility data matrix.
2.2.4.1 Household supply voltage

To show the suitability of the model for grid simulations, the influence of the charging strategies on the load of the low-voltage grid is analyzed. In Figure 15, the household supply voltage of different households for the bidirectional trading algorithm is shown. Due to a high coincidence of charging and discharging activities, relatively high voltage peaks in both positive and negative direction occur. This is because of the fact that all vehicles are supplied with the same price curves and react in a similar way. At eight times during that week, the regarded low-voltage segment even feeds power back into the medium-voltage grid. However, the performed simulation does not allow any general conclusions on the effects of the proposed management strategies on the power grid. For that, Monte Carlo methods have to be applied to take into consideration different grid structures and different user behavior.

![Figure 15: Supply voltage of households for bidirectional trading, vertical gridline at 3 p.m. of each weekday, house no. 1 is directly behind the low-voltage transformer, house no. 20 is at the end of the low-voltage string.](image)

2.2.4.2 Charging cycles

Using the PHEV battery as a bidirectional storage system for the grid with energy trading at the electricity market will lead to increased charging cycles of the battery.

Table 3 shows the equivalent full charging cycles of simulated vehicles for unidirectional charging and the bidirectional price-optimized algorithm during the simulation period of 150 hours. It can be seen that the variation between the average values of the different vehicle sets is rather small. Supposing a vehicle lifetime of 10 years, the battery has to deliver approximately 1,210 equivalent full charging cycles with the unidirectional charging algorithm and around 2,310 with the bidirectional algorithm. In other words, the participation in energy trading roughly doubles the cycle load during the lifetime of the battery. However the influence of aging due to cycling remains below the expected cycle lifetime and therefore poses no significant contribution to the overall aging of the battery. The overall aging remains dominated by calendaric aging.
Table 3: Equivalent full charging cycles during simulation period (approx. 150 hours); average, minimum and maximum value of the five vehicle sets

<table>
<thead>
<tr>
<th>Charging algorithm</th>
<th>Average</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unidirectional</td>
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<td>1.9</td>
<td>2.4</td>
</tr>
<tr>
<td>Bidirectional trading</td>
<td>4.0</td>
<td>3.6</td>
<td>4.3</td>
</tr>
</tbody>
</table>

2.2.4.3 State of charge

To investigate the influence of the charging algorithm on the battery SOC, SOC histograms for the time periods when the vehicles are plugged in (\(f_{\text{standstill}}\)) were calculated. The reference case “uncontrolled charging” is shown in Figure 16 as well as the SOC distribution for the times when the vehicle is not plugged in at home (\(f_{\text{driving}}\)). Mobility data show (BMVBS, 2009) that the vehicles are plugged in at home during 80% (\(P_{\text{standstill}} = 0.8\)) of a week and, accordingly, not plugged in during 20% (\(P_{\text{driving}} = 0.2\)) of the time. Each bar shows the average value of the respective SOC interval for all vehicles. The error bars show the maximum positive and negative deviations among the average values of the five sets.

As the vehicles are charged immediately after arrival, the batteries are at SOCs above 90% for more than 95% of the standstill period.

![Figure 16: SOC histogram during stay for uncontrolled charging and for times not plugged in at home ("driving")](image)

As explained in section 2.1, especially a high battery SOC shortens the battery lifetime. Therefore, the SOC-optimized charging algorithm was introduced. The SOC histogram for that charging algorithm is shown in Figure 17. Without any implications for the vehicle driver, it is possible to keep the SOC below 90% for more than 70% of the standstill time. In the optimization scheme purely based on the lowest price for electricity that fraction was only 45%. This means that the SOC-optimized charging algorithm combines the cost-reducing effect of using cheap electricity prices with the battery-life-extending effect of lowering the SOC during the standstill time.
The battery SOC distribution is especially interesting for bidirectional charging algorithms. Using these charging algorithms increases the cycle number. However, as can be seen from Figure 18, it drastically decreases standstill times at high SOCs, which outweighs the effect of the extra cycles. As battery aging is dominated by calendaric aging in PHEV applications, the bidirectional charging can reduce time shares at high SOCs by lowering the SOC to less aging-intensive levels after use.

The bidirectional SOC-optimized charging algorithm for example is able to keep the battery at SOCs below 30% for more than 30% of the standstill time. Compared to uncontrolled charging, this has positive effects on battery lifetime.
2.2.4.4 Battery lifetime

Battery lifetime $t_{\text{life}}$ is estimated for the different charging algorithms and 20 °C battery temperature by weighting the respective capacity lifetimes for certain SOCs with the frequency of occurrence of these SOCs:

$$
t_{\text{life}} = t_{\text{life, standstill}} + t_{\text{life, driving}} = p_{\text{standstill}} \cdot \sum_{i=1}^{\frac{8}{p}} \frac{c_i}{f_i \cdot \text{standstill}} + p_{\text{driving}} \cdot \sum_{i=1}^{\frac{8}{p}} \frac{c_i}{f_i \cdot \text{driving}}
$$

$c_i$ is the calendar life in the $i$-th SOC-range (based on Figure 6), $f_i$ is the frequency of occurrence of this SOC-range and $p$ is the proportion of driving or standstill operation.

The SOC-optimizing bidirectional algorithm can for example increase battery lifetime by around 60% compared to uncontrolled charging (see Table 4). It can also be seen that intelligent charging strategies have to be used in order to reach the intended battery lifetime of 10 years (BMBF, 2010), which equals the minimum vehicle lifetime. Note that the quantitative results are only valid for the specific cells tested, but the general behavior can be considered to be similar for other types of lithium-ion batteries.

<table>
<thead>
<tr>
<th>Charging algorithm</th>
<th>Uncontrolled</th>
<th>Unidirectional</th>
<th>Bidirectional</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
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<td>Price-opt.</td>
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<tr>
<td></td>
<td></td>
<td>SOC-constricted</td>
<td>Trading</td>
</tr>
<tr>
<td>Lifetime / years</td>
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<td>8.0</td>
<td>7.2</td>
</tr>
</tbody>
</table>

2.2.4.5 Mobility costs

To compare the economic impact of the different charging algorithms, the mobility costs per 100 electrically-driven kilometers including battery depreciation are calculated. The battery depreciation is calculated by applying the annuity method with the following parameters:

- Interest rate: 8%
- Investment costs = Battery costs (10 kWh: €5,000). According to Nemry et al. (2009), $700 per kWh is a reasonable price estimate for PHEV batteries in the short and medium term.
- Depreciation time: Battery lifetime
- Residual value of battery at end of lifetime: €0

The resulting mobility costs for a car with a total annual mileage of 11,000 km (average value of the simulated vehicles) are shown in Figure 19. Bidirectional price-optimized charging shows ca. 37% lower electricity costs compared to uncontrolled charging. The highest reduction (-29%) in battery costs can be reached with SOC-constricted bidirectional charging.
First of all, it has to be noted that mobility costs related to battery aging are about twice as high as the costs related to energy purchase, independently of the energy management strategy adopted. This leads to the conclusion that a strong focus has to be put on battery-aging effects during the development of intelligent charging algorithms. Second, it can be shown that managed charging has the potential to reduce the battery related TCO by about 30% as compared to uncontrolled charging. Savings are generated by a reduction of the electricity cost as well as the costs due to battery aging, and the relative savings in both parts turn out to be about the same.

A sensitivity analysis of the factors battery costs and interest rate is shown in Table 5. The share of battery costs on the mobility costs is increased by around 15% when doubling the assumed battery costs. Intelligent charging algorithms, therefore, become more important with higher battery costs. The sensitivity analysis shows that the assumed interest rate of course has effects on the absolute values of the battery costs per 100 km. However, only a minor influence on the basic conclusions of this study is observed.
2.3 Business models and consumer needs

In the following, two different approaches are discussed to model and forecast the adoption rates and the diffusion process of AFVs in general, and PHEVs and BEVs in particular, depending on varied surrounding conditions. First, the potential demand for privately used AFVs is analyzed, based on a nationwide survey conducted in Germany among (potential) car buyers. Based on a stated preference discrete choice experiment, the attributes’ influence on vehicle choice is estimated and the consumers’ willingness-to-pay for the improvement of the attributes’ values is calculated. In a scenario analysis, the impact of monetary and non-monetary policy measures on vehicle choice probabilities is then simulated. Second, a multi-agent-based simulation model is constructed to predict the potential diffusion process of AFVs in the next couple of years, taking the dissimilarities between vehicle alternatives and consumer groups into account. In a scenario analysis, the impact of potential policy measures on the shape and speed of the diffusion of the different vehicle alternatives is assessed.

A more comprehensive description of the following results is given in Hackbarth and Madlener (2011) and Neumann (2011), respectively.

2.3.1 Consumer preferences for alternative fuel vehicles

2.3.1.1 Introduction

The purpose of this study is to assess the relative impact of the most important vehicle attributes, such as purchase price, fuel cost, driving range, fuel availability, CO₂ emissions, refueling time, and governmental incentives, on the potential demand for AFVs. Additionally, we tackle the question of how much vehicle buyers are willing to pay for an improvement of principal vehicle characteristics, such as a reduction of the purchase price, an extension of the driving range or the acceleration of the battery recharging process for electric vehicles. On this basis, we simulate how such beneficial changes affect the potential market shares of the different propulsion technologies in a scenario-based analysis, whereby we predominantly focus on the effects that assorted governmental incentive schemes wield on vehicle choice. Moreover, we examine the acceptance of alternative fuels compared to gasoline and diesel for distinct consumer groups, distinguished by socio-demographic characteristics. Taken together, this information could be particularly helpful for policy-makers and industrial decision-makers aiming to increase the adoption rate of AFVs in the future by focusing on the improvement or subsidization of the most influential vehicle features, and by specifically adjusting their incentive schemes, marketing campaigns, and products, respectively, to the preference differences between consumer segments.

Our analysis is based on a thorough, Germany-wide, web-based stated preferences discrete choice experiment, carried out among 711 potential car buyers in July and August of 2011. Our study builds on the rich body of literature on the demand for AFVs, which has been primarily carried out in the US (Beggs et al., 1981; Calfee, 1985; Bunch et al., 1993; Golob et al., 1993; Brownstone and Train, 1999; Brownstone et al., 2000; Axsen et al., 2009; Hidrue et al., 2011; Musti and Kockelman, 2011) and Canada (Ewing and Sarigöllü, 1998; Ewing and Sarigöllü, 2000; Horne et al., 2005; Potoglou and Kanaroglou, 2007; Mau et al., 2008; Axsen et al., 2009), but also in parts of Europe (Dagsvik et al., 2002; Batley et al., 2004; Caulfield et al., 2010; Mabit and Fosgerau, 2011; Lebeau et al., 2012; Achtnicht, 2012; Achtnicht et al., 2012; Daziano and Achtnicht, 2012; Ziegler, 2012), South Korea (Ahn et al., 2008), and Japan (Ito et al., 2013). The works of Achtnicht (2012), Achtnicht et al. (2012), Ziegler (2012), and Daziano and Achtnicht (2012), which are all based on the same data set, have to be pointed out, as they are, to the best of our knowledge, the only ones considering the German market, and thus more closely related to our research than others. Similarly to this literature, our analysis is
based on a broad variety of drivetrain technologies and vehicle characteristics, i.e. we also consider conventional, natural gas, hybrid, biofuel, electric, and hydrogen vehicles vis-a-vis purchase price, fuel cost, CO₂ emissions, and service station availability. However, we essentially expand the limitations of these studies in two ways. First, we introduce plug-in hybrid electric vehicles (PHEVs) and their particularities – two different refueling options with varying refueling times – as choice alternatives in a discrete choice experiment. Second, we characterize some of the vehicle alternatives with additional attributes, i.e. the driving range on a full tank and/or battery, the refueling and/or recharging time, and potential governmental actions to incentivize the respective vehicle choice, an approach which has not been taken for Germany before. From our point of view, the inclusion of the driving range and the recharging time is essential in order to more realistically analyze consumer preferences regarding electric mobility. We are, therefore, able to contribute to the current research and debate about the best strategy for a fostering of electric vehicles by estimating willingness-to-pay (WTP) measures for driving range, battery fast-charging, and governmental monetary and non-monetary incentives, and by analyzing the effect of their improvement in a scenario-based simulation.

On that account, we methodologically follow the approach used in Brownstone and Train (1999) and apply a mixed error components logit (MXL) model in addition to a multinomial logit (MNL) model. The MXL model allows for both correlation between the different vehicle alternatives and taste persistency in repeated choices of a single respondent in a parsimonious way and, hence, leads to better results regarding model fit than does the standard MNL model.

2.3.1.2 Survey design and data

The data for our empirical analysis of the potential demand for AFVs in Germany were collected in a nationwide, web-based survey conducted in July and August 2011. The sample was drawn from a commercial online panel, with the restriction that the last vehicle purchase of potential respondents did not date back more than one year, or that the potential respondents intended to purchase a new car within the next year. In total, 711 respondents completed the survey. A stated preferences discrete choice experiment was at the center of our survey. Respondents were asked to choose the vehicle they preferred most from a set of hypothetical passenger cars. The experiment consisted of seven different fuel types, which also served as labels for the vehicles: conventional (gasoline, diesel), natural gas (CNG, LPG), hybrid, PHEV, electric, biofuel, and hydrogen. The wide range of fuels was chosen to cover all propulsion technologies that are already available on the German market, or at least will be in the near future, such as hydrogen (for fuel cell electric vehicles). The seven types of vehicles considered were additionally described by up to eight attributes: (1) purchase price, (2) fuel cost, (3) CO₂ emissions, (4) driving range, (5) fuel availability, (6) refueling time, (7) battery recharging time, and (8) policy incentives. We selected these attributes because they do not only correspond to the most common vehicle characteristics applied in the aforementioned earlier studies, but also to the most important vehicle features affecting the car purchase decision-making process in Germany. Table 6 shows in detail the attributes used and their levels by fuel type.

To increase realism in the hypothetical vehicle choices, the purchase price was customized for each respondent based on statements about the (expected) price range of their latest or next car, respectively. Specifically, it was allowed to vary from this value by ±25% for all types of vehicle alternatives.

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4 To be precise, PHEVs have already been introduced in a choice experiment by Musti and Kockelman (2011). However, in their survey, the different vehicle alternatives were only described by purchase price and fuel cost at fixed values (thus not varied by design), so that, for example, refueling/recharging time was disregarded.
### Table 6: Attributes and levels of the discrete choice experiment

<table>
<thead>
<tr>
<th>Variable</th>
<th>Alternative (Fuel type)</th>
<th>Number of levels</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase price</td>
<td>Conventional, LPG/CNG, Hybrid, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>75%, 100%, 125% of stated reference value (in €)</td>
</tr>
<tr>
<td>Fuel cost per 100 km</td>
<td>Conventional, LPG/CNG, Hybrid, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>€5, €15, €25</td>
</tr>
<tr>
<td>CO₂ emissions</td>
<td>Conventional, LPG/CNG, Hybrid</td>
<td>3</td>
<td>50%, 75%, 100% of average current vehicle</td>
</tr>
<tr>
<td></td>
<td>PHEV, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>0%, 50%, 100% of average current vehicle</td>
</tr>
<tr>
<td>Driving range</td>
<td>Conventional, LPG/CNG, Hybrid, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>400 km, 700 km, 1,000 km</td>
</tr>
<tr>
<td>Fuel availability</td>
<td>Conventional, Hybrid</td>
<td>2</td>
<td>100 km, 400 km, 700 km</td>
</tr>
<tr>
<td></td>
<td>LPG/CNG, PHEV, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>60%, 100% of all stations</td>
</tr>
<tr>
<td>Refueling time</td>
<td>Conventional, LPG/CNG, Hybrid, PHEV, Biofuel, Hydrogen</td>
<td>2</td>
<td>5 min, 10 min</td>
</tr>
<tr>
<td>Battery recharging time</td>
<td>PHEV, Electric</td>
<td>3</td>
<td>10 min, 1 h, 6 h</td>
</tr>
<tr>
<td>Policy incentives</td>
<td>PHEV, Electric, Biofuel, Hydrogen</td>
<td>3</td>
<td>None, No vehicle tax, Free parking and bus lane access</td>
</tr>
</tbody>
</table>

Fuel cost was displayed in Euro per 100 km to avoid the unit conversion of other fuel consumption measures (e.g. Euro per liter, kWh or kg), thus making it easily comparable between the different vehicle alternatives, whether propelled by liquid or gaseous fuels or electricity. Identical attribute levels were used for all seven vehicle alternatives studied.

CO₂ emissions were described as being in proportion to the average vehicle of the respondents’ favorite car segment, in order to establish more realistic choice situations as if they were characterized by a fixed, segment-invariant measure (e.g. gram of CO₂ per kilometer). Additionally, CO₂ emissions were allowed to vary by vehicle alternative. Thus, in contrast to conventional and natural gas vehicles, the CO₂ emissions of the non-fossil fuel vehicles were additionally allowed to be zero.

The driving range was defined as the distance that could be traveled on a full tank and/or battery. As the cruising radius of electric vehicles is limited compared to other propulsion technologies, the levels of the driving range attribute were restricted for the electric vehicle in the experiment in order to increase realism.

Fuel availability was modeled with alternative-specific values as well, since a very low density of service stations selling conventional fuels (20% of all stations) is very unrealistic in the near future. Furthermore, the fuel availability levels used in the experiment are even more unrealistic for most of the AFVs from today’s perspective. However, refueling station densities below 20% would have frequently led to a rejection of the respective alternatives.

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5 For example, an online search revealed that, in 2012, 14,732 gasoline filling stations existed in Germany. At almost 7,500 filling stations natural gas was sold (LPG: 6,577, CNG: 911), while only 2,073 recharging options were publicly accessible for electric vehicles, and bioethanol was available at 337 filling stations. The number of hydrogen filling stations had a low double digit figure (about 35).
As the length of the battery-charging process is a crucial factor for a substantial market penetration of electric vehicles, we incorporated the recharging time in our experiment. The attribute levels have a great bandwidth to cover current charging options (standard power outlet, 6 hours to fully charge the battery) but also prospective infrastructural means, such as fast-charging (1 hour) or battery-switching stations (10 minutes).

Since the massive market diffusion of alternative fuels might lead to a prolongation of the refueling process – e.g. due to a decreasing number of fuel pumps that are available per particular fuel type at existing service stations when the number of fuel types increases – we also took the refueling time into account. However, the main reason for doing so was to constantly remind respondents of the unfamiliar particularities of PHEVs. These particularities include two different energy sources with probably dissimilar refueling times and, thus, the possibility to nevertheless travel long distances with only short refueling stops by use of the internal combustion engine, even though battery charging is time-consuming.

As already mentioned, several reasons exist for the utilization of governmental policy incentives as a vehicle attribute in the experiment. First, the German government is considering the introduction of non-monetary incentives (permission for bus lane usage, special parking areas) for (some) AFVs to accelerate their adoption (Bundesregierung, 2011). Second, it has already introduced a monetary incentive – motor vehicle tax exemptions for electric vehicles (BMF, 2012). Third, according to Dena (2010), the motor vehicle tax is one of the most important attributes that German car buyers take into account in their car purchase decisions. Finally, the results concerning the influence of non-monetary incentives on alternative fuel vehicle choice are mixed in the transportation literature. Thus, an evaluation of the effectiveness of such policy measures in the case of Germany is necessary.

The wide range of seven vehicle alternatives and up to eight attributes leads to a large number of potential vehicle combinations and choice tasks, which is impossible for a respondent to handle. On this account, an alternative-specific, completely randomized fractional factorial design was generated. Each respondent was confronted with 15 separate choice sets, which in our pretest proved to be a manageable amount without leading to noteworthy fatigue or rejection. To reduce task complexity, each separate choice set consisted of only four out of the seven different vehicle alternatives.

The sample size of 711 respondents, facing 15 choice sets each, led to 10,665 observations. These were used to estimate an MNL and an MXL model, both of which will be introduced in detail in the following.

### 2.3.1.3 Methodological approach and model specification

Our empirical analysis of the stated preference vehicle choice data is mainly based on an MXL model, which, as in our case, extends the MNL model by the inclusion of error components. As a consequence, the MXL model is able to account for unobserved correlation between choice alternatives. Additionally, it is capable of capturing the panel nature of stated preference discrete choice experiments, which are usually characterized by repeated choices of respondents (e.g. 15 consecutive choice tasks in our study).

Assuming utility-maximizing behavior, in every choice set the respondents select the alternative that renders the highest level of utility. Unfortunately, utility is unobservable by the researcher, so it has to be modeled as a random variable. Thus, drawing directly from Brownstone and Train (1999) and Train (2003), the utility $U_{nj}$ that decision-maker $n$ receives from alternative $j$ from a finite set of $J$ alternatives (e.g. passenger cars, as in our case) is assumed to be given by
\[ U_{nj} = V_{nj} + \eta_{nj} + \epsilon_{nj}, \]

where \( V_{nj} \) is the deterministic or observable part of utility, and \( \eta_{nj} \) together with \( \epsilon_{nj} \) represents the stochastic or unobservable portion of utility. Usually \( V_{nj} \) and \( \eta_{nj} \) are defined as being linear in parameters, so that \( V_{nj} = \beta' x_{nj} \), \( \eta_{nj} \) is denoted as \( \eta_{nj} = \mu_{nj} z_{nj} \), leading to

\[ U_{nj} = \beta' x_{nj} + \mu_{nj} z_{nj} + \epsilon_{nj}, \]

where \( x_{nj} \) is a vector of observed attributes of the vehicle alternative \( j \) and socio-demographic characteristics of the respondent \( n \), \( z_{nj} \) is a vector of observable variables relating to alternative \( j \), \( \beta' \) is a vector of unknown fixed parameters, \( \mu_{nj} \) is a random vector with zero mean, and \( \epsilon_{nj} \) is a random term that is independent and identically distributed according to the type I extreme value distribution.

The correlation between alternatives in unobserved attributes is induced by the random terms in \( \mu_{nj} z_{nj} \), which can be interpreted as error components.

In our model specification, we decided in favor of a correlation structure comparable to the nested logit model – i.e. the different vehicle alternatives are grouped into mutually exclusive nests – because, following on extensive tests with numerous nested and cross-nested specifications of the error components, this fits our data best regarding log likelihood. In such an equivalent to the nested logit model, the error components are specified as follows: for each distinct nest \( k \), a dummy variable \( d_{jk} \) is created, so that \( d_{jk} = 1 \) for each alternative \( j \) in the nest and \( d_{jk} = 0 \) otherwise. With \( K \) non-overlapping nests and \( z_{nj} \) defined as a vector composed of these dummy variables, the error components are

\[ \mu_{nk} z_{nj} = \sum_{k=1}^{K} \mu_{nk} d_{jk}. \]

As a consequence, \( \mu_{nk} \) enters the utility of each alternative in nest \( k \), inducing correlation among these alternatives. Since it does not enter the utility functions of any of the alternatives in other nests, alternatives in different nests are uncorrelated. The random term \( \mu_{nk} \) is specified to be independent and identically normally distributed \( \mu_{nk} \sim N(0, \sigma_{nk}) \), with the variance \( \sigma_{nk} \) capturing the size of the correlation between alternatives in the same nest (Brownstone and Train, 1999; Train, 2003).

With regard to our data, a specification of the error components leading to the following three exclusive nests performed best in terms of model fit. The first nest comprises conventional, hybrid and natural gas vehicles. The second nest contains PHEVs and electric vehicles, whereas biofuel and hydrogen vehicles are grouped in the last nest. Even though we chose this nesting structure due to its statistical performance, this substitution pattern is also absolutely plausible, as apparently more similar vehicle alternatives or fuel types are assorted and, thus, correlated in unobserved factors. For instance, the three vehicle alternatives grouped together in the first nest are the ones exclusively running on fossil fuels. Furthermore, they are also the best-known by the potential car buyers, as they currently have the greatest market shares. In the second nest, vehicle alternatives are clustered that are exclusively electrically propelled or at least drive electrically for the most part, and, thus, share the unique and unfamiliar characteristic of having a plug. The remaining two vehicles clustered together in the third nest are both powered by liquid non-fossil fuels, namely biofuel and hydrogen, which are almost non-existent at fuel stations in Germany, resulting in a high unfamiliarity with both fuels. Additionally, hydrogen and biofuel vehicles have identical features in our experiment, which possibly made them highly substitutable from the respondents’ point of view. Hence the perceived similarity between some of the fuel types (vehicles) is absolutely reasonable, as is the consequence of the correlation structure of our model, namely that more similar vehicles draw more demand from each other than from dissimilar vehicle alternatives.
Given the specified utility functions and values for $\mu_{nk}$, the conditional choice probabilities are logit as in the standard MNL model. Thus, the probability that person $n$ selects alternative $i$ can be expressed as

$$P_{ni} = \frac{\exp(\beta'x_{ni} + \sum_{k=1}^{K} \mu_{nk}d_{jk})}{\sum_{j=1}^{J} \exp(\beta'x_{nj} + \sum_{k=1}^{K} \mu_{nk}d_{jk})}.$$  \hspace{1cm} (5)

However, since $\mu_{nk}$ is a random variable and hence not given, the (unconditional) choice probability of alternative $i$ being chosen by decision-maker $n$ is obtained by integrating the standard logit choice probability in eq. (5) over all values of $\mu_{nk}$, weighted by the density of $\mu_{nk}$. Furthermore, if decision-makers are repeatedly observed in choice situations, such as in our survey, this panel effect should be taken into account. In our model, this is realized by the inclusion of individual specific error components that are constant over the $T$ choice occasions that each respondent has to face. Hence, the probability that person $n$ chooses a specific sequence of alternatives $\{i_t\}_{t=1}^{T}$ is given by the integral of the product of logit formulas, i.e.

$$P_{ni} = \int_{\mu_{n1}}^{\mu_{nT}} \prod_{t=1}^{T} \left[ \frac{\exp(\beta'x_{nt} + \sum_{k=1}^{K} \mu_{nk}d_{jk})}{\sum_{j=1}^{J} \exp(\beta'x_{nj} + \sum_{k=1}^{K} \mu_{nk}d_{jk})} \phi(\mu_{nt} | 0, \sigma_t) \right] d\mu_{nt} \ldots d\mu_{nk}.$$  \hspace{1cm} (6)

Unfortunately, the choice probability in eq. (6) cannot be calculated exactly, as the integrals do not have a closed form. Thus, in the MXL model, the unconditional choice probabilities have to be approximated through simulation by repeatedly drawing values of $\mu_{nk}$ from their distributions, calculating the corresponding conditional choice probabilities, and averaging the results. To ensure the robustness of the results, we used 1,000 Halton draws for the maximum simulated likelihood estimation (Brownstone and Train, 1999; Train, 2003).

The variables entering the deterministic portion of utility in our model are given in Table 7 and are discussed in detail in the following. They can roughly be separated into two groups. First, the attributes used to describe the different vehicle alternatives in the discrete choice experiment, and, second, the socio-demographic characteristics of the respondents. To be more precise, the fuel types are included as alternative-specific constants (ASCs), with conventional fuel (gasoline/diesel) acting as the base alternative.\footnote{The ASC of an alternative captures the average effect of all unobserved factors (i.e. that are not included in the model, but are associated by respondents with the ‘label’ of the alternative) on its utility, all else being equal. In this respect, the ASCs can be interpreted as the average preference for the respective fuel types, ceteris paribus (e.g. Train, 2003).}

As the findings in the literature are inconsistent, we do not have any specific expectations about the final order of popularity of the different propulsion technologies among respondents. However, we do anticipate specific impacts on choice probability for the respective vehicle attributes. For instance, we expect that purchase price, fuel cost, CO$_2$ emissions, refueling time, and battery recharging time all have a negative sign, and we suppose the sign to be positive for driving range, fuel availability, and the two governmental incentives. Additionally, some vehicle attributes are interacted with socio-demographic and attitudinal variables.
Table 7: Definition of variables used in the model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPG/CNG</td>
<td>1 if fuel type is natural gas (LPG/CNG), 0 otherwise</td>
</tr>
<tr>
<td>Hybrid</td>
<td>1 if fuel type is hybrid, 0 otherwise</td>
</tr>
<tr>
<td>PHEV</td>
<td>1 if fuel type is PHEV, 0 otherwise</td>
</tr>
<tr>
<td>Electric</td>
<td>1 if fuel type is electric, 0 otherwise</td>
</tr>
<tr>
<td>Biofuel</td>
<td>1 if fuel type is biofuel, 0 otherwise</td>
</tr>
<tr>
<td>Hydrogen</td>
<td>1 if fuel type is hydrogen, 0 otherwise</td>
</tr>
<tr>
<td>Purchase price</td>
<td>Purchase price in thousands of €</td>
</tr>
<tr>
<td>Fuel cost</td>
<td>Fuel cost in € per 100 km</td>
</tr>
<tr>
<td>CO₂ emissions</td>
<td>Percentage of CO₂ emissions of an comparable average current vehicle of the respondents’ favorite car segment</td>
</tr>
<tr>
<td>Driving range</td>
<td>Driving range on a full tank/battery in km</td>
</tr>
<tr>
<td>Fuel availability</td>
<td>Percentage of filling/recharging stations with proper fuel</td>
</tr>
<tr>
<td>Refueling time</td>
<td>Refueling time in minutes</td>
</tr>
<tr>
<td>Battery recharging time</td>
<td>Battery recharging time in minutes</td>
</tr>
<tr>
<td>Incentive 1 (No vehicle tax)</td>
<td>1 if incentive is granted, 0 otherwise</td>
</tr>
<tr>
<td>Incentive 2 (Free parking and bus lane access)</td>
<td>1 if incentive is granted, 0 otherwise</td>
</tr>
<tr>
<td>Stated purchase price &lt; €20,000</td>
<td>1 if respondent stated to spend €20,000 at most, 0 otherwise</td>
</tr>
<tr>
<td>Age &lt; 44 years</td>
<td>1 if respondent is younger than 44 years of age, 0 otherwise</td>
</tr>
<tr>
<td>High environmental awareness</td>
<td>1 if respondent is more environmentally aware than 60% of the sample, 0 otherwise</td>
</tr>
<tr>
<td>Parking lot equipped with socket</td>
<td>1 if respondent has access to a parking lot equipped with a socket, 0 otherwise</td>
</tr>
<tr>
<td>Share of city trips &gt; 60%</td>
<td>1 if respondents’ share of city trips on overall annual trips is greater than 60%, 0 otherwise</td>
</tr>
<tr>
<td>High educational level</td>
<td>1 if respondent has higher education entrance qualification or university (of applied sciences) degree, 0 otherwise</td>
</tr>
<tr>
<td>Car segment mini or small</td>
<td>1 if respondent indicated the purchase of a mini or small car, 0 otherwise</td>
</tr>
</tbody>
</table>

2.3.1.4 Empirical results and discussion

This section describes the empirical results of the two estimated discrete choice models and the calculations of consumers' WTP for an improvement of selected vehicle attributes. In a further step, the impact of various policy scenarios on the potential demand for AFVs is simulated.

Discrete choice models

The estimation results from applying both the MNL model and the MXL model are given in Table 8. In both models, all experimentally varied vehicle attributes, except refueling time, show a significant impact on the choice decision, and the estimated coefficients all have the expected sign. However, three differences between the models are salient. First, the MXL specification performs significantly better than the MNL specification, regarding model fit. Second, although the significance level of two parameters is lower in the MXL model (Share of city trips > 60% × Electric; High educational level × PHEV), the contrary is true for a larger number of other variables. Finally, the three error components are highly significant, thus pointing towards correlation in the unobserved part of utility between the
respective vehicle alternatives (fuel types) in the three different non-overlapping nests of our MXL model. Therefore, in the following detailed discussion of the estimation results, we focus on the MXL model parameters.

As expected, both of the main vehicle expense factors – purchase price and fuel cost per 100 km – have a negative impact on the choice decisions and both enter our model significantly. On top of that and further in line with our expectations, the results indicate that individuals who have stated a maximum purchase price of €20,000 are endowed with a higher price sensitivity, as their purchase price parameter is about twice as large. A similar pattern can be observed for the influence that vehicles’ CO₂ emissions exert on respondents’ stated choice. Specifically high vehicle emissions are disfavored by all car buyers in general, as shown by the strongly significant (and expectedly) negative parameter, but are rejected even more by environmentally aware consumers, as the more than twice as large coefficient suggests.

Driving range enters the model significantly and positively, as anticipated, because frequent refueling stops are time-consuming and inconvenient. It also affects the car-purchasing decision concerning electric vehicles much more strongly, compared with all other fuel types. This result was expected, since the driving range was modeled alternative-dependently by design to cover for the currently exclusively short driving ranges of electric vehicles. Strikingly, however, is the almost doubled value of the coefficient, indicating that car buyers assign a very high value to an improvement of extremely limited driving ranges. The same holds true for the density of the filling station network, as a widespread refueling infrastructure decreases the risk of being stranded with an empty tank or battery. Thus, it is not surprising that fuel availability impacts vehicle choice significantly and with a positive sign. Refueling time, on the other hand, does not seem to be a crucial factor during vehicle purchase decisions. This holds at least if it does not exceed the upper bound of 10 minutes (as in our experimental design), since it does not enter the final model significantly although with the expected sign.

The case looks entirely different for the battery recharging time, which is highly significant and negatively signed, indicating that a prolongation of the recharging process strongly decreases the utility of the respective vehicle. Interestingly, and confirming our assumption, the magnitude of this effect is dependent on the degree of electrification of the considered vehicles. This implies that the impact of a lacking fast-charging infrastructure on the choice of a purely electric vehicle is more severe (twice as large) than for a bi-fueled PHEV.

Governmental incentives also play an important role in vehicle choice situations, regardless of whether they are of monetary or non-monetary nature, as both positively influence vehicle demand significantly. This result indicates that the already enacted vehicle circulation tax exemption for electric vehicles in Germany is able to increase vehicle demand, and that free parking or the permission for the usage of bus lanes, both of which are currently under consideration in Germany as well, have the potential to further promote AFVs in a relatively inexpensive way.

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7 The purchase price parameter for individuals with a stated purchase price of €20,000 or less results from the summing up of the general purchase price parameter and the purchase price interaction coefficient (purchase price × stated purchase price < €20,000).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. err.</th>
<th>Coefficient</th>
<th>Std. err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPG/CNG</td>
<td>-0.20931**</td>
<td>0.12616</td>
<td>-0.27490**</td>
<td>0.11670</td>
</tr>
<tr>
<td>Hybrid</td>
<td>-0.47973***</td>
<td>0.12391</td>
<td>-0.57398***</td>
<td>0.11992</td>
</tr>
<tr>
<td>PHEV</td>
<td>-0.77118**</td>
<td>0.11242</td>
<td>-0.89602***</td>
<td>0.12701</td>
</tr>
<tr>
<td>Biofuel</td>
<td>-0.59732***</td>
<td>0.11163</td>
<td>-0.61928***</td>
<td>0.13633</td>
</tr>
<tr>
<td>Purchase price</td>
<td>-0.04560***</td>
<td>0.00221</td>
<td>-0.04993***</td>
<td>0.00112</td>
</tr>
<tr>
<td>Purchase price × Stated purchase price &lt; €20,000</td>
<td>-0.04657***</td>
<td>0.00573</td>
<td>-0.05096***</td>
<td>0.00394</td>
</tr>
<tr>
<td>Fuel cost</td>
<td>-0.04604***</td>
<td>0.00135</td>
<td>-0.05324***</td>
<td>0.00891</td>
</tr>
<tr>
<td>CO₂ emissions</td>
<td>-0.00192***</td>
<td>0.00040</td>
<td>-0.00203***</td>
<td>0.00043</td>
</tr>
<tr>
<td>CO₂ emissions × High environmental awareness</td>
<td>-0.00231***</td>
<td>0.00063</td>
<td>-0.00247***</td>
<td>0.00058</td>
</tr>
<tr>
<td>Driving range × Conventional, LPG/CNG, Hybrid, PHEV, Biofuel, Hydrogen</td>
<td>0.00149***</td>
<td>0.00018</td>
<td>0.00173***</td>
<td>0.00021</td>
</tr>
<tr>
<td>Fuel availability</td>
<td>0.00423***</td>
<td>0.00036</td>
<td>0.00457***</td>
<td>0.00034</td>
</tr>
<tr>
<td>Battery recharging time × Electric</td>
<td>-0.00041***</td>
<td>0.00015</td>
<td>-0.00049***</td>
<td>0.00017</td>
</tr>
<tr>
<td>Battery recharging time × Electric</td>
<td>0.01869***</td>
<td>0.03145</td>
<td>0.23486***</td>
<td>0.03115</td>
</tr>
<tr>
<td>Incentive 1 × PHEV, Electric, Biofuel, Hydrogen</td>
<td>0.15210***</td>
<td>0.03173</td>
<td>0.16370***</td>
<td>0.03354</td>
</tr>
<tr>
<td>Age &lt; 44 years × LPG/CNG</td>
<td>-0.05221</td>
<td>0.10825</td>
<td>-0.05065</td>
<td>0.10135</td>
</tr>
<tr>
<td>Age &lt; 44 years × Hybrid</td>
<td>0.13580</td>
<td>0.10700</td>
<td>0.18529*</td>
<td>0.10199</td>
</tr>
<tr>
<td>Age &lt; 44 years × Electric</td>
<td>-0.06368</td>
<td>0.08114</td>
<td>-0.04682</td>
<td>0.11686</td>
</tr>
<tr>
<td>Age &lt; 44 years × Biofuel</td>
<td>0.40460***</td>
<td>0.09316</td>
<td>0.45415***</td>
<td>0.11566</td>
</tr>
<tr>
<td>Parking lot equipped with socket × LPG/CNG</td>
<td>-0.07103</td>
<td>0.10715</td>
<td>-0.07143</td>
<td>0.09757</td>
</tr>
<tr>
<td>Parking lot equipped with socket × Hybrid</td>
<td>0.06376</td>
<td>0.10560</td>
<td>0.07386</td>
<td>0.09875</td>
</tr>
<tr>
<td>Parking lot equipped with socket × PHEV</td>
<td>0.28682***</td>
<td>0.08022</td>
<td>0.34321***</td>
<td>0.11782</td>
</tr>
<tr>
<td>Parking lot equipped with socket × Biofuel</td>
<td>0.23410**</td>
<td>0.09101</td>
<td>0.29119***</td>
<td>0.11357</td>
</tr>
<tr>
<td>Parking lot equipped with socket × Hydrogen</td>
<td>0.12364</td>
<td>0.09255</td>
<td>0.14218</td>
<td>0.10894</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × LPG/CNG</td>
<td>-0.29337**</td>
<td>0.14868</td>
<td>-0.38150***</td>
<td>0.14159</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × Hybrid</td>
<td>-0.21769</td>
<td>0.14554</td>
<td>-0.28813*</td>
<td>0.13401</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × PHEV</td>
<td>-0.04638</td>
<td>0.10832</td>
<td>-0.05329</td>
<td>0.16098</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × Electric</td>
<td>0.35730***</td>
<td>0.11733</td>
<td>0.36854**</td>
<td>0.15236</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × Biofuel</td>
<td>-0.03488</td>
<td>0.12486</td>
<td>-0.07381</td>
<td>0.14212</td>
</tr>
<tr>
<td>Share of city trips &gt; 60% × Hydrogen</td>
<td>-0.09827</td>
<td>0.12762</td>
<td>-0.15454</td>
<td>0.14939</td>
</tr>
<tr>
<td>High educational level × LPG/CNG</td>
<td>-0.01612</td>
<td>0.10637</td>
<td>-0.00085</td>
<td>0.09904</td>
</tr>
<tr>
<td>High educational level × Hybrid</td>
<td>0.00006</td>
<td>0.10479</td>
<td>0.00465</td>
<td>0.09900</td>
</tr>
<tr>
<td>High educational level × PHEV</td>
<td>0.24094***</td>
<td>0.07984</td>
<td>0.28753***</td>
<td>0.11986</td>
</tr>
<tr>
<td>High educational level × Electric</td>
<td>-0.03441</td>
<td>0.09015</td>
<td>0.01308</td>
<td>0.11734</td>
</tr>
<tr>
<td>High educational level × Biofuel</td>
<td>0.33700***</td>
<td>0.09228</td>
<td>0.38518***</td>
<td>0.10911</td>
</tr>
<tr>
<td>High educational level × Hydrogen</td>
<td>0.09212</td>
<td>0.09291</td>
<td>0.11086</td>
<td>0.11757</td>
</tr>
<tr>
<td>Car segment mini or small × LPG/CNG</td>
<td>-0.19323</td>
<td>0.12839</td>
<td>-0.18776</td>
<td>0.12743</td>
</tr>
<tr>
<td>Car segment mini or small × Hybrid</td>
<td>-0.23917*</td>
<td>0.12720</td>
<td>-0.25898**</td>
<td>0.11439</td>
</tr>
<tr>
<td>Car segment mini or small × PHEV</td>
<td>-0.01650</td>
<td>0.09505</td>
<td>0.01909</td>
<td>0.15523</td>
</tr>
<tr>
<td>Car segment mini or small × Electric</td>
<td>0.43300***</td>
<td>0.10350</td>
<td>0.47736***</td>
<td>0.14405</td>
</tr>
<tr>
<td>Car segment mini or small × Biofuel</td>
<td>0.05272</td>
<td>0.10910</td>
<td>0.05960</td>
<td>0.13066</td>
</tr>
<tr>
<td>Car segment mini or small × Hydrogen</td>
<td>-0.03763</td>
<td>0.11083</td>
<td>-0.04626</td>
<td>0.14045</td>
</tr>
</tbody>
</table>

**Error components**

| \( \alpha_i \) (Conventional, LPG/CNG, Hybrid) | 0.74401*** | 0.04540 |
| \( \alpha_2 \) (PHEV, Electric) | 0.84178*** | 0.04252 |
| \( \alpha_3 \) (Biofuel, Hydrogen) | 0.33329*** | 0.09388 |

**Persons (Choices)**

| 711 (10665) | 711 (10665) |

**Log likelihood**

| -12637.94 | -12168.13 |

**\( \hat{\rho}^2(0) \)**

| 0.391 | 0.414 |

**\( \hat{\rho}^2(c) \)**

| 0.108 | 0.141 |

**Note:** Statistical significance is displayed as *** \( p < 0.01 \), ** \( p < 0.05 \), and * \( p < 0.1 \); Incentive 1 = No vehicle tax; Incentive 2 = Free parking and bus lane access

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However, our results show that new car buyers on average hold a reservation against AFVs, which would of course be a huge barrier to their extensive diffusion. To be more precise, we estimated an MXL model without interactions between the ASCs and socio-demographic and attitudinal dummy variables (not reported here), to gain an undistorted picture of the general acceptance of the different fuel types in the German population. Since all fuel type coefficients have a negative sign and are highly significant, alternative fuels on average seem to be less preferred compared to conventional fuels, which is the base alternative, with electric vehicles being valued most negatively.

Fortunately, this general and partially very high reluctance is mitigated in some consumer groups, as indicated in Table 4, by the significant interaction terms between the socio-demographic variables and the different ASCs. More precisely, these consumer groups can be described by age, educational level, environmental awareness, preferred vehicle segment, availability to plug in a vehicle at home, and amount of car trips in an urban area, as in our model. For instance, the probability to choose electric or hybrid vehicles is higher for younger individuals, as revealed by the (highly) significant positive coefficients of the two corresponding interaction terms (Age < 44 years × ASC). Thus, since younger consumers are more likely to adopt technological innovations at an early stage, this result is absolutely reasonable, especially for electric vehicles as a potentially disruptive technology.

Moreover, apart from having a more pronounced sensitivity for vehicles’ CO₂ emissions, environmentally aware car buyers also have an increased likelihood to purchase AFVs, regardless of the actual environmental friendliness of the respective vehicle, as revealed by the highly significant and positive interaction parameters (High environmental awareness × ASC).

Absolutely reasonable is the elevated choice probability for PHEVs and electric vehicles, when consumers at home have access to a parking lot equipped with a socket, as suggested by the positively signed and highly significant interaction terms (Parking lot equipped with socket × ASC), since the charging infrastructure is sparse at present. This finding may further point to a sort of discomfort or uncertainty regarding public charging (e.g. risk of vandalism or of being left without the possibility to plug-in/recharge the battery).

Furthermore, the demand for natural gas and hybrid vehicles is lower for individuals who predominantly use their car for city trips, while they are more likely to buy an electric vehicle (Share of city trips > 60% × ASC). A possible explanation for this finding might be the existing notion of current electric vehicles being limited in range, which is why they are also promoted as city cars, and natural gas and hybrid vehicles being very fuel-efficient and, thus, cost-effective on longer distances.

The probability of purchasing a PHEV or a biofuel vehicle, on the other hand, increases with the educational level of car buyers (High educational level × ASC). Finally, car segment is also a relevant attribute in fuel type choice, as the significant interaction coefficients show (Car segment mini or small × ASC). While consumers who indicated the purchase of a small vehicle are also more likely to choose an electric vehicle, the contrary is true for hybrid vehicles. A reason for this might be the aforementioned city car image of electric vehicles, and the fact that hybrid drivetrains are currently predominantly used in larger-sized vehicles.

Summing up, it seems that German car buyers at present are comparatively reluctant toward AFVs, which could be problematic in terms of AFVs’ fast and successful diffusion, and specifically applies to electric cars, the least preferred vehicle alternative. However, the results also show that some consumers are more sensitive to new vehicle technologies and fuel types than others. In other words, the most promising target group for the adoption of all kinds of AFVs are younger, well-educated, and environmentally aware car buyers, who also have the possibility to plug in the car at home, in case the next car has an electrified drivetrain, while for the diffusion of hybrid and electric vehicles, the
respective car segment should also be taken into account. Additionally, marketing should focus on drivers with a higher share of urban trips to accelerate the demand for electric vehicles, or on consumers who mostly drive on highways to speed up the adoption of hybrid and natural gas vehicles. Still, a prerequisite for a purchase decision in favor of AFVs is that their characteristics become competitive to those of conventionally fueled vehicles, because our estimation results show that, except for refueling time, all considered monetary and non-monetary vehicle attributes significantly influence vehicle choice. This statement also holds for the aforementioned very AFV-friendly consumers.

Willingness-to-pay for vehicle attributes

The monetary value, and thus the importance that car buyers ascribe to the diverse vehicle features, can be quantified by measuring their respective WTP. The WTP is the maximum monetary amount that an individual is willing to pay for a marginal improvement of another commodity (here: vehicle attribute), leaving the level of utility unchanged. Based on the estimation results reported in Table 8, the WTP is calculated as the ratio of the coefficient of a specific vehicle attribute and the coefficient of the purchase price, holding everything else constant. Consumers’ marginal WTP for improvements of the most important vehicle characteristics is shown in Table 9. As can be seen, individuals with a stated purchase price below €20,000 are willing to pay only half as much for beneficial changes in other vehicle features, compared to respondents who indicated the purchase of a more expensive car. This finding reflects their markedly larger price sensitivity (purchase price parameter value) and the greater importance of the vehicle price during the purchase decision in relation to other vehicle features, due to the much more pronounced budget constraints of this consumer group. Nevertheless, the calculated WTP values for the remaining vehicle attributes are considerable, even for consumers with lower stated purchase prices.

<table>
<thead>
<tr>
<th>Table 9: Marginal WTP for changes in selected vehicle attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image-url" alt="Table 9" /></td>
</tr>
</tbody>
</table>

Firstly, depending on the targeted price range of their next vehicle, car buyers are willing to expend between approximately €530 and €1,070 for fuel cost savings of €1 per 100 km. This result indicates that the average German driver with an annual mileage of about 15,000 km is willing to accept a payback period of around 3.5 to 7 years for an investment in fuel consumption reduction measures. This finding is reasonable, as it covers the medium vehicle duration of possession of 6-7 years (DAT,
2012). This holds true all the more for drivers with higher annual mileages, for whom the amortization period of fuel economy improvements diminishes even further. Secondly, the WTP to abate 1% of the CO₂ emissions of a current average car ranges from about €20 to €40 and from €45 to €90, depending on the budget and the environmental awareness of the respondent. In other words, environmentally aware consumers are willing to pay twice as much for an emissions reduction as environmentally unaware consumers are, all else equal. Additionally, we can see that environmentally conscious consumers with lower stated vehicle purchase prices still appraise an emissions reduction higher than less environmentally concerned individuals without this €20,000 budget constraint, and thus are willing to pay more for it. Thirdly, for every kilometer of additional driving range, respondents are willing to pay a markup of between €8 to €17 and €16 to €33 when purchasing a non-electric and an electric vehicle, respectively, indicating the twice as high importance of an expansion of the currently short electrically propelled operating radius, which, however, still is much less than the actual costs for such an increase in driving range (e.g. even with optimistic battery costs of €300/kWh every additional kilometer of battery electric range costs €50-60). Fourthly, the WTP for a 1% expansion of the refueling infrastructure of the corresponding fuel approximately comes to lie between €45 to €92. Fifthly, consumers are willing to pay between about €5 to €18 for every saved minute in battery recharging time, depending on their stated purchase price and the drivetrain technology (PHEV or fully electric vehicle). What can be seen is that respondents are willing to spend much higher amounts for a decrease in recharging time for purely electric vehicles, which is reasonable, as these do not have a backup propulsion technology like PHEVs and, thus, strongly depend on short recharging periods. We find that a charging time reduction from 6 hours to 10 minutes would be worth from about €1,750 to €3,500 for PHEVs and €3,150 to €6,300 for electric vehicles. Finally, car buyers are willing to pay considerable amounts for the two different governmental incentives considered in our study. For instance, their WTP for a vehicle circulation tax exemption over the entire lifetime of the vehicle ranges between approximately €2,330 and €4,700. For an assumed lifetime of the vehicle of 10 years, these values appear to be realistic, although rather for larger-sized diesel cars (see footnote 8 for an exemplary calculation). The WTP for the possibility to park free of charge and the allowance to use bus lanes amounts to between €1,620 and €3,280, which are quite substantial WTP amounts.

In summary, it can be stated that German car buyers are willing to pay considerable amounts for the improvement of vehicle attributes. However, for a translation of these findings into realistic potential vehicle demand forecasts, or for an assessment of the effects that changes in vehicle attributes might have on future market shares of the different fuel types, the parameter estimates in Table 8 have to be coupled with current and actual data on vehicle attributes or scenarios of their levels in the future.

**Scenario simulations**

In order to determine realistic market shares of conventional and alternative propulsion technologies with the aid of our model coefficients, we first have to describe the German vehicle market conditions in a representative manner. This status quo or base case is shown in Table 10 and is derived by defining an average car for each drivetrain technology or fuel type based on current market data or discounted expected values, i.e. for hydrogen, but partly also for PHEVs and electric vehicles, reported in the literature (ADAC, 2012a; ADAC, 2012b; ADAC, 2012c; ADAC, 2012d; BMWi, 2012; CEP, 2012; Daziano and Achtenicht, 2012; Grüning et al., 2011; McKinsey, 2010; and Wietschel et al., 2010). The base case scenario also displays the present situation in Germany concerning governmental incentives and fuel availability, as today only electric vehicles are tax-exempt and other beneficial legislations have not yet been enacted, and since the service station density varies substantially by fuel type (see footnote 5).
Table 10: Specification of the base case scenario

<table>
<thead>
<tr>
<th></th>
<th>Purchase price (€)</th>
<th>Fuel cost (€)</th>
<th>CO₂ emissions (%</th>
<th>Driving range (km)</th>
<th>Fuel availability (%)</th>
<th>Refueling time (min)</th>
<th>Battery recharging time (min)</th>
<th>Incentive 1</th>
<th>Incentive 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>21,800</td>
<td>9.0</td>
<td>100</td>
<td>1,000</td>
<td>100</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LPG/CNG</td>
<td>23,900</td>
<td>6.5</td>
<td>84</td>
<td>1,000</td>
<td>50.9</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>26,700</td>
<td>7.5</td>
<td>77</td>
<td>1,000</td>
<td>100</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PHEV</td>
<td>30,200</td>
<td>5.5</td>
<td>31</td>
<td>750</td>
<td>43.3</td>
<td>5</td>
<td>240</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Electric</td>
<td>36,800</td>
<td>4.0</td>
<td>0</td>
<td>175</td>
<td>14.1</td>
<td>480</td>
<td></td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Biofuel</td>
<td>22,900</td>
<td>9.0</td>
<td>23</td>
<td>750</td>
<td>2.3</td>
<td>5</td>
<td></td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Hydrogen</td>
<td>33,800</td>
<td>7.5</td>
<td>0</td>
<td>750</td>
<td>0.2</td>
<td>5</td>
<td></td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>


The main focus of our scenario analysis, however, is the description of the impact that different policy decisions or actions of the automotive industry could have on the adoption of AFVs in general and electrified vehicles in particular, as the latter are a cornerstone of future individual mobility concepts in Germany. In total, we consider nine different scenarios, distinguishable by the level of governmental intervention and subsidization or by the size of the steps taken by the car manufacturers, while holding all other attributes constant at their base levels. A more detailed illustration of the scenarios is provided in the following.

In addition to the aforementioned base case scenario, we examine the influence of an expansion of governmental incentives (i.e. vehicle circulation tax exemption, bus lane access, and free parking) for PHEVs, electric, and hydrogen cars, on the vehicle market in the second scenario. In scenario three, we analyze the effect that purchase premiums of €5,000 for electric and hydrogen vehicles and €2,500 for PHEVs have on vehicle demand, while we look at an even stronger decline of prices in the fourth scenario, resulting in an identical purchase price of €21,800 for all vehicles. The two scenario results give a sense of the effectiveness of governmental purchase price subsidies, as currently granted in many countries worldwide, or of price decreases, e.g. due to technical innovations or economies of scale in the vehicle production in general, and battery and fuel cell production in particular. In the fifth scenario, we consider the influence of battery leasing contracts, as presently offered by some car manufacturers to promote electric vehicles, on their market share. Based on available average leasing contracts, we assume a monthly fee of €80 for an annual mileage of 10,000 km, which equals to €9.6/100 km in additional fuel cost, and an according purchase price reduction of €10,000, resulting in a remaining surcharge of €5,000 for the purchase of electric vehicles. A substantial increase in the cruising radius of electric vehicles to 750 km, e.g. due to disruptive technological innovations that leave all other vehicle attributes unchanged, and its impact on vehicle choice decisions is studied in scenario 6. In scenario 7, we look at the consequences that an expansion of the service station infrastructure to 100% for all alternative fuels has on their choice probability. A massive reduction of the battery recharging time to 5 minutes, making the length of the charging process comparable to the duration of refueling stops, and its effect on the demand for electrified vehicles is regarded in scenario 8. With this we can assess whether the higher investment costs for fast-charging or battery swapping stations are justifiable. Finally, in scenario 9, we consider a combination of scenarios 2, 3, 7, and 8, i.e. governmental monetary and non-monetary incentives and the provision of an area-wide refueling and fast-charging infrastructure, in order to get an impression about the influence of a concerted action of the administration and the private sector (as to the configuration of the service station network) on the market shares of the different propulsion technologies.
The market shares of the different fuel types are calculated based on our sample, i.e. the actual distribution of socio-economic characteristics among respondents, and the model coefficients. Furthermore, the choice situation underlying the simulations is modeled as being unrestricted, so that, for each individual, one single choice set is assumed, in which all seven vehicle alternatives (fuel types) are available, and represented by the attribute levels of the respective scenario. The choice probabilities of the different propulsion technologies in the different scenarios are first calculated on an individual level and then averaged to obtain sample values (using 1,000 draws). The predicted market shares of the different fuel types in the base case (scenario 1) and the other eight distinct scenarios are reported in Table 11.

### Table 11: Simulated market shares subject to the different scenarios and their relative changes compared to the base case in parentheses (in %)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Conv.</th>
<th>LPG/CNG</th>
<th>Hybrid</th>
<th>PHEV</th>
<th>Electric</th>
<th>Biofuel</th>
<th>Hydrogen</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Base case (see Table 6)</td>
<td>30.35</td>
<td>17.82</td>
<td>20.08</td>
<td>10.85</td>
<td>2.24</td>
<td>12.47</td>
<td>6.19</td>
</tr>
<tr>
<td>2: Incentives for PHEVs, electric, biofuel, and hydrogen vehicles</td>
<td>27.01</td>
<td>15.83</td>
<td>17.34</td>
<td>13.83</td>
<td>2.26</td>
<td>15.86</td>
<td>7.87</td>
</tr>
<tr>
<td>3: Purchase premiums for PHEVs, electric, and hydrogen vehicles</td>
<td>28.89</td>
<td>16.96</td>
<td>18.79</td>
<td>12.23</td>
<td>3.02</td>
<td>11.68</td>
<td>8.43</td>
</tr>
<tr>
<td>4: Purchase price of €21,800 for all vehicles</td>
<td>23.14</td>
<td>16.01</td>
<td>20.60</td>
<td>14.38</td>
<td>4.86</td>
<td>9.82</td>
<td>11.19</td>
</tr>
<tr>
<td>5: Battery leasing contract for electric vehicles of €80/month</td>
<td>30.19</td>
<td>17.74</td>
<td>19.92</td>
<td>10.77</td>
<td>2.83</td>
<td>12.39</td>
<td>6.16</td>
</tr>
<tr>
<td>6: 750 km driving range for electric vehicles</td>
<td>29.58</td>
<td>17.37</td>
<td>19.21</td>
<td>10.34</td>
<td>5.45</td>
<td>12.07</td>
<td>5.98</td>
</tr>
<tr>
<td>7: 100% fuel availability for all AFVs</td>
<td>25.74</td>
<td>18.87</td>
<td>16.87</td>
<td>11.73</td>
<td>2.77</td>
<td>16.00</td>
<td>8.02</td>
</tr>
<tr>
<td>8: Battery recharging time of 5 min</td>
<td>29.79</td>
<td>17.49</td>
<td>19.45</td>
<td>11.75</td>
<td>3.28</td>
<td>12.19</td>
<td>6.05</td>
</tr>
<tr>
<td>9: Combination of scenarios 2, 3, 7, and 8</td>
<td>21.39</td>
<td>15.64</td>
<td>13.03</td>
<td>18.08</td>
<td>5.47</td>
<td>12.65</td>
<td>13.74</td>
</tr>
</tbody>
</table>

Beginning with the base case, we see that conventional vehicles capture about one third of the market and that the market shares of natural gas and hybrid vehicles amount to approximately 20% and 18%, respectively. Biofuels and PHEVs are chosen by about 11-12% of the (potential) car buyers, while hydrogen and electric vehicles are the most preferred option for only about 6% and 2% of the vehicle adopters, respectively.

In scenario 2, we look at governmental monetary and non-monetary incentives granted for all vehicles that (mostly) run on non-fossil fuels, i.e. PHEVs, electric vehicles, and cars fueled with biofuel or hydrogen, while all other attribute values are equal to those in the base case scenario. Such a policy intervention increases the choice probability for biofuel and hydrogen vehicles as well as PHEVs by...
approximately 27%, and electric cars by less than 1%, compared to the base case, while the market shares of hybrid vehicles diminish by about 13%, and 11% for conventional and natural gas vehicles.

In scenario 3, subsidies, as they are currently granted in several European countries, reduce the investment cost of PHEVs, electric, and hydrogen vehicles, and lead to purchase prices of €27,700 for PHEVs, €31,800 for electric vehicles, and €28,800 for hydrogen cars. Such a governmental promotion strategy increases the choice probability for hydrogen vehicles by approximately 36%, electric cars by about 35%, and PHEVs by almost 13%, compared with the base case scenario, while all other fuel types lose market shares (conventional and natural gas vehicles roughly 5%, and hybrid and biofuel vehicles about 6%).

The effect of identical purchase prices of all vehicle alternatives is analyzed in scenario 4. It increases the choice probability significantly: for electric cars by 117%, hydrogen vehicles by almost 81%, PHEVs by approximately 33%, and hybrid cars by more than 2%, compared to the base case, while the market shares of the remaining vehicle alternatives decrease (for conventional and biofuel cars by about 23% and 21%, respectively, and natural gas vehicles by 10%).

The availability of battery leasing contracts for electric vehicles considered in scenario 5 increases the choice probability by about 26%, correspondingly drawing market shares from all other vehicle alternatives from between 0.5% to 0.8%. Thus, battery leasing contracts appear to be unable to considerably push the demand for electric vehicles. However, this finding should be treated with some caution, as we simply convert the monthly cost of the battery leasing contract into additional fuel cost, whereas it is reasonable that car buyers will evaluate a fixed monthly battery leasing payment differently from an increase in fuel cost. Furthermore, we do not consider the benefit of battery leasing contracts as a risk reduction measure, given the unfamiliar technology and unknown battery lifetime, which could bias our simulation results and thus lead to an underestimate of their influence on the choice of electric vehicles.

The improvement of the driving range for electric vehicles to 750 km, tackled in scenario 6, and thus resulting in a driving range comparable to most other AFVs, leads to a substantial increase in demand for electric vehicles of more than 143%, while the market shares of all other fuel types diminish by approximately 3% to 5%, relative to the base case, drawing most heavily from the two other electrified vehicle alternatives.

In scenario 7, the service station density is assumed to be the same for all vehicles, so that in this respect, all AFVs are competitive with conventional cars. Such a massive investment in the refueling infrastructure decreases the choice probabilities of conventional and hybrid cars by about 15-16%, while the demand for all other vehicle alternatives increases by between 6% (for natural gas cars) and about 30% (for hydrogen vehicles).

The reduction of the battery recharging time to 5 minutes (scenario 8), making the duration and thus the comfort of the refueling process similar to all other vehicle options, leads to an increase in the market shares of the two plug-in vehicle types (i.e. to more than 46% for electric vehicles and 8% for PHEVs), while all other vehicle options are chosen less frequently, compared to the base case scenario, by between about 2-3%.

In scenario 9, governmental monetary and non-monetary incentives and the provision of a spatially comprehensive refueling and fast-charging infrastructure, leads to a substantial loss in the demand for conventional vehicles of 30%, while all other AFVs reach almost equal market shares (13-18%), whereas PHEVs even become the second-most popular vehicle alternative. The only exception are
electric vehicles, with a market share of merely about 5%, which compared to the base case nevertheless show more than a doubling in the choice probability.

In summary, the scenario simulations show that conventional vehicles can be expected to further dominate the vehicle market, as they feature the highest choice probability in all scenarios. Natural gas and hybrid vehicles are the most likely chosen AFVs, although this difference in preference for the various AFVs vanishes, the more pronounced the market-based policy intervention is (e.g. scenario 9). In all scenarios except scenario 9, (partially) electrically propelled vehicles do not gain substantial market shares (PHEVs mostly take fifth place in choice probability) and electric vehicles consistently feature the lowest demand. Furthermore, it can be seen that hydrogen vehicles only capture a small market share and are the second most disliked option after electric vehicles in almost all scenarios (except for scenarios 4 and 9). Interestingly, car buyers choose biofueled cars even when the density of gasoline stations offering biofuel is low.

When comparing the different policy measures in the eight scenarios with each other and with the base case, we can analyze how the different actions impact the choice probabilities for the different fuel/propulsion types. For instance, the market share of natural gas and biofuel vehicles is largest in scenario 7, for PHEVs and hydrogen in scenario 9, and for electric vehicles in scenarios 6 and 9. The influence on hybrid vehicles is, except for a strong negative impact in scenario 9, quite small across all other scenarios, with the highest choice probability found in scenario 2. Conventional fuels lose market shares in all scenarios, with this influence being lowest in scenario 5. Overall, the strongest impact on the vehicle market is found in scenarios 4, 7, and 9. Furthermore, we find evidence that the choice probabilities of some AFVs (PHEVs, biofuel, and hydrogen vehicles) could be increased quite easily and in a relatively budget-friendly way (scenario 2), or at least with a relatively manageable governmental purchase grant (scenario 3), while such financial and non-monetary governmental incentives are unable to effectively accelerate electric vehicle adoption unless the subsidies are substantial (as in scenario 4). Opposed to this, battery leasing contracts have almost no influence on all vehicle alternatives, since even electric vehicles only slightly gain market share (scenario 5). A very interesting finding is that an increase in the driving range to 750 km for electric vehicles (scenario 6) has the same effect as monetary and non-monetary incentives and a fast-charging infrastructure taken together (scenario 9). A fully developed refueling infrastructure, in contrast, mainly increases the demand for those vehicle alternatives that run on liquid or gaseous fuels and currently suffer from a sparse filling station density (scenario 7), such as hydrogen and biofuel vehicles. Furthermore, the results of scenario 8 show that just accelerating the recharging process alone does not markedly increase the choice probability of plug-in vehicles. Finally, and surprisingly, a massive market-based intervention by the government (scenario 9), which we assumed to be beneficial at least for all non-fossil fueled AFVs, shows almost no effect on the market share of biofuel cars. These findings from our study could be relevant both for public and private decision-makers aiming to promote consumer adoption of alternative vehicle technologies.

2.3.2 Modeling the diffusion of alternative fuel vehicles

As mentioned above, AFVs, such as PHEVs and BEVs, offer a large potential to reduce fossil fuel consumption in the transportation sector. However, these technologies have not achieved a substantial market share yet, mainly due to shortcomings in the most important vehicle attributes: purchase price and fuel cost, utilization comfort, and technical performance. Thus, to increase the adoption rate of AFVs, the influences of these parameters on the diffusion process have to be quantified. Political and industrial decision-makers would then be able to adjust their strategies and accelerate the speed of the diffusion process, e.g. by introducing monetary incentives, such as purchase price subsidies, tax
exemptions or bonus programs, or by focusing on the improvement of the most relevant vehicle attributes or the most promising vehicle technologies.

However, due to the innovative character of the vehicle technologies, the estimation of the impact that these major parameters exert on vehicle adoption cannot be entirely grounded on historical data. Agent-based modeling (ABM) is a useful solution to this problem. Thus, in this section, we develop a concept for a multi-agent based simulation model to predict the diffusion of alternative fuel vehicles in the future. Since each vehicle technology has specific advantages and disadvantages, which may be relevant for different consumer groups, our model takes this heterogeneity into account. In a scenario-based analysis these assumptions (regarding specific characteristics of the alternative propulsion technologies) are varied to assess the impact of potential policy measures on the diffusion process.

2.3.2.1 Diffusion of innovations models

The focus of diffusion research is the analysis of patterns and speed of the diffusion of innovations, which can be described as the sum of multiple adoptions (acquisitions of the product by the consumers).

The innovation diffusion process depends on three major elements:

- **Characteristics of the innovation**: What are the objective characteristics (costs and benefits of the adoption) of an innovation?

- **Characteristics of the potential adopters**: The objective characteristics of an innovation are only the basis for their evaluation by different entities (e.g. organizations or single persons), since the way these characteristics are interpreted is influenced by socio-economic and socio-psychological characteristics of potential adopters. This leads to the fact, that during the diffusion process different categories of entities (consumer groups) are adopting the innovation. For example, ‘innovators’ are typically described as being young, not risk-averse, highly educated, and financially well-endowed, while ‘laggards’, who have a high degree of skepticism towards innovations and, hence, are the last to adopt them, typically are of higher age and financially poorly equipped.

- **Environmental context**: The environmental context consists of the societal culture and the political conditions in which the diffusion process takes place and determines the overall acceptance (e.g. degree of ‘innovativeness’ of the society) and suitability of innovations.

**Traditional innovation diffusion models**

The fundamental basis of innovation diffusion is the innovation decision process of potential adopters. Rogers’ (1962) model of the innovation decision process is depicted in Figure 20.

At first, individuals are not aware of the existence of an innovation. When they become aware of its existence (‘Knowledge’) they suffer from a large uncertainty about the innovation’s (relative) advantages and disadvantages and its functions, so that they start to gain information about the innovation’s characteristics (‘Persuasion’), which is often done through conversation with other individuals, especially peers. Thus, in this second stage, individuals inform themselves about the innovation and start to form an attitude towards, or an opinion about, the innovation based on its perceived characteristics. During this phase, an intensive evaluation of the innovation’s advantages and disadvantages, with regard to the individual’s needs, takes place. Van den Bulte and Lilien (2001) name some causal mechanisms for social influence on diffusion processes:
- **Normative pressures and competitive concern**: Individuals (or companies in a competitive market) might feel under pressure to adopt a product or innovation when parts of their (social) environment (or competitors) already have adopted it (which might give them an advantage in competition).

- **Performance network effect**: Some innovations become more and more advantageous with an increasing number of adopters.

In the third stage ('Decision'), an individual chooses to adopt or reject the innovation and subsequently brings it into use ('Implementation'), which leads to a slow loss of its innovative character from the individual's perspective. In the last stage ('Confirmation'), an individual seeks reinforcement of an innovation decision already made, or reverses a previous decision to adopt or reject the innovation if exposed to conflicting messages about the innovation. An individual is permanently reflecting on the benefits of the adoption and rejection decision, which also has to be considered when modeling the diffusion process.

Other traditional diffusion theories have their origin in scientific models of epidemiology, which describe diffusion as a process of social infection or contagion. Thus, with an increasing number of infected individuals (adopters) the infection (adoption) rate in the whole society increases as well. Therefore, exponential functions are the most common way to mathematically model a curve for diffusion processes over time. The Bass diffusion model (Bass, 1967) is a formal way to portray the innovation diffusion process. In contrast to Rogers' (1962) explanation of diffusion, the Bass model allows for a mathematical description of the gradual increase of adopters over time, depending on the influence of mass communication or personal communication on non-adopters. The effect of personal communication increases with the number of adopters. Modeling of the timing of adoption of different types of innovations by different types of consumers is possible.
The Bass model is kept very simple: The specification of only two parameters (influence of mass communication \( q \), and personal communication \( p \)) allows to model diffusion processes of different innovations or products from different industries. The shape of the diffusion curve is determined by the parameters \( p \) and \( q \). The parameter \( p \) determines the curve’s slope in an early stage. It can be understood as a measure for personal communication from one individual to the other and, therefore, is important for the adopter share in the beginning of the diffusion process. Accordingly, \( q \) forms the curve in the end of the diffusion process and can be understood as a measure for mass communication. The more individuals already adopted the innovation, the more likely non-adopters will imitate this behavior.

Low values for \( p \) and high values for \( q \) results in the typical S-shaped curve of diffusion processes.

The Bass diffusion model is a common and easy-to-use tool to predict the characteristics of innovation diffusion. The model was validated for the diffusion processes of many products. However, it neglects the fact that innovation diffusion is not a macro-economic process. The S-shaped curve does not just ‘happen’, it is the result of multiple adoptions. Further weaknesses exist, e.g.:

- Traditional models usually focus on communication as the only or the main control lever for innovation diffusion, similar to infection processes. This naturally results in S-shaped curves.
- Neither the behavior of individuals nor of any other influencing parameters (e.g. price, availability of competitive products, behavior of other agents) are integrated in the model. For example, sudden price spikes could result in other diffusion patterns than an S-curve.
- Due to each innovation’s novelty, the available information is incomplete, which makes the determination of the parameters a difficult task. They have to be estimated on the basis of already existing similar products. This leads to inaccuracies and to a limited informative value of the model.

As a result, the traditional models that are used to explain the diffusion of innovations are, in many cases, an oversimplification of reality. For the description of more complex processes other methods, such as ABM, have to be used.

**Agent-based innovation diffusion models**

ABM is a powerful tool to investigate complex behavioral patterns and to gain a deeper understanding of the simulated real-world system (Bonabeau, 2002). This information could then be used, for instance, for detailed policy recommendations.

An ABM is a mapping of a real-world system, which is characterized by interactions of individuals or organizations. This system is modeled as a collection of autonomous decision-making entities called “agents” (Bonabeau, 2002). The fundamental principles of an agent are, firstly, his ability to evaluate his environment and, secondly, to independently decide based on predefined rules (Macal and North, 2010). Each agent is situated in an environment of other agents, with whom he can interact, and capable of evaluating his decisions with respect to the environmental context.

Two difficulties arise in designing ABMs (Wooldridge, 2002):

- **Micro-level of the model:** Agents can be equipped with many features and decision-making algorithms. The tasks that an agent has to fulfill in the modeled world can differ a lot between models. Hence, a standard definition of an agent is not possible. For each application, the parameters describing the agents have to be redefined.
• **Macro-level of the model:** The way the agents are linked to each other affects their interaction. Interaction and therefore communication is one the main drivers of innovation diffusion. Therefore, the society design may have a large impact on the model results. Thus, it is not possible to define one single standard society design which is optimal for each application.

ABM enables researchers to solve the major shortcomings of the traditional models of innovation diffusion, by basing macro-level effects (as described by the Bass model) on complex micro-level processes ("bottom-up-approach"). The underlying idea is to transfer the Bass model into a more complex ABM. Agents may be consumers, companies or links between different entities. In our case, the focus lies on consumer behavior and especially their decisions to adopt or reject an innovation, here an AFV. Several studies analyzed the diffusion of alternative fuels and electrified drivetrains in the last couple of years. Wakolbinger (2006) and Kiesling et al. (2009) focus on the adoption process of a second-generation biofuel called ‘BioFit’ in Austria. In their model, agents use a utility function to evaluate different options from a set of fuels and adopt the fuel with the highest value of utility. Walkolbinger (2006) uses a special network of agents in her model to mimic the population distribution in Austria, so that the disclosure of information about an innovation (in this case a new biofuel) from consumer to consumer is more likely in densely populated regions. In addition, the refueling infrastructure in major cities, such as Vienna, is assumed to be further developed, leading to a higher availability of biofuels in these urban regions, which leads to varying usability values depending on the geographical region.

Van Vliet et al. (2010) follow a different approach in their study. Instead of limiting their view to the consumers, they designed a model to describe the mutual dependency of supply and demand. A higher demand for biofuel is followed by the need to increase the production of this fuel. If the supply is not able to satisfy the increase in fuel demand, the prices will rise, which in turn leads to lower adoption rates. In contrast to previous studies, usability functions are not used in their study, but rather a filter algorithm is applied. In each step of the filtering process, all fuels are evaluated. If a filter criterion is not met, the appropriate fuel is marked as ‘not suitable’. If all filter criteria have been applied, at least one fuel remains. Finally, one fuel is randomly selected from the remaining options and adopted.

Recent work by Eppstein et al. (2011) analyzes the market penetration of PHEVs. The focus of the model is the evaluation of potential factors influencing the market penetration of electrified vehicles. Several levers, such as governmental policies, are examined. In this study, consumers can choose between a conventional vehicle with an internal combustion engine (ICE), hybrid vehicle (HEV), and a PHEV. Agents evaluate the given alternatives by ‘desirability’, which is basically a utility function. The relative benefits from the given alternatives are calculated for each agent. Vehicles differ only by fuel type (ICE vs. HEV vs. PHEV), fuel efficiency, and purchase price. It is assumed that other parameters such as safety and reliability are very similar across these choices. Consumer agents are characterized by several attributes, such as typical years of car ownership, annual mileage, vehicle age, and vehicle fuel type. The agents are implemented in a social network, which they are observing. The number of PHEV adopters in the network plays a crucial role in the agents’ adoption decision. The authors indicate that seven factors affect PHEV market penetration: gasoline price, PHEV purchase price and battery range, the consumers’ potential to assess their own fuel costs, the comfort level of PHEVs and the weight consumers place on different reasons to save gasoline. The possibility to utilize these levers differs widely. While it is rather simple to offer tax exemptions for PHEVs which would directly affect the purchase price of PHEVs, the battery range is a matter of research and development and, therefore, can neither be adjusted directly nor within a short period of time. Furthermore, Eppstein et al. (2011) found that the development of the market share of conventional vehicles is nearly
unaltered by certain parameter value changes. Instead, only the proportion between HEVs and PHEVs differs among the different scenarios considered. Thus, they conclude that PHEVs rather compete with HEVs than with conventional ICE vehicles.

While Eppstein et al. (2011) focus on consumers, Zhang et al. (2011) model the whole automotive market to assess the factors which influence the diffusion of AFVs. Manufacturers, consumers and governmental agencies are modeled as the key market participants. Each agent group has different aims, i.e. the manufacturers are trying to maximize their profit, while the consumers try to optimize their benefits from vehicle ownership. Zhang et al. (2011) studied the influence of three diffusion mechanisms: technology push, market pull and regulatory push. Single levers, such as tax exemptions, were not considered. To obtain consumer preferences, a survey among more than 7,000 participants was carried out. In the model, the consumer agents directly correspond to one of the survey participants, so that no consumer groups with equal weights for different vehicle attributes had to be defined.

Zhang et al. (2011) found that technology push is the most effective way to speed up the diffusion process of alternative fuel vehicles, which is consistent with the results of the study of Eppstein et al. (2011). Although EVs were also considered in this study, the results show no significant market penetration of this technology, regardless of the diffusion mechanism.

The study of Sullivan et al. (2007) expands on the two aforementioned studies by introducing a further agent group, the fuel producers, and by describing the vehicles and consumer agents with additional attributes, e.g. the vehicle performance is considered and consumers have preferences for special brands and vehicle features. Simulation results show that without the introduction of incentives, such as tax exemptions, vehicles with highly electrified drive trains will not reach a significant market penetration within the next twenty years.

Summarizing the results, recent ABMs do not attempt to explain the diffusion of innovations by a single trigger. This means that neither the ‘communication in social networks’ nor the ‘evaluation of innovations based on their characteristics’ is used as sole explanation. Rather, both aspects are considered and integrated into a common usability function.

Regarding the algorithms it can be concluded that decision-making strategies are modeled very similarly among the presented studies on the diffusion of alternative drive systems. Usability functions are used to calculate the utility for each agent and for each vehicle, respectively. However, the attributes and parameters of the agents vary greatly.

Of particular interest are the factors which influence the diffusion of alternative drive systems. It was found that especially the decisions of governmental institutions have a large influence on the diffusion speed. Tax exemptions and other financial subsidies turn out to be the most effective way to significantly accelerate the market penetration of alternative drive systems.

2.3.2.2 Agent-based simulation model for AFV diffusion in Germany

In the following, the central components of our ABM are described. This includes the agents, the parameters and the algorithms on which the model is based. The model was programmed with the ‘NetLogo’ freeware, which was developed at the Northwestern University in Illinois, USA (Wilensky, 1999).

Our model world consists of 22,500 simulated agents (potential vehicle buyers), which are linked through a simple social network. Within the purchase decision, agents have to compare various influencing factors (vehicle attributes). Hence, a requirement of the model is that all factors ultimately
have to be unit-less or at least have the same unit. For example, it is not possible to directly compare purchase costs (in currency units) with mileage (in distance units). Furthermore, all possible influencing factors have to be set within the same interval, since otherwise factors with wider boundaries would automatically be more important than narrow factors. To meet these requirements, all variables within our model are normalized. In compliance with Kim et al. (2011) all variables are normalized between 0 and 1.

In our model, the agents are assigned to different variables: weights, vehicle type, vehicle age, minimum vehicle age, mileage, and benefits. These variables are explained in the following.

Weights

The weights vector \( w_i \) with \( i \) = price, popularity, convenience, emissions and performance differs between agent (consumer) types. The consumer groups used in our model and their respective vehicle attribute weights are based on the results of van Vliet et al. (2010) and Kim et al. (2011). However, to meet the requirements of a sufficient number of different agents, the weights are randomly assigned to the agents within a small interval, according to Table 12. For each agent type, the most characteristic weight is highlighted grey and bold and dependent on the other weights, so that they sum up to 1.

For example, for the ‘green’ type of agent, all weights are randomly assigned within the given intervals. The weight for vehicle emissions is the missing sum to 1 and, therefore, varies in an interval from 0.3 to 0.8, with an average of 0.55. Although the emission weight is varying among an interval, it is always the most important variable for this consumer group.

Table 12: Frequency and weights of the respective agent types with highlighted respective dependent variable

<table>
<thead>
<tr>
<th>Frequency</th>
<th>60%</th>
<th>20%</th>
<th>10%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w_i ) / Agent type</td>
<td>Majority</td>
<td>Conformists</td>
<td>Greens</td>
<td>Petrolheads</td>
</tr>
<tr>
<td>Price</td>
<td>( 0.2 – 0.8 )</td>
<td>( 0.1 – 0.25 )</td>
<td>( 0.1 – 0.2 )</td>
<td>( 0.1 – 0.2 )</td>
</tr>
<tr>
<td>Popularity</td>
<td>( 0.1 – 0.3 )</td>
<td>( 0.3 – 0.8 )</td>
<td>( 0.0 – 0.15 )</td>
<td>( 0.1 – 0.2 )</td>
</tr>
<tr>
<td>Emissions</td>
<td>( 0.0 – 0.1 )</td>
<td>( 0.0 – 0.1 )</td>
<td>( 0.3 – 0.8 )</td>
<td>( 0.0 – 0.05 )</td>
</tr>
<tr>
<td>Performance</td>
<td>( 0.0 – 0.1 )</td>
<td>( 0.0 – 0.1 )</td>
<td>( 0.0 – 0.05 )</td>
<td>( 0.45 – 0.8 )</td>
</tr>
<tr>
<td>Convenience</td>
<td>( 0.1 – 0.3 )</td>
<td>( 0.1 – 0.25 )</td>
<td>( 0.1 – 0.3 )</td>
<td>( 0.0 – 0.1 )</td>
</tr>
<tr>
<td>( \sum )</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
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</tbody>
</table>

Vehicle type

The vehicle type variable determines which type of propulsion technology the respective agent owns. This can be either a conventional ICE vehicle, a HEV, a PHEV or a BEV.

As for the consumer weights, the attributes of the vehicles are described in normalized values. Each type of vehicle has certain advantages and disadvantages. For example, on the one hand, a PHEV has lower pollutant emissions than a conventional vehicle but, on the other hand, is more expensive (Eppstein et al., 2011). To reflect these differences in vehicle characteristics, five attributes are used, as in van Vliet et al. (2010) and Eppstein et al. (2011). Since the ICE vehicle is the reference vehicle its parameters were set to 1, except for the vehicle price which was set to 0.5, because all other drivetrain options are (currently) more expensive. The parameters and their values are shown in Table 13. These
parameter values were chosen to map the differences in vehicle characteristics as they are perceived by potential car buyers. For example, the ‘well-to-wheel’ emissions of BEVs strongly depend on the existing electricity generation mix. However, for potential consumers of BEVs the ‘end-of-pipe’ emissions are directly observable. Sullivan et al. (2007) found that HEVs are evaluated more positively with respect to their emissions than they actually are. Since an electric car can drive locally emission-free, this will disproportionately and positively affect the perceived characteristics of this vehicle type with respect to emissions. Accordingly, the BEV will be assessed best regarding emissions. Consequently, this parameter was set to 0.05. The parameters for HEVs and PHEVs were set accordingly.

The parameters price and fuel consumption are derived according to actual values and are set in relation to the ICE reference vehicle (Eckstein, 2010). Convenience subsumes attributes such as usability, service and refueling comfort, loading space, and driving comfort. If there are special non-monetary benefits for driving a certain type of vehicle, it will also increase convenience, for example, free parking for BEVs in the city center. The convenience of PHEVs and BEVs is lower than for HEVs and ICEs because they typically have to be recharged every day or even more often. At the same time, these cars usually are lighter and smaller than conventional vehicles, which negatively affects parameters such as loading space and driving comfort and, in consequence, the overall convenience as well. A similar approach for the parameter ‘size’ was chosen by Sullivan et al. (2007).

Performance represents attributes such as engine power, dynamic drive, attractive design and attractive sound design. These are typical attributes of sports vehicles and typically less pronounced in PHEVs and BEVs. There are exceptions (for example the already existing Tesla Roadster), but even if the torque-characteristic of electrified drivetrains allows sportive driving as well, the typical electric vehicle is dimensioned for gentle driving. Sullivan et al. (2007) followed a similar approach.

<table>
<thead>
<tr>
<th>Table 13: Parameters of the different drivetrain systems</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Price</strong></td>
</tr>
<tr>
<td>ICE</td>
</tr>
<tr>
<td>HEV</td>
</tr>
<tr>
<td>PHEV</td>
</tr>
<tr>
<td>BEV</td>
</tr>
</tbody>
</table>

**Vehicle age**

The variable vehicle age reflects the current age of the vehicle (in months) owned by the respective agents.

**Minimum vehicle age**

Minimum vehicle age describes the number of months before a vehicle owner decides to buy a new vehicle, which does not have to be of a different fuel type necessarily compared with the current vehicle. In Germany, the vehicle age is almost randomly distributed between 0 and 10 years (Höpfner et al., 2009) and decreases nearly linearly to 0 with increasing age. For that reason, in our model the minimum vehicle age is assigned randomly in the interval between 6 and 120 months each time the
agents purchase a new vehicle. This is surely a simplification of the reality, but the results of our model were very robust against changes in the minimum vehicle age distribution.

**Mileage**

Mileage is the normalized value of the annual mileage of each agent. The value for the normalized mileage was randomly assigned among all agents and varies between 0.1 and 1.

An important issue regarding mileage is ‘range anxiety’ (Tate et al., 2008). Theoretically, BEVs with a cruising range of 130 km are suitable for about 90% of the German drivers and their daily trips. However, the actual value is lower due to range anxiety, which describes the mostly irrational fear to be stranded with a completely discharged battery at the roadside. Therefore, we assume in our model that BEVs are only suitable for those 50% of the consumers with the lowest annual mileage. Thus, if the agent is about to choose a BEV and his value for mileage is above 0.5, the agent is assumed to choose a PHEV instead.

**Benefits**

Benefits from each drivetrain are the result of the respective usability function of each consumer. The benefit vector is called $b_j$ with $j = \text{ICE, HEV, PHEV and BEV}$. The drivetrain concept with the highest benefit is chosen in the decision-making process. For reasons of simplification, diesel- and gasoline-fuelled vehicles are aggregated to conventional ICE vehicles and, thus, not described by distinct characteristics. This approach is common practice in all recent studies (Zhang et al., 2011; Eppstein et al., 2011; Sullivan et al. 2007). The fuel price is normalized just like all other values. Surveys show that consumers tend to evaluate spending on fuel and therefore fuel prices disproportionately high compared to vehicle purchase prices. The fuel price in our model has to represent that fact. Calculations with our model have shown reasonable results with a start value of 0.5, which represents the perceived relation between the vehicle purchase price and the spending on fuel in the eyes of the consumers. Annual price increases of 0.012 (0.001 per month) were assumed. This reflects expected increases in gasoline prices in the future.

**Algorithm**

In the following, the algorithm of the diffusion simulation model will be described in detail. A simplified flow chart of the model is shown in Figure 21.

‘NetLogo’ counts the time in ‘ticks’. In the simulation each tick equals one month in reality. At first, all parameters are set up and after every model year, i.e. every 12 months, the prices for each of the AFVs are updated. The price for a conventional ICE car increases by 1% per year. The normalized price is annually decreased by 2% for HEVs, 3% for PHEVs and 6% for BEVs (Wallentowitz et al., 2009).

As mentioned before, the fuel price is set to increase by 0.001 each tick (month), so that it ends up at 0.86 at $t = 360$.

If the vehicle age of an agent exceeds his personal minimum vehicle age, the agent will decide about a new vehicle. If all decisions in a tick are made, the plots and outputs are updated and a new iteration begins. This process is set to run for 360 ticks which equals 360 months or 30 years in real world time.
The decision-making algorithm of the agents (consumers), which is shown in Figure 22, is based on Rogers (1962) decision-making scheme. However, the steps ‘Knowledge’ and ‘Persuasion’ are left out, because the examination of information flows and media influence was not the core of this study. Furthermore, recent studies (Zhang et al., 2011; Eppstein et al., 2011; Sullivan et al. 2007) left out these steps as well to eliminate the influence of information flows on the model results. For this reason, the level of confirmation is not implemented in the model. Instead, the agents calculate new benefits when they decide about purchasing a new vehicle under the assumption of full information, which is a common assumption in the literature.
The exchange of perceptions with peers through the social network takes place during the acquisition process. A drivetrain concept gains ‘social benefit’, when the neighbors of an agent have adopted the respective vehicle. In our model, an agent’s neighborhood consists of eight neighbors. When the agent decides about the purchase of a new car, he reviews the vehicles his neighbors have adopted. For example, if three neighbors have adopted a BEV, the ‘social benefit’ for BEVs would be $3/8 = 0.375$.

With the presented parameters, it is possible to calculate the benefits using a utility function for each drivetrain system and for each agent with the respective weights. The benefits are calculated as follows:

\[
b_{j,k}(t) = w_{\text{price},k} \cdot [(1 - p_{j}(t)) + FP(t) \cdot (1 - FC_j) \cdot KM_k] + w_{\text{emissions},k} \cdot (1 - EM_j) + w_{\text{performance},k} \cdot (P_j) + w_{\text{convenience},k} \cdot (1 - C_j) + w_{\text{popularity},k} \cdot \left(\frac{NN_{j,k}}{8}\right),
\]

where $b_{j,k}(t)$ is the benefit of drivetrain system $j$ at time $t$ for agent $k$, $w_{i,k}$ is the weight of the parameter $i$ for agent $k$, $p_{j}(t)$ is the normalized price of drivetrain system $j$ at time $t$, $FP(t)$ is the normalized fuel price at time $t$, $FC_j$ is the normalized fuel consumption of drivetrain system $j$, $KM_k$ is the normalized mileage of agent $k$, $EM_j$ is the normalized value for the emission of drivetrain system $j$, $P_j$ is the normalized value for the performance of drivetrain system $j$, $C_j$ is the normalized convenience of drivetrain $j$, and $NN_{j,k}$ is the number of neighbors of agent $k$, who have adopted drivetrain system $j$.

The drivetrain with the highest benefit is adopted by the agent. The agent is assigned a new minimum car age and the actual car age is reset to 0. The number of adoptions of the different drivetrain systems are counted and plotted at every tick to observe the development of the vehicle diffusion.

**Scenario design**

We designed three scenarios with two sub-scenarios for evaluating different PHEV and BEV promotion strategies. Basically, these scenarios represent two different strategies, or a combination of these:

- **Tax exemptions**: The sales tax (VAT) has a share of about 20% of the total purchase costs of a BEV in Germany. In turn, a tax exemption will have a great effect on the purchase price. If the tax is removed, this would in our model correspond to a decrease of the normalized price for BEVs of 0.2. For PHEVs, a reduction of 0.1 is assumed due to the lower degree of electrification, and thus the probably lower degree of subsidization. This strategy is represented by scenario 1. In the first sub-scenario of scenario 1, scenario 1a, only BEVs are promoted, while in sub-scenario 1b both PHEVs and BEVs experience tax exemptions.

- **Non-monetary incentives**: AFVs could also be promoted by granting non-pecuniary facilities. For example, bus or car-pool lanes could be opened to BEVs and PHEVs or special and attractive parking lots could be offered to owners of (highly) electrified vehicles, maybe even free of charge. This would most certainly have a positive impact on the convenience factor. Another option to strengthen the convenience of PHEVs and BEVs is to widely improve the recharging infrastructure for electrified vehicles. For example, recharging stations could be set up at parking lots, at best operated wirelessly using electric induction. This strategy is represented by scenario 2. In the first sub-scenario 2a of scenario 2, only BEVs are promoted, while in sub-scenario 2b both PHEVs and BEVs are supported.
Scenario 3 with its two sub-scenarios is a combination of scenarios 1 and 2. In the first sub-scenario 3a of scenario 3, only BEVs are promoted via tax exemptions and incentives that improve their convenience factor, while in sub-scenario 3b both PHEVs and BEVs are supported.

The scenarios and the underlying assumptions are summarized in Table 14.

<table>
<thead>
<tr>
<th></th>
<th>Base scenario</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
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<tr>
<td></td>
<td>1a</td>
<td>1b</td>
<td>2a</td>
<td>2b</td>
</tr>
<tr>
<td>Price&lt;sub&gt;PHEV&lt;/sub&gt;</td>
<td>see Table 13</td>
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<td>- 0.1</td>
<td>-</td>
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<td>Price&lt;sub&gt;BEV&lt;/sub&gt;</td>
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<td>- 0.2</td>
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<td>-</td>
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<tr>
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<td>-</td>
<td>+ 0.1</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>+ 0.3</td>
<td>+ 0.3</td>
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</table>

2.3.2.3 Results and discussion

Each scenario was simulated five times in order to mitigate the influence of random phenomena. In the following, the average results of the scenario analysis are subsequently presented for every scenario.

**Base scenario**

The base scenario uses the values from Table 13 and serves as a reference for the three scenarios characterized by the different degrees of subsidization (Table 14). The resulting market shares the different drivetrain technologies gain among new car purchases and their consequential share of the total vehicle population are shown in Figure 23.

From the start, PHEVs and BEVs have a small, but stable market share. This is due to the group of ‘green’ consumers who purchase PHEVs or BEVs once the mileage constraint is met. HEVs begin to penetrate the market after slightly more than 8 years ($t = 100$). After 20 years ($t = 240$) HEVs have a higher market share than conventional vehicles. At the end of the simulation, HEVs have a dominant market position. The market penetration of PHEVs starts at about 11 years ($t = 130$). Their market share rises steadily and reaches 30% by the end of the simulation. In contrast, BEVs have a nearly constant market share with on average about 5-7% until the end of the simulation. It can be concluded that without promotion, BEVs will remain a niche product and PHEVs are able to penetrate the vehicle market without promotion, but will not be as successful as HEVs, which can be able to dominate the market even without governmental subsidies. The model predicts that the market share of conventional vehicles will decrease to less than 20% in approximately 20-25 years.

The overall vehicle population is a result of the evolution of the vehicles’ market shares over time. It shows the same effects as the market share plot, but with some delay. However, the curves for the respective vehicle population are more stable than those for the market share due to the fact that the total vehicle population does not change rapidly but steadily over time, as the renewal of the total vehicle stock takes time.
Scenario 1

Scenario 1 investigates the strategy of tax exemptions to promote BEVs (sub-scenario 1a) or to foster both BEVs and PHEVs (sub-scenario 1b) simultaneously.

Scenario 1a

The results of scenario 1a are shown in Figure 24. Tax exemptions for BEVs have a significant effect on their market share, as it increases from 5% at the beginning up to 9% after 30 years ($t = 360$). However, the model still predicts a relatively small market penetration of BEVs compared to all other drivetrain technologies. The gain in market share of BEVs comes at the expense of market share losses for both PHEVs and ICEs, compared to the base case. The point in time when the market penetration of the other vehicle technologies accelerates approximately stays the same as in the base scenario. Furthermore, HEVs are nearly unaffected by the promotion of BEVs via tax exemptions.
**Scenario 1b**

In scenario 1b, tax exemptions are granted for both PHEVs and BEVs. The simulation results are shown in Figure 25. HEVs are now almost completely suppressed by PHEVs, which gain a market share of approximately 70% at the end of the simulation \((t = 360)\). This is more than a doubling compared to the base scenario. On the other side, the purchase price reduction of BEVs does not have a significantly positive effect on their market share. In fact, BEVs even gain a lower market share than in the base scenario, even though they are subsidized. Obviously, consumers favor the purchase of PHEVs over BEVs when both options are eligible. This leads to a cannibalization of BEVs. Regarding the point of time of an acceleration of the diffusion process, PHEVs are starting about 50 months earlier to substantially penetrate the market compared to the base scenario.

After 30 years, and comparable with the base scenario, conventional ICE vehicles defend a market share of about 10% which can be explained by the group of ‘petrolheads’ who unwaveringly favor ICE vehicles. This market share development of ICE vehicles thus stays about the same among the following scenarios.

![Figure 25: Market shares of the different drivetrain technologies among new car purchases and share of the vehicle population in scenario 1b](image)

**Scenario 2**

In scenario 2, the prices remain the same as in the base scenario, but the convenience parameters are improved for BEVs alone (sub-scenario 2a) or PHEV and BEV jointly (sub-scenario 2b).

**Scenario 2a**

In scenario 2a, only the convenience of BEVs is upgraded and set to 0.5 *ceteris paribus*. BEVs are then able to achieve a market share of about 11%, while this boost starts relatively early, as shown in Figure 26. Thus, at the end of the simulation (i.e. after 30 years at \(t = 360\)), the total BEV population is more than twice as high compared to the base scenario (market share of 7%). The additional market share of BEVs comes at the cost of HEVs, whose market share decreases. However, the dominant market position of HEVs stays untouched and is comparable to the base scenario. Compared with scenario 1a, the increase in BEV convenience seems to be slightly more effective than tax exemptions, regarding market share. PHEVs and ICEs are unaffected by the higher BEV market share.
Scenario 2b

In scenario 2b the convenience of both BEVs and PHEVs is upgraded. Even though the convenience of BEVs is not further improved, compared to scenario 2a, their market share is increasing (see Figure 27). This is due to the fact that the additional convenience of PHEVs draws market share from HEVs. Thus, obviously, the replacement of HEVs by PHEVs as dominant vehicle technology has a positive effect on the BEVs as well. The vehicle population of PHEVs almost doubles compared to the base scenario. The dominant position of HEVs is resolved and their market penetration starts later than in the base scenario. As mentioned above, the development of the ICE vehicle market share is not negatively affected and stays very similar to the base scenario.
Scenario 3

Scenario 3 is basically a combination of scenarios 1 and 2. In sub-scenario 3a, the purchase price of BEVs is subsidized and simultaneously their convenience is improved. In sub-scenario 3b, both BEVs and PHEVs benefit from governmental incentives and, hence, improvements in both vehicle attributes (purchase price and convenience).

Scenario 3a

In scenario 3a, BEVs end up with a market share that is three times higher than in the base scenario. PHEVs are positively influenced as well, even though their parameters were not changed compared to the base scenario. The lower amount of HEVs (due to the accelerated diffusion of BEVs) leads to less neighbors with this vehicle type and, as a result, PHEVs are not dominated by HEVs through the social factor. The results are also depicted in Figure 28.

![Figure 28: Market shares of the different drivetrain technologies among new car purchases and share of the vehicle population in scenario 3a](image)

Scenario 3b

Even though in scenario 3b the price for BEVs is lowered by 20% and at the same time their convenience is more than doubled, this does not lead to a significantly higher market share at the end of the simulation period ($t = 360$) compared to the base scenario (see Figure 29). The main reason for this finding is the market domination by PHEVs, which begins after approximately 5 years ($t = 60$) and mainly draws market shares from HEVs.
To summarize the results of the three scenarios, in Figure 30 and Figure 31 the market shares and the overall shares of the different drivetrain technologies in the entire vehicle population at the end of the simulation ($t = 360$) are compared and discussed in the following. As can be seen, when ignoring scenarios 3a and 3b from our considerations for the time being, a tax exemption has the largest effect on the diffusion of PHEVs (scenario 1b). However, in scenario 1b, the market share of BEVs decreases at the same time, as they are cannibalized by PHEVs. Furthermore, in our simulation the tax exemptions are paid over the entire time period, which suggests the assumption that these substantial market shares for PHEVs and BEVs are not easily affordable by the government in the long run. Alternatively, decreasing battery prices induced through governmental funding of basic research could cause the same effect or at least parts of it at lower cost.

The diffusion process of BEVs, in contrast, is highly dependent on an improvement of their convenience. Differently to tax exemptions, this might be realized at lower costs or, in other words,
without losing high amounts of tax revenues. However, some costly investments to build up the infrastructure for electrified vehicles would have to be made as well by the government, albeit this option would obviously be more sustainable, since spending on infrastructure is a long-term investment, and tax exemptions for vehicles are not, as their lifetime is typically much shorter. The government could further improve the convenience of electrified vehicles through non-monetary incentives, such as special parking lots for fully electrified vehicles or the allowance to use bus lanes, both of which are relatively cost-efficient promotion strategies.

An interesting finding is that the cannibalization of market shares of BEVs, when PHEVs and BEVs are simultaneously promoted monetarily (scenario 1b), while this is not the case if BEVs and PHEVs are both simultaneously supported by an increase in vehicle convenience (scenario 2b). The resulting combined market share of both drivetrain technologies of 70% is considerable, while at the same time this scenario is one of the cheapest solutions for governments to significantly increase the market share of electrified vehicles.

Figure 31: Average vehicle population at t = 360 depending on scenario

Figure 32 shows the best options to increase the market share of PHEVs and BEVs, respectively. As can be seen, the most effective strategy is to increase the market share of PHEVs is to decrease the purchase price (through governmental subsidies) and to increase the convenience at the same time (scenario 3b). This result is certainly not surprising. However, a price cut without an accompanying investment in the improvement of vehicle convenience (infrastructure etc.) is nearly equally effective (scenario 1b).
The most effective strategy for BEVs is also a simultaneous improvement of vehicle convenience and subsidization of the purchase price, leaving all other drivetrain technologies unsupported (scenario 3a). Nevertheless, increasing the convenience alone is still a good and a more cost-effective alternative and, after all, leads to a doubling of the market share compared to the base scenario (scenario 2a). The market share is additionally increased when PHEVs are promoted at the same time and in the same way, i.e. via increasing convenience (scenario 2b). The simultaneous promotion of PHEVs via (additional) tax exemptions has an opposite effect (scenario 1b, scenario 3b).

The forecasts for the future market shares of BEVs of this study comply with the bandwidth of market share projections that can be found in the literature (see Figure 33). However, the predicted range of possible market shares is rather wide in the different studies. One drawback of our study is the fact that only two of the parameters that could affect future diffusion processes of electrified drivetrains were evaluated.
3 Conclusions and recommendations

PHEVs and BEVs offer the potential to reduce the ecological impact of traffic and the ecological impact of the power sector at the same time. By feeding power back into the grid (V2G), the vehicle batteries become active elements of the electricity grid and can facilitate the integration of renewable energies. In our research, we tackled several open topics regarding potential hurdles and benefits of a widespread diffusion of AFVs in general, and PHEVs and BEVs in particular.

Battery lifetime and integration into low-voltage grids

On the one hand, V2G provides the possibility of decreasing the total cost of ownership (TCO) for PHEV and BEV by, for example, lowering the electricity costs. On the other hand, the power-feedback is commonly assumed to have a lifetime-decreasing effect on the vehicle batteries. In order to investigate the effects of different charging algorithms on the battery operating conditions, a simulation setup to model electric vehicles in a grid segment was introduced. Based on this, the resulting mobility costs (electricity plus battery depreciation costs) and their compatibility with the distribution grid were analyzed. The simulation model used real-world mileage data from mobility statistics and electricity price data from the European Energy Exchange (EEX) in Leipzig for producing representative results. Comprehensive cyclic (NCA and NMC batteries) and calendaric (NMC batteries) aging tests were performed with lithium-ion battery cells. These tests showed an exponential relationship between cell voltage (SOC) and lifetime. Considering the fact that high battery SOCs decrease battery lifetime, different charging strategies were implemented: Uncontrolled charging as the reference case, unidirectional price- and SOC-optimized charging as well as bidirectional energy trading with and without SOC constraint.

A first grid simulation showed that price-sensitive charging strategies may lead to an increased grid load due to the coincidence of charging operations. This could be solved, for example, by shifting the price signals in time between different users. The battery simulation results show that by applying intelligent charging algorithms, battery lifetime can be increased and charging costs can be reduced simultaneously. The economic impact of longer battery lifetime is approximately two times higher than the revenues that can be gained by energy trading. The results also show that it is difficult to reach the intended battery lifetime of 10 years for vehicle applications without oversizing the battery. By applying intelligent charging strategies, oversizing can be reduced or even omitted altogether. This is due to the fact that standstill times are dominating the battery operation and since, with uncontrolled charging, the battery SOC is above 90 % during more than 80 % of the time. In order to reach the lifetime goals of the vehicle batteries, it is therefore essential to implement intelligent charging strategies. Oversizing the battery to limit the maximum SOC in order to reach the lifetime goals can be considered to be a costly alternative, as either the electric driving range is decreased or the battery costs are increased.

The quick introduction of price-variable electricity tariffs with, for example, a 24-hour prediction of hourly electricity prices and regulations for the power-feedback of electric vehicles would foster the introduction of electric mobility: Intelligent charging algorithms would then be able to reduce mobility costs by minimizing electricity consumption costs and decreasing battery depreciation at the same time.

Business models and consumer needs

Two approaches were used to model and forecast the adoption and diffusion of AFVs in general and PHEVs and BEVs in particular, depending on varied surrounding conditions.
First, the potential demand for privately used AFVs was analyzed by using discrete choice data from a nation-wide survey in Germany and applying both a standard MNL model and an MXL model specification. By expanding earlier studies and additionally taking recharging time, driving range, and governmental incentives as crucial vehicle features into account, and, furthermore, considering PHEVs and their unique characteristics as a vehicle alternative, we find that attributes impact vehicle choice either positively, as in the case of driving range, fuel availability, and governmental monetary and non-monetary incentives, or negatively, as in the case of purchase price, fuel cost, CO₂ emissions, and recharging time. Furthermore, we find that German car buyers are currently very reluctant towards adopting AFVs, especially electric and hydrogen vehicles, which could be a great barrier in terms of their fast and successful diffusion and for achieving the very ambitious goal of the German government to get 1 million electric cars on the road by 2020. However, our results also show that PHEVs are far less likely to be rejected than fully electric vehicles and that not all consumers have equally pronounced reservations against AFVs. In other words, especially younger, highly educated, and environmentally conscious consumers, and to some extent also urban drivers of small cars with access to a parking lot equipped with a socket, are more prone to buy new vehicle technologies in general and plug-in cars in particular. Hence, marketing strategies could be tailored such that they target specifically these consumer groups for effectively increasing the adoption rates (or sales figures) of certain AFVs. On the contrary, and in light of the ongoing demographic change resulting in an aging population, our results could also lead to the opposite conclusion that the most relevant target group for policy-makers and car manufacturers should be middle-aged and elderly people, as they still have strong reservations against electric vehicles, and thus could threaten the prospects for individual electric mobility of private vehicle users and, consequently, the ambitious goal of the German government to become a lead market. Therefore, information campaigns or the possibility to test electric vehicles in the field could be especially customized for these consumer groups to reduce their unfamiliarity with, and reservations against, electric mobility.

Additionally, we find that German car buyers are willing to pay considerable amounts for an improvement of the most important vehicle features. However, notable differences in the WTP can be observed, depending on the consumer group or the respective vehicle alternative. For instance, the marginal WTP for the mitigation of CO₂ emissions is more than twice as large for highly environmentally aware (potential) adopters, compared with adopters with low environmental consciousness. A similar doubling can be observed for the driving range of electric versus other vehicles, and for a reduction in battery recharging time between PHEVs and full electric cars. This finding indicates that a fast-charging option is not equally important for all plug-in vehicles, and thus could be relevant for the recharging infrastructure investment strategy. Furthermore, households with low stated purchase prices (< €20,000) are only willing to pay about half the amount that households without this budget constraint are willing to expend for the improvement of vehicle features.

The scenario analysis revealed that conventional vehicles remain dominant in terms of market share, and that hybrid and natural gas vehicles are the AFVs most likely to be chosen. As these propulsion technologies are currently the most renowned and available AFVs, and as they also have the farthest-developed refueling infrastructure and do not suffer from short driving ranges or high purchase prices surcharges, this finding is not too surprising. Strikingly, however, our results show that choice probabilities of some AFVs, such as PHEVs and biofuel vehicles, could be increased in a relatively cost-efficient way by granting vehicle tax exemptions, or by allowing the usage of bus lanes and presenting possibilities for free parking. Thus, to promote AFVs, the German government should think about the introduction of these incentives and not limit these measures to electric vehicles. Contrary to that finding, fully electric and hydrogen vehicles only gain in demand if multiple policy measures are
implemented or at least the subsidization of the vehicle purchase is substantial. Thus, financial incentives as they are used in some European countries today, and also lobbied for by German car manufacturers, are found to be insufficient to significantly increase adoption rates. Furthermore, our results suggest that an expansion of the refueling/recharging infrastructure density or the acceleration of the recharging process alone is not sufficient for increasing the diffusion of electric vehicles, but that these two measures should rather be implemented jointly. Finally, and also very interestingly, our findings indicate that an increase in the driving range of fully electric vehicles to 750 km, leaving all other vehicle attributes unchanged, affects the adopters’ choice probability in the same way as would a market based multiple policy intervention strategy, comprising a purchase price subsidy, a tax waiver, bus lane usage, free parking, and a widespread fast-charging infrastructure. However, it should be noted that without substantial purchase price or electricity price surcharges these two potential support schemes are not economically viable today and in the near future. Thus, in order to reach the very ambitious electric mobility goal of the German government, the government could increasingly focus on and promote PHEVs (e.g. with subsidies and non-monetary incentives), as they are not burdened by limited cruising ranges and thus could serve as a means to make car drivers familiar with electric mobility, without putting them at risk of being stranded due to an empty battery.

Finally, an ABM was constructed to model and project the future diffusion of alternative drive systems and to review the influence of various parameters on the potential diffusion pathways. We focused on electrified drivetrains, namely HEVs, PHEVs and BEVs, which were described by five attributes (purchase price, fuel consumption, convenience, performance and emissions). Furthermore, we took four consumer groups (majority, conformists, greens, petrolheads), which differed in their socio-economic characteristics, into account. In a scenario based analysis we assessed the impact of governmental incentives on the diffusion process of the different vehicle technologies. Our results suggest that tax exemptions and convenience improvements can indeed help to promote PHEVs and BEVs. However, different levels of effectiveness among the different promotion strategies occur, which have to be considered. The diffusion of electrified vehicles can be promoted by both price cuts and improvements in convenience. However, a simultaneous promotion of both PHEVs and BEVs does not necessarily lead to higher market shares of both drivetrain technologies.

Nevertheless, this study shows that governments are able to promote alternative drivetrains, if the support focuses mainly on the improvement of vehicle convenience, e.g. through the (publicly or privately funded) provision of a comprehensive recharging infrastructure. However, as already mentioned, the cost effectiveness of such an infrastructure expansion cannot be assumed today.

4 Further steps, future developments and proposed actions

Battery-aging behavior is crucial for the economic efficiency of offering V2G services. The consideration of battery aging costs in charging management algorithms can be an important step for the commercialization of that technology. Another interesting field of research is the interaction of several PHEVs with V2G-capable chargers in a distribution grid. Investigations of the grid stability and the proper functioning of the management algorithms for a fleet of vehicles should be conducted. In future work, battery-lifetime modeling could be refined by extending the tests to further lithium-ion cell chemistries and improving the battery-aging model. Mobility statistics about the driving behavior for a whole year instead of one week could improve the accuracy of the simulation results. Grid simulations could be performed by applying Monte Carlo simulation methods to generalize some of the results.
Furthermore, a charging algorithm which optimizes revenues from energy trading, balancing power delivery and lifetime extending effects in the vehicle battery could be implemented.

Further research is also needed with regard to the types of potential adopters that are particularly influenced by the vehicle attributes currently disfavoring PHEVs and BEVs, e.g. short driving ranges and lengthy recharging processes, and their respective WTP for their improvement, to individually customize incentive and subsidization schemes or marketing and sales programs. Furthermore, up to now very few studies have investigated the causal interactions between decisions of consumers and vehicle manufacturers and governmental policies. Still, these dynamics have a major influence on the development path a new technology forge and should be studied in more depth. To reach a better understanding about these manifold interactions, we plan to refine our ABM of the diffusion of AFVs, e.g. by diminishing the simplifying assumptions regarding vehicle attribute weights, fixed consumer groups, and the adoption decision process. Furthermore, as in reality a large uncertainty about the characteristics of vehicles with alternative drivetrains exists, the inclusion of this uncertainty in the model would lead to more accurate results. The communication among agents and information flows through mass communication should be implemented as well in future research. Furthermore, interesting approaches for a more realistic distribution and linkage of agents exist (e.g. combination of population density and the so-called 'small-world' network).

5 Literature


6 Attachments

6.1 List of Abbreviations

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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ABM</td>
<td>Agent-based Model</td>
</tr>
<tr>
<td>AER</td>
<td>All-electric Range</td>
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<td>AFV</td>
<td>Alternative Fuel Vehicles</td>
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<td>ASC</td>
<td>Alternative-specific Constant</td>
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<tr>
<td>BDEW</td>
<td>Bundesverband der Energie- und Wasserkraftwirtschaft e.V.</td>
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<tr>
<td>BEV</td>
<td>Battery Electric Vehicle</td>
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<tr>
<td>CCU</td>
<td>Charging Control Unit</td>
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<td>CNG</td>
<td>Compressed Natural Gas</td>
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<td>DSL</td>
<td>DlgSILENT Simulation Language</td>
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<td>E.ON ERC</td>
<td>E.ON Energy Research Center</td>
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<td>EEG</td>
<td>Erneuerbare Energien-Gesetz (Renewable Energy Law)</td>
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<td>Institute for Future Energy Consumer Needs and Behavior</td>
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<td>Institute for Power Electronics and Electrical Drives</td>
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<td>KWK-G</td>
<td>Kraft-Wärme-Kopplungsgesetz (Combined Heat and Power Law)</td>
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<td>LPG</td>
<td>Liquefied Petroleum Gas</td>
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<td>NCA</td>
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<td>Institute for Power Generation and Storage Systems</td>
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<td>VAT</td>
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<td>VDE</td>
<td>Verband der Elektrotechnik, Elektronik, Informationstechnik e.V.</td>
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<td>WTP</td>
<td>Willingness-to-pay</td>
</tr>
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6.4 Publications generated by the project

De Doncker, R. W., Sauer, D. U., van Treek, D., Bösing, M., Hennen, M., Lunz, B. et al.,
VDE-Studie Elektrofahrzeuge - Bedeutung, Stand der Technik, Handlungsbedarf
Study by VDE ETG Taskforce Elektrofahrzeuge. Available online: www.vde.de.

Ernst, C.-S., Hackbarth, A., Lunz, B., Madlener, R., Sauer, D. U., Eckstein, L.,
Optimal Battery Size for Serial Plug-in Hybrid Vehicles: A Model-Based Economic Analysis for Germany

Ernst, C.-S., Hackbarth, A., Lunz, B., Madlener, R., Sauer, D. U., Eckstein, L.,
Battery Sizing for Serial Plug-in Hybrid Vehicles: A Model-Based Economic Analysis for Germany
Energy Policy 39 (10), Pages 5871-5882, October 2011

Hackbarth, A., Schürmann, G., Madlener, R.,
Plug-in-Hybridfahrzeuge: Wirtschaftlichkeit und Marktchancen verschiedener Geschäftsmodelle
Energiewirtschaftliche Tagesfragen, 59 (7), Pages 60-63, July 2009

Hackbarth, A., Madlener, R.,
Consumer Preferences for Alternative Fuel Vehicles: A Discrete Choice Analysis

Lunz, B., Pollok, T., Schnettler, A., De Doncker, R. W., Sauer, D. U.,
evaluation of Battery Charging Concepts for Electric Vehicles and Plug-in Hybrid Electric Vehicles, 9th International Advanced Automotive Battery & EC Capacitor Conference, AABC-09, June 2009, Long Beach, CA, USA

Lunz, B., Sinhuber, P., Sauer, D. U.,
Potenziale von Energiespeichern zur Elektrifizierung des Nahverkehrs
Lunz, B., De Doncker, R. W., Sauer, D. U.,
Comparison of Standard- and Fast-Charging of Plug-In Hybrid Electric and Pure Electric Vehicles
International Advanced Mobility Forum, IAMF 2010, Geneva, March 2010

Lunz, B., De Doncker, R. W., Sauer, D. U.,
Analyse von Ladeinfrastrukturkonzepten für Elektromobilität, VDE-Kongress 2010, Leipzig, November 2010

Lunz, B., Yan, Z., Gerschler, J. B., Sauer, D. U.,
Influence of Plug-in Hybrid Electric Vehicle Charging Strategies on Charging and Battery Degradation Costs
Energy Policy 46 (7), Pages 511–519, July 2012

Madlener, R., Ruschhaupt, J.,
Modeling the Influence of Network Externalities and Quality on Market Shares of Plug-in Hybrid Vehicles

Mazur, C., Madlener, R.,
Assessing the Power Sector-related Environmental and Cost Impacts of Plug-in Hybrid Electric Vehicles in Germany
FCN Working Paper No. 20/2010, November 2010

Rosekeit, M., Lunz, B., Sauer, D. U., De Doncker, R.W.,

Rosekeit, M., Lunz, B., Sauer, D. U., De Doncker, R.W.,
Bi-directional Charger for Electric vehicles as Energy Storage in the Smart Grid,
Mitgliederinformation der Energietechnischen Gesellschaft des VDE, January 2013

6.5 Short CV of scientists involved in the project

*Dipl.-Volksw. André Hackbarth* studied Economics at Heidelberg University. Since October 2007 he is working as a research associate at the Institute for Future Energy Consumer Needs and Behavior (FCN) at RWTH Aachen University. Currently, his research is on the adoption and diffusion of alternative-fuel vehicles in Germany with a special focus on attitudinal and economic factors and their impact on consumer decision making.

*Dipl.-Ing. Benedikt Lunz* studied electrical engineering at the University Erlangen-Nürnberg and at KTH Stockholm with a focus on electricity supply and power electronics. Since September 2008 he is working as research associate at the Institute for Power Generation and Storage Systems within the E.ON Energy Research Center at RWTH Aachen University. His work is focused on electro mobility with special respect to Plug-in Hybrid Electric Vehicles and their grid integration.
Prof. Reinhard Madlener studied Commerce and Finance as well as Pedagogics at the Vienna University of Economics and Business Administration (WU Wien) and then also Economics at the Institute for Advanced Studies Vienna (IHS). He obtained his PhD at WU Wien in the Economics and Social Sciences (Dr. rer. soc. oec.), specializing in General Economics, Environmental Economics, and Statistics. Before taking up his position at RWTH Aachen University in June 2007, he was Managing Director of the Institute for Advanced Studies Carinthia (1999-2000), Assistant Professor at the Centre for Energy Policy and Economics (CEPE), ETH Zurich (2001-2007), Lecturer at the Faculty of Economics, University of Zurich (since 2003), and Senior Researcher at the German Institute of Economic Research / DIW Berlin (2007). Among others, he was Visiting Fellow at the University of Illinois (Urbana-Champaign), the European University Institute (Florence, Italy), and the University of Warwick (Coventry, UK). Prof. Madlener is one of five full professors of the E.ON Energy Research Center (E.ON ERC), established at RWTH Aachen University end of 2006, Director of the Institute for Future Energy Consumer Needs and Behavior (FCN) founded by him in June 2007, Research Professor at the German Institute of Economic Research (DIW Berlin), and RWTH Director of JARA-Energy, and President of the Swiss Association for Energy Economics (SAEE). He has published extensively in energy economics and related fields.

Prof. Dirk Uwe Sauer received his diploma in Physics in 1994 from University of Darmstadt. From 1992-2003 he worked as a research scientist and senior scientist at Fraunhofer Institute for Solar Energy Systems ISE in Freiburg/Germany. In 2003 he received his Ph.D. at Ulm University on battery modeling and system optimization. From 10/2003 to 09/2009 he was Juniorprofessor at RWTH Aachen University for “Chemical Energy Conversion and Storage Systems” at the Institute for Power Electronics and Electrical Drives (ISEA), later as well Institute for Power Generation and Storage Systems (PGS, E.ON ERC). In 10/2009 he was appointed Professor at RWTH Aachen University for “Electrochemical Energy Conversion and Storage Systems” at the Institute for Power Electronics and Electrical Drives (ISEA) and Institute for Power Generation and Storage Systems (PGS, E.ON ERC). Prof. Sauer was member of the VDE/ETG Task Force on Energy Storage Systems (2006-2009). In 2010, he became member of the German National Platform for E-Mobility (NPE).

Prof. Rik W. De Doncker received his Ph.D. degree in electrical engineering from the Katholieke Universiteit Leuven, Belgium in 1986. In 1987, he was appointed a Visiting Associate Professor at the University of Wisconsin, Madison, where he lectured and conducted research on field-oriented controllers for high-performance induction motor drives. In 1988, he was a General Electric Company Fellow in the microelectronic center, IMEC, Leuven, Belgium. In December 1988, he joined the General Electric Company Corporate Research and Development Center, Schenectady, NY, where he led research on drives and high-power soft-switching converters, ranging from 100 kW to 4 MW, for aerospace, industrial, and traction applications. In 1994, he joined Silicon Power Corporation (formerly GE-SPCO) as Vice President, Technology. He worked on high-power converter systems and MTO devices and was responsible for the development and production of 15 kV medium-voltage transfer switch. Since October 1996, he has been professor at RWTH Aachen University, Aachen, Germany, where he leads the Institute for Power Electronics and Electrical Devices. He has published over 180 technical papers and is holder of 20 patents, with several pending. Prof. De Doncker was member of the IEEE IAS Executive Board and is Past President of IEEE Power Electronics Society (PELS). He is member of the EPE Executive Council. He was founding Chairman of the German IEEE IAS-PELS Joint Chapter. Prof. De Doncker is also the recipient of the IAS Outstanding Achievement Award and the PES Custom Power Award. In 2006 he was appointed Director of the E.ON Energy Research Center. In 2010, he became member of the German National Platform for E-Mobility (NPE) and led the VDE/ETG Task Force Study on E-Mobility.
6.6 Project timeline

Since three parts of the project could not be finished in time, the project and its final report were split into two parts. The delay during the processing of the three work packages occurred due to the following reasons:

**Battery lifetime**: The battery tests started in time but due to the good aging behavior of the cells tested a reliable extrapolation cannot be made.

**Simulation of PHEVs in the distribution grid**: The simulation of mobile storage devices (PHEVs) in the distribution grid within the software DigSilent Powerfactory was very complex. A co-simulation of Powerfactory and MATLAB had to be used which increased the implementation effort significantly.

**Consumer preferences**: The design and the implementation of our discrete-choice experiment was very complex, since more variables were considered than in comparable studies. Additionally, the modeling of future diffusion paths of AFVs was an extensive task as well.

Moreover, as one of the goals of the project was to build up knowledge and skills, we applied some of the models and methodologies for the first time, which prolonged the finalization of the project.

6.7 Activities within the scope of the project

**Presentations at workshops and conferences:**

Ernst, C.-S., Hackbarth, A., Lunz, B., Madlener, R., Sauer, D. U.,
Economic Analysis for Plug-in Hybrid Electric Vehicles in Germany,
2nd Technical Conference "Advanced Battery Technologies for Automobiles and Their Electric Power Grid Integration", February 2010, Mainz, Germany

Hackbarth, A., Madlener, R.,
Consumer Preferences for Alternative Fuel Vehicles: A Discrete Choice Analysis
12th IAEE European Conference, September 2012, Venice, Italy

Lunz, B.,
Evolution of Batteries and Charging Concepts
Seminar Clean Mobility, Limburg Catholic University College, December 2008, Diepenbeek, Belgium

Lunz, B.
Elektrofahrzeuge: Speicherkraftwerke auf Rädern
Smart Grids - Eine Herausforderung für die Energieversorger und Netzbetreiber, March 2009, Mainz

Lunz, B., De Doncker, R. W., Sauer, D. U.,
Electric Vehicle Charging Concepts - User and Battery Aspects
Energy Delta Convention, EDC 2009, November 2009, Groningen, Netherlands

Lunz, B., Sauer, D. U.,
Ergebnisse der VDE-Speicherstudie
FVEE-Workshop "Elektrochemische Energiespeicher und Elektromobilität", January 2010, Ulm
Lunz, B., Sauer, D. U.,
Technologie und Auslegung von Batteriesystemen für die Elektromobilität
Solar Mobility, February 2010, Berlin

Lunz, B., Sauer, D. U.,
e-mobility und erneuerbare Energien - eine win-win-Situation
Anwenderforum MobiliTec, MobiliTec2010, April 2010, Hannover

Lunz, B., Sauer, D. U.,
Energy Storage Systems for Electric Vehicles
Electrical Energy Storage Workshop, June 2012, Mondragón University, Mondragón, Spain

Madlener, R., Mazur, C.,
Assessing the Power Sector-related Environmental and Cost Impacts of Plug-in Hybrid Electric Vehicles in Germany
33rd IAEE International Conference, June 2010, Rio de Janeiro, Brasil

Madlener, R., Mazur, C.,
Assessing the Power Sector-related Environmental and Cost Impacts of Plug-in Hybrid Electric Vehicles in Germany
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Schürmann, G., Madlener, R., Hackbarth, A.,
Plug-in Hybridfahrzeuge: Marktentwicklung, Marktchancen und ökonomisch interessante Fragestellungen
6th International Conference in Energy Economics (IEWT), February 2009, Vienna, Austria
Plug-in Hybrid Electric Vehicles for CO$_2$-Free Mobility and Active Storage Systems for the Grid

Project Synopsis

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Categories E.ON ERC focus:

- Small Scale CHP
- Large Power Plants
- Energy Storage
- Energy Efficiency
- Consumer Behavior
- Energy Economics Modeling
- Energy and Buildings
- Power Electronics
- Distribution Networks
- Renewable Energy
- Carbon Storage (CCS)
- Others

Type of project report: Final Project Report – Part 2
Start and end date of project: July 2008 - June 2010
Project in planned timelines: yes no (see section 6.6)

Participating Chairs of E.ON ERC:

- Automation of Complex Power Systems (ACS)
- Energy Efficient Buildings and Indoor Climate (EBC)
- Future Energy Consumer Needs and Behavior (FCN)
- Applied Geophysics and Geothermal Energy (GGE)
- Power Generation and Storage Systems (PGS)

Acknowledgments:

This project was supported by a grant of E.ON ERC gGmbH, Project No. 04-019.