

## DEFINE: Development of an Evaluation Framework for the Introduction of Electromobility

Two electromobility scenarios for Germany: Market  
development and their impact on CO<sub>2</sub> emissions of  
passenger cars in DEFINE

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## Summary

The electric vehicle market penetration and the vehicle stock in Germany up to 2030 are derived as part of the developed modelling framework DEFINE that analyses emission and economic effects of market introduction of electromobility. The vehicle stock data is integrated into an electricity dispatch model to illustrate the interactions of electric vehicles' power demand and the electricity production. Finally, the CO<sub>2</sub> emissions of transport and electricity sector are analysed to show the net CO<sub>2</sub> impact of electromobility.

Two scenarios are developed to compare the impact of different electric vehicle market developments and to better understand the impact of policy measures for electromobility market support. Three policy measures that improve the economics of electric vehicle usage in comparison to conventional car usage are applied in the EM<sup>+</sup> (electromobility<sup>+</sup>) scenario. The continuation of current policies is assumed in the BAU (business as usual) scenario.

As a first step for derivation of the electric vehicle market, mobility data has been analysed to understand restrictions for electromobility usage. The access to a battery charging spot is a relevant requirement for electric driving. Roughly 70 % of car owners in Germany have a parking spot at their property at their disposal and have the opportunity to install a private charging station. Differences are evident when comparing car owners in core cities (40 – 50 % parking at their own properties) and the outskirts of cities and rural areas (70 – 80 %). Further restrictions for BEV usage occur in the case of long trips that exceed maximum mileage of BEV. This occurs more frequently for mid-size and large cars. Surprisingly, more trips exceeding the maximum mileage of BEV are conducted by car owners in core cities and the restrictions with regard to long trips are more cumbersome for these car owners.

A conjoint analyse has been conducted to simulate the purchase decisions of new car buyers. Approximately 1,500 potential new car buyers were shown a set of a conventional car, a PHEV/REEV and a BEV with randomly varying characteristics to simulate a purchase decision (18 times) and statistical methods are applied to simulate the selection process between potential cars with different propulsion systems in 2020 and 2030. The analyses show higher acceptance of PHEV/REEV than for BEV and the selection of electric vehicles increases from nearly 50 % in the BAU scenario to nearly 58 % in the EM<sup>+</sup> scenario. This effect of a higher selection rate of electric vehicles is especially evident with large cars. There is the tendency that purchase of an electric vehicle is the highest with mid-size cars and, counter-intuitively, with car buyers that do not have the possibility of parking the car at their own properties. New car buyers that live in the core city also show higher acceptance of electric vehicles.

The results from the conjoint analysis and the analysis of mobility data are combined to obtain a potential market development that is attenuated by application of a market diffusion factor which considers the lack of variety of electric vehicle models and the time period that is required by the car makers to establish the electric vehicle production facilities and processes. The derived market development is used as input for the TEMPS (**t**ransport **e**missions and **p**olicy **s**cenario) model to calculate the vehicle stock and the energy consumption of its cars. The policy measures of EM<sup>+</sup> scenarios show their efficiency to support electric vehicle market penetration and more than 5.1 million electric vehicles (~ 13 % of vehicle stock) are registered in 2030. The electric vehicle stock is considerably smaller in the BAU scenario and nearly 10 % of the vehicle stock (3.9 million) are electric driven cars.

Mobility data has been used to derive electric car usage patterns for a complete year (hourly resolution) in order to add the charging of electric vehicles to the DIW electricity dispatch model.

Information on connectivity to charging stations has been added according to the assumptions of the development of charging infrastructure. Two charging modes are applied in the electricity dispatch modelling: user-driven charging (batteries are fully recharged immediately after being connected to a charging station) and cost-driven charging (the cost of electricity production is minimised upon the condition that all trips of the considered electric vehicle usage patterns are satisfiable). The electricity production capacities and the electricity consumption of the other application sectors are derived from the *Netzentwicklungsplan Strom 2013* (German Network Development Plan for Electricity 2013) for the time period up to 2030.

The application of electromobility lowers the CO<sub>2</sub> emissions of the transport sector, but might increase the emissions that arise from electricity production due to the additional demand for electricity. Thus, a net CO<sub>2</sub> balance of emission changes of the transport and the electricity sector compared to a base scenario with no electric vehicles has been prepared for both scenarios of DEFINE. The increase of the CO<sub>2</sub> emissions of the electricity sector outweighs the emission mitigation of the transport in the BAU scenario and the net CO<sub>2</sub> emissions rise by 1.0 – 1.6 M t CO<sub>2</sub> in 2030 in comparison to the scenario without electric vehicles. The net CO<sub>2</sub> emissions increase up to 2020 in the EM<sup>+</sup> scenario, but there is a net GHG benefit in 2030 which is mainly facilitated by better energy efficiency levels of conventional cars (driven by lower emission targets of CO<sub>2</sub> emission regulation). It is obvious from the net CO<sub>2</sub> balance that the addition of electric vehicles to the energy system not only increases the use of renewable capacities, but also enhances the operation hours of fossil power plants when the framework conditions of the *Netzentwicklungsplan Strom 2013* are applied.

It is evident that there is a difference in electricity production by simulating varying charging modes of electric vehicles. User-driven charging adds an inflexible load curve to the electricity sector and the electric vehicles are recharged immediately and as fast as possible after being connected to the grid. Thus, renewable energy is accidentally integrated into the energy system, but also fossil power plants enhance their operation in hours at which fossil power plants are the marginal electricity production capacity. Cost-driven charging minimises the cost of electricity production and shifts the recharging of electric vehicles (and the additional power production) preferably to hours of renewable surplus production and to hours at which lignite and hard-coal power plants are the marginal capacity of the power market (night hours). Thus, the renewable capacities are integrated to a maximum and the net CO<sub>2</sub> emissions of electricity production are smaller than with user-driven charging.

Full GHG emission benefit is gained when no additional CO<sub>2</sub> emissions are produced in the electricity sector compared to the base case with no electromobility. Renewable capacities which produce the amount of energy that is consumed by the electric vehicle stock are added to the electricity production fleet. Whether and how these added renewable capacities can be integrated into the energy system is analysed. Electricity dispatch model runs that apply user-driven charging for the EM<sup>+</sup> scenario show no additional CO<sub>2</sub> emissions of the electricity generation sector and the CO<sub>2</sub> net benefit is as high as 6.8 M t CO<sub>2</sub> in 2030. The integration of the added renewable capacities does not succeed as perfectly when the cost-driven charging mode is simulated. The net CO<sub>2</sub> benefit of the market introduction of electric vehicles is as high as 6.5 M t CO<sub>2</sub> in this case since some charging is still shifted to low short-term marginal cost production of lignite and hard-coal power plants.

This study, which has been conducted as part of the DEFINE project, shows that there are policy measures which strongly facilitate the market introduction of electric vehicles. The electric vehicle stock increases from 3.9 million (BAU) to more than 5.1 million (EM<sup>+</sup>) passenger cars. It is also seen that electromobility contains the potential of CO<sub>2</sub> emission mitigation of the transport sector,



but this potential is not exploited automatically. The electricity production capacities have to be carefully assessed in order to not add CO<sub>2</sub> emissions in the electricity production sector compared to a scenario without electromobility. This has been carried out in this study and additional renewable capacities are added to the electricity production fleet derived from the *Netzentwicklungsplan Strom 2013*. Finally, it is illustrated that it is possible to achieve the full potential of GHG emission mitigation of electric vehicles and that electric vehicles are able to fulfil their role as one part of a GHG emission mitigation strategy for the transport sector.



## 1. Background and motivation

Anthropogenic greenhouse gas emissions have to be reduced in the future to meet the global climate protection targets and to prevent an increase in global temperature that is more than 2 degrees. Germany set the target to reduce its overall GHG emissions by 80 to 95 % in 2050 compared to 1990. No GHG emission targets are set for the transport sector but the final energy consumption is supposed to be reduced by 40 % in 2050 compared to 2005.

One of the strategies for reducing the final energy consumption and GHG emissions of the transport sector is the increasing use of carbon-free electricity. Electromobility is one major option to use electricity in the transport sector and makes electricity use available for the motorised private transport. Thus, electromobility is also shown as an integral part of GHG emission reduction in all studies on climate protection scenarios for Germany up to 2050 (Nitsch et al. 2012, Schlesinger et al. 2010, Repenning et al. 2014).

As a consequence, the German government has started a strategy to establish Germany and German car makers as a leading market and leading innovators of electromobility. A target of 1 million electric vehicles in 2020 and 6 million electric vehicles in 2030 was set for the German vehicle stock in 2010. Focus regions in which the use of electric vehicles is tested and financially supported has been established and financial support programs for R&D for electric vehicles have been developed. Today, all major car makers have invested into the development of electric vehicles and first low volume serial production has started.

Electric vehicle usage implies a shift from mineral oil-based fuel to electricity as the energy carrier for the transport sector and a new – potentially flexible – electricity demand is added to the electricity system. Even though the impact on the electricity sector might be considered small with few electric vehicles and a small share of total electricity consumption, the interaction of the electric vehicles and the electricity system is nevertheless worth analysing. Additionally, the supply of carbon-free electricity is not guaranteed as long as non-renewable electricity production capacities are an integral part of the energy system.

Therefore, this study deals with two issues with regard to electromobility. First, two scenarios of the market penetration of electric vehicles are developed and the impact of policy measures applied to support the electric vehicle market is shown. As a second issue, the interactions of electromobility and electricity production are analysed to understand whether and how the framework conditions have to be designed for electromobility to achieve its full potential in terms of GHG emission reduction.

### 1.1. DEFINE – Consortium and concept

DEFINE – Development of an Evaluation Framework for the Introduction of Electromobility – is being conducted by a consortium of research institutions from Austria (Institut für Höhere Studien - IHS, Wien; Umweltbundesamt - UBA, Wien; Institut für Energiesysteme und Elektrische Antriebe - ESEA, TU Wien), Poland (Center for Social and Economic Research - CASE) and Germany (Deutsches Institut für Wirtschaftsforschung - DIW, Berlin; Oeko-Institut - ÖI, Berlin), which are developing a modelling framework to analyse the GHG emissions and the economic impact of the introduction of electromobility. The consortium is funded by the national funding institutions that are responsible for the coordination of the ERA-NET Transport Trans-national call *electromobility+*.

Detailed bottom-up modelling of electric vehicle market development in Austria (UBA) and Germany (ÖI) is combined with electricity dispatch modelling of the Austrian (ESEA) and German

(ESEA and DIW) electricity production markets. The results of the electricity dispatch modelling are used together with transport sector modelling to determine the GHG emissions and energy demand impact of the market introduction of electric vehicles. The data from Austria and Germany are used as input in a top-down CGE economic model from IHS that is enhanced with a more detailed representation of the transport sector in DEFINE. This model can be used to show economic effects that are caused by market penetration of the new technology of electromobility. Additionally, CASE supports IHS for representation of Poland with the CGE model and a case study for Poland is being conducted.

Oeko-Institut used its previous experience with regard to electromobility to support the consortium-wide discussion and lead the scenario development process within the consortium. For Germany, the market penetration and the stock development of electric vehicles were derived and electric car usage patterns were created as an input for the electricity dispatch modelling conducted by DIW. Furthermore, the GHG emission effects of electromobility were quantified by Öko-Institut.

## 2. Defining two scenarios – Business-As-Usual (BAU) and Electromobility<sup>+</sup> (EM<sup>+</sup>)

All analyses within the DEFINE project were conducted for two different scenarios to show effects of different development patterns of electromobility. Moreover, both scenarios are required to enable the calibration of the CGE modelling framework that has been developed within the DEFINE project.

- The Business-As-Usual (BAU) scenario assumes no relevant changes in legislation and the continuation of current policies. No special measures for market success of electromobility are applied in this scenario.
- The Electromobility<sup>+</sup> (EM<sup>+</sup>) scenario shows a more favourable environment for market success of electromobility. Policies that are advantageous for electromobility are assumed.

A scenario development workshop was held with all project partners to identify the required parameters for all models used within the DEFINE project. The assumptions for these parameters and the policy measures that are applied in the EM<sup>+</sup> scenario were subsequently harmonised to ensure consistency for all modelling work conducted within the DEFINE framework. The modelling parameters can be divided into two groups with regard to changes between the scenarios.

- The framework conditions are general parameters that are needed for modelling work and are not necessarily transport-sector-specific. These parameters remain equal for both scenarios.
- Policy measures are applied in the EM<sup>+</sup> scenario to support electromobility market development. Parameters which are affected by these measures vary between both scenarios. For Germany, these policy measures are:
  - a) more ambitious CO<sub>2</sub> emission targets of the EU CO<sub>2</sub> regulation on new passenger cars,
  - b) higher energy taxes on fossil fuel, and
  - c) implementation of a feebate system to support ultra-low emission vehicles.

In the following, only the relevant parameters for modelling work that is conducted by Oeko Institut are shown and consist of assumptions for passenger car technology and cost development, on charging infrastructure development and on energy prices and taxation.

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In DEFINE, electromobility is defined as electric drive passenger cars. Rail traffic, potential electric drive freight road traffic, e-bikes and potential other means of electric transport are not considered in DEFINE. The time span covered in DEFINE is the market introduction phase of 2010 up to 2030.

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## 2.1. Passenger car technology and costs

The required data for evaluation of potential future market shares of electric vehicles is the technical configuration and the retail prices of conventional (CV) and electric cars. In general, electric vehicles are divided into two subgroups:

- Battery electric vehicles (BEVs) are solely driven by an electric engine. The driving mileage is restricted to smaller distances than is the case with conventional cars. The battery of battery electric vehicles is externally charged from the grid which may result in a long charging time.
- Plug-in hybrid electric (PHEV) and range extender electric (REEV) vehicles have two powertrains (electric engine and internal combustion engine) for propulsion. Both systems differ in terms of the combination of both engines. Since most hybrid electric vehicles will probably not have pure parallel or serial engine architectures, both types of hybrid cars are pooled together in all analyses in DEFINE. The internal combustion engine enables – if required – longer driving mileage and faster refuelling. PHEV and REEV are either externally charged from the grid or can use diesel or gasoline as fuel.

Conventional cars are gasoline and diesel cars that contain an internal combustion engine. Electric hybridisation is one possibility to achieve higher efficiency in conventional cars (HEVs: hybrid electric vehicles). Thus, conventional cars may also use an electric engine and a battery that is charged by an internal energy recovery system. The difference to plug-in hybrids is the lack of the possibility to charge the batteries of hybrid electric vehicles externally. Therefore, HEV are put together with conventional diesel and gasoline cars in DEFINE.

Additionally, the vehicle stock is divided further into three size classes for all analyses in DEFINE: small, mid-size and large. This classification is carried out by the KBA classification.

- small: city car (Mini/Kleinstwagen), supermini (Kleinwagen)
- mid-size: small family car (Kompaktklasse), multi-purpose vehicle (Minivan/Großraum-Van)
- large: large family car (Mittelklasse), executive car (Obere Mittelklasse), luxury car (Oberklasse), sport utility vehicle (Geländewagen), sport coupes (Sportwagen).

The classification of all passenger cars into the different propulsion system groups and the three size classes applies for all parts of modelling in DEFINE and most results will be shown with the vehicles classified in this way.

An existing database for vehicle efficiencies and technology costs is used in DEFINE to determine average retail prices as a function of vehicle efficiency. This database uses data from several studies on the potentials and the costs of CO<sub>2</sub> mitigation technologies in cars. The methodology of the database and the final results were discussed with stakeholders from the car manufacturing

industry and science to solidify the quality of the cost data of the potential future vehicles and are summarised in Hülsmann et al. (2014).

The database requires assumptions for battery costs and technology-specific parameters for cost calculation of electric vehicles (see Table 2-1). Additionally, the electrical range of both BEVs and PHEV/REEVs is required in order to obtain cost data from the database and to determine the market share of electric vehicles. The electrical range of the average BEV in DEFINE is assumed to be 150 km in both scenarios. PHEV/REEVs are capable of driving 50 km in full electric mode. BEVs are assumed to be not available in the large size class up to 2030 due to the high battery costs and the additional weight that would be necessary for an assumed electric mileage of 150 km.

**Table 2-1: Assumptions of battery costs and battery technology development**

	Specific battery costs	Mass specific capacity	Depth of discharge*
	€ <sub>2010</sub> /kWh	kWh/kg	%
2010	600	0.105	80 / 65
2020	280	0.105	85 / 70
2030	200	0.150	90 / 75

\* The first value is assumed for BEV, the second value is assumed for PHEV/REEV.

Source: Authors' own assumptions

The costs and retail prices of conventional cars are strongly dependent on the efficiency of vehicles and it is assumed that the efficiency of conventional vehicles is mainly driven by the EU CO<sub>2</sub> regulation for new passenger cars. Different CO<sub>2</sub> emission targets in 2030 are set for the BAU and the EM<sup>+</sup> scenarios to enforce better fuel efficiency – and in consequence higher retail prices – for conventional cars in the EM<sup>+</sup> scenario. Increasing market shares of electric vehicles reduce the fuel efficiency requirements for conventional cars with regard to the EU CO<sub>2</sub> regulation and have to be considered when deriving the CO<sub>2</sub> emission levels of conventional cars. It is assumed that the emission level of conventional cars is 5 g CO<sub>2</sub>/km higher in 2020 and 10 g CO<sub>2</sub>/km (BAU) or 12.5 g CO<sub>2</sub>/km (EM<sup>+</sup>) higher in 2030 than the overall emission target for all new passenger cars.

Data from 2010 (EEA 2011) shows an unequal distribution of specific CO<sub>2</sub> emissions of new registered cars within the EU. Specific CO<sub>2</sub> emissions of car registrations in Germany were 7.8 % higher than the overall EU average. This effect can be attributed to higher sales in the large car segments and to higher motorization compared to the EU average. No changes in the car sales structure within the EU are assumed and the CO<sub>2</sub> emissions of conventional cars remain 7.8 % higher than the overall EU emissions of conventional cars. Therefore, fuel efficiency increases of 29 % in 2020 and by 41 % (BAU) or 49 % (EM<sup>+</sup>) in 2030 are assumed for conventional cars with regard to 2010. A summary of all assumptions and requirements of the CO<sub>2</sub> emission reductions of conventional cars is shown in Table 2-2.

**Table 2-2: Assumptions of average specific CO<sub>2</sub> emission of conventional cars, 2010 - 2030**

	$e_{\text{target,all,EU}}$	xEV effect	$e_{\text{CV,EU}}$	$e_{\text{CV,Germany}}$
	g CO <sub>2</sub> /km	g CO <sub>2</sub> /km	g CO <sub>2</sub> /km	g CO <sub>2</sub> /km
2010	-	-	140.3	151.2
2020 (BAU/EM <sup>+</sup> )	95	5	100	107.8
2030 (BAU)	72.5	10	82.5	88.9
2030 (EM <sup>+</sup> )	60	12.5	72.5	78.1

Source: Authors' own assumptions

A feebate system is applied as a policy measure in the EM<sup>+</sup> to support the market penetration of low emission passenger cars. The feebate system consists of a fee for new cars that exceed the requirements of the EU CO<sub>2</sub> regulation for new cars and donates a rebate to low emission cars. The fee for high emission cars is set as equal to the penalty of the CO<sub>2</sub> regulation (95 €<sub>2010</sub> per g CO<sub>2</sub>/km above the target value). It is assumed that the conventional cars exceed the emission target by 7.8 % (see above) to calculate the fees which are added to the retail price of the conventional passenger cars.

Electric vehicles are assumed to be supported in the feebate system with decreasing rebates over time and the electrification level. BEV vehicles are granted a double rebate compared to PHEVs and REEVs and the rebate is reduced from 2020 to 2030. All assumptions of the fees and the rebates with regard to the feebate system are summarised in Table 2-3.

**Table 2-3: Assumptions of fees and rebates of the feebate system in EM<sup>+</sup> scenario**

	Fee for conventional cars (€ <sub>2010</sub> )			Rebate (€ <sub>2010</sub> )	
	small	mid size	large	BEV	PHEV
2020	569	625	698	2140	1070
2030	338	386	449	549	275

Source: Authors' own assumptions

## 2.2. Fuel and electricity retail prices

Fuel and electricity prices strongly differ and are significant for the calculation of the kilometre costs of car usage. Consequently, assumptions have to be made for all energy carriers that are used for cars in order to model the purchase decisions relating to new cars. The retail prices of the fuels and electricity consist of the following cost factors:

- production costs,
- energy taxes,
- value added tax (VAT), and
- miscellaneous costs.

All cost factors other than energy taxes are held constant between the BAU and EM<sup>+</sup> scenarios. Higher fuel taxes are applied in the EM<sup>+</sup> scenario to support electric vehicle market development and to offset lower kilometre cost and lower state income that would result from the better efficiency of new conventional cars.

The basic assumptions relating to fuel prices are taken from the scenarios that were compiled for the derivation of the German government’s Energy Concept (*Energiekonzept*) (Schlesinger et al. 2010). Retail prices for fuels are adopted directly for the BAU scenario.

The production and the miscellaneous costs are derived from the fuel price data in Schlesinger et al. (2010) and are kept constant in the EM<sup>+</sup> scenario. The VAT level (19 %) remains equal as well. A change of fuel taxation – based on energy content and CO<sub>2</sub> content of the fuel (50-50 split) – is assumed and the gasoline retail prices were set at 1.70 €<sub>2010</sub>/l in 2020 and at 2.30 €<sub>2010</sub>/l in 2030.

Special taxation on electricity for car usage is assumed in 2030 for both scenarios and the tax level based on the energy content of conventional fuels is added to the general electricity taxes. An overview of all assumptions for fuel and electricity retail prices for car owners is given in Table 2-4.

**Table 2-4: Assumptions of energy retail prices for car users**

	Production/ miscellaneous costs	Energy tax	Value added tax	Retail price	Retail price
	€ <sub>2010</sub> /GJ	€ <sub>2010</sub> /GJ	€ <sub>2010</sub> /GJ	€ <sub>2010</sub> /GJ	€ <sub>2010</sub> /l
BAU - gasoline					
2020	23,6	17,3	7,8	48,7	1,57
2030	31,1	14,8	8,7	54,6	1,77
BAU - diesel					
2020	24,6	11,3	6,8	42,6	1,52
2030	30,8	9,6	7,7	48,2	1,72
BAU - electricity					
2020	52,5	4,9	10,9	68,2	
2030	56,7	18,5	14,3	89,5	
EM <sup>+</sup> - gasoline					
2020	23,6	20,6	8,4	52,6	1,70
2030	31,1	28,7	11,4	71,2	2,30
EM <sup>+</sup> - diesel					
2020	24,6	20,9	8,6	54,1	1,93
2030	30,8	29,1	11,4	71,4	2,55
EM <sup>+</sup> - electricity					
2020	52,5	4,9	10,9	68,2	
2030	56,7	18,5	14,3	89,5	

Source: Authors’ own assumptions (derived from Schlesinger et al. 2010)

### 2.3. Charging infrastructure

Information on charging infrastructure is required in different models of the DEFINE modelling cluster. The maximum charging power at charging stations is an essential information for the electricity dispatch models within the DEFINE network. The charging time and availability of charging stations are parameters that are needed in the derivation of the acceptance and the market share of electric vehicles.



All assumptions relating to the charging infrastructure are considered to be framework parameters and remain constant in both scenarios. Generally, it will be distinguished between charging at the car owners' private property and (semi-)public (i.e. at work, public space, shopping malls etc.) charging infrastructure which can be used by all electric vehicle owners. Low charging power (3.7 kW) is assumed to be available at private properties. Medium power charging stations (11 kW) are assumed to be constructed in the (semi-)public area, but the availability of the (semi-)public infrastructure is limited<sup>1</sup>. Fast charging stations with higher power rates are assumed not to be set up in both scenarios. The charging losses are considered to be 10 % of the electricity that is drawn from the electricity grid.

### 3. Market shares and stock of electric vehicles

Vehicle stock development is required to calculate the energy demand and the CO<sub>2</sub> emissions of the passenger cars. It is also a relevant parameter when analysing the economic effects of market penetration of electric vehicles. Therefore, the market shares and the vehicle stock development up to 2030 are used in DEFINE:

- as a result in itself,
- as input data for the electricity dispatch modelling (in combination with the electric vehicle usage patterns), and
- as input data for the calibration of the CGE economic modelling.

The main input for the vehicle stock derivation is the registration data of new cars. Scrappage rates and annual mileage of vehicles of the passenger car stock are taken from Oeko Institut's eMobil 2050 study (Hacker et al. 2014) and the vehicle stock is calculated with the TEMPS<sup>2</sup> model (see Hacker et al. (2014) for more information on the methodology of TEMPS).

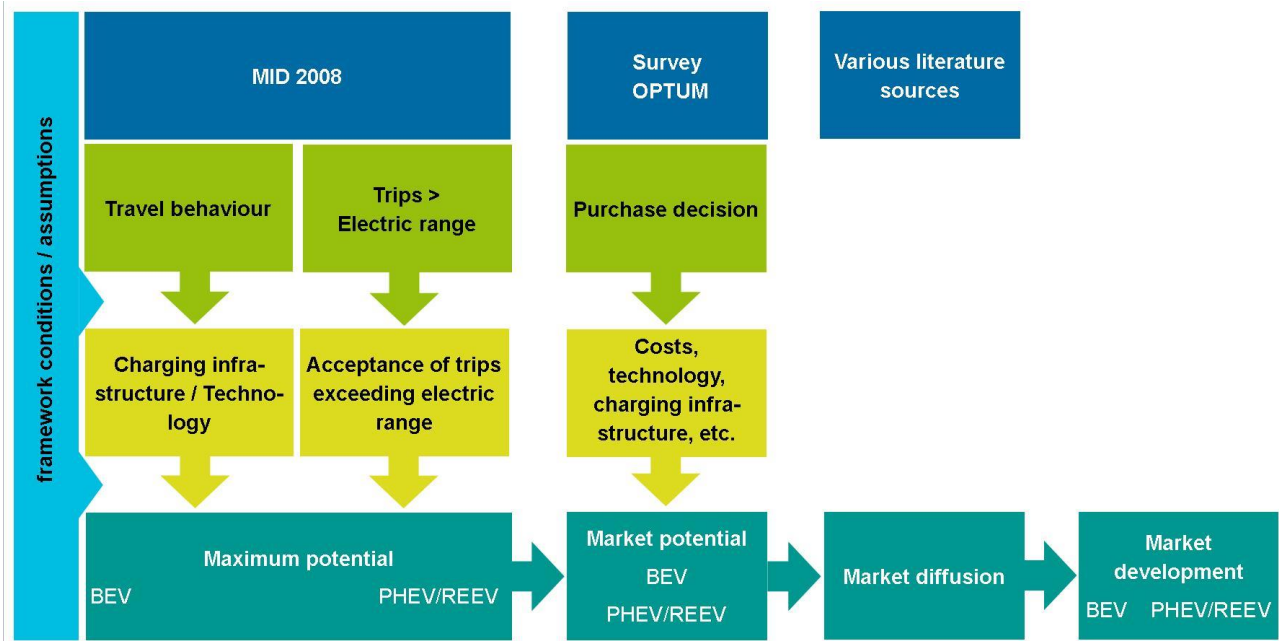
#### 3.1. Methodology and interim results

Various characteristics of electric vehicles, the charging infrastructure and the costs of buying and using a vehicle are assumed to influence the purchase decisions of new car buyers. Furthermore, the supply of electric vehicles is considered in new car registration modelling since the car makers require time to establish the manufacturing processes and the manufacturing sites of electric vehicles and to provide a similar degree of variety in terms of car models and equipment as is the case with conventional cars. A scheme of how the market shares of electric vehicles are derived in DEFINE is shown in Figure 3-1.

<sup>1</sup> The following is assumed: The maximum number of electric vehicles is set to 15 % (2020) and 25 % (2030) of the cars that would require semi-public infrastructure since they do not own a parking spot at the owner's property.

<sup>2</sup> Transport **E**missions and **P**olicy **S**cenarios.

Figure 3-1: Scheme of methodology for derivation of market share of electric vehicles



Source: Authors' own diagram

The modelling of new car registrations is generally split into the three size classifications (small, mid-size and large) and into two different spatial planning categories: core city and outskirts/rural areas<sup>3</sup>. The allocation of new car registrations to the spatial classifications is assumed to be equal to the distribution of car ownership in *Mobilität in Deutschland 2008 (MiD 2008)*. The new car registration modelling shows only the category *conventional car* and an assumption is needed to subdivide the conventional cars into gasoline and diesel vehicles. Official data for new passenger car registrations in Germany (KBA 2011) is applied and the ratio between new gasoline and diesel cars is held constant over time (Table 3-1).

Table 3-1: Assumptions of new car registration structure – spatial resolution and conventional vehicles structure

	Vehicle stock/new car registrations		New car registrations (conventional cars)	
	Core city	Outskirts/rural area	Diesel	Gasoline
Total	24%	76%	42%	58%
Small	24%	76%	9%	91%
Mid-size	24%	76%	42%	58%
Large	23%	77%	68%	32%

Source: Authors' own calculations, MiD 2008, KBA 2011

<sup>3</sup> The cars are divided as follows (BBSR classification ROB2005): core city – Kernstadt, outskirts/rural areas – Verdichtete Kreise, Ländliche Kreise.

### 3.1.1. General demand of transportation – Analysis of MiD 2008 data

One of the main assumptions for the derivation of the market penetration of electric vehicles is that there are no fundamental changes in the mobility behaviour of car owners up to 2030 and electric vehicles must enable the same driving patterns as today. The source for car usage patterns is the MiD 2008 representative survey which shows the mobility patterns for one day of all members of around 26,000 German households. The data of MiD 2008 was collected within the time span of more than a year to level out seasonal effects of mobility behaviour.

The data on mobility behaviour is provided on the individual level, i.e. each trip of all interviewees is listed as one dataset of the database. Therefore, the data of MiD 2008 is processed in such a way that all trips of a single car are pooled together in one dataset to create a car usage database. This processing step is also used to delete erroneous data (e.g. duplicate datasets, overlapping car usage of several users, implausible velocity or trip length of cars, merely vocational trips<sup>4</sup> etc.) from the dataset. Additionally, trips with a parking time of less than 15 minutes are merged to one trip to reduce the number of trips.

The new car usage database is applied to the technical configurations of electric vehicles and to the charging infrastructure assumed in DEFINE. Each car usage dataset is tested for

- the single trip mileage (only applies for BEVs),
- the daily mileage (only applies for BEVs),
- the parking locations (potential charging location) and
- the parking duration

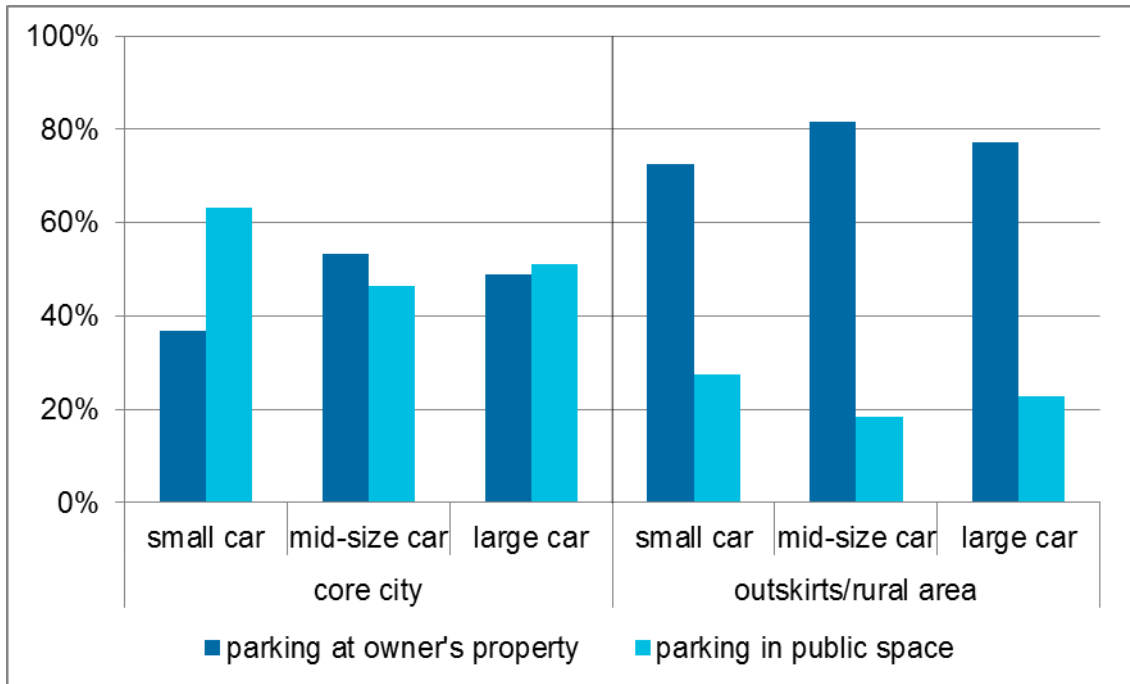
in order to verify the potential of electrical vehicles to fulfil the current car usage. The single trip length and daily mileage are only tested in the case of BEVs since PHEV/REEVs can use their internal combustion engines and refuel the vehicle without major time restrictions. However, trip length and daily mileage do not impose heavy restrictions on BEV usage when the car usage of just one day is analysed.

Potential electric vehicle car usage is more limited due to the charging infrastructure requirement. The database is divided into two groups: cars that have a parking spot at the car owner's property and cars that do not have a parking spot at the car owner's property. The second group of cars requires semi-public charging infrastructure and the assumptions for the availability of (semi-)public charging infrastructure are applied (see chapter 2.3). Therefore, the maximum potential of electric vehicles is limited to 15 % (2020) and 25 % (2030) of all cars that require (semi-)public infrastructure. No restrictions are assumed for cars that can potentially be charged at the car owner's property. An overview of the share of the cars that can potentially be charged at the owner's property is given in Figure 3-2.

It is evident that cars in the city centre are parked less frequently at the car owner's property when being parked *at home* and the limitations resulting from (semi-)public charging infrastructure requirements are higher for car owners who live in the core city. A second trend is seen with regard to the car size. Mid-size and large cars are parked more often at the car owner's property than small cars and are less subject to semi-public infrastructure restrictions.

<sup>4</sup> Information on purely professional trips ("rein berufliche Wege") was gathered separately and the trips were added subsequently to the dataset. The detail level of these trips does not fulfil the requirements of the methodology applied for market share development in DEFINE.

**Figure 3-2: Share of car parking location when the car is parked at home**

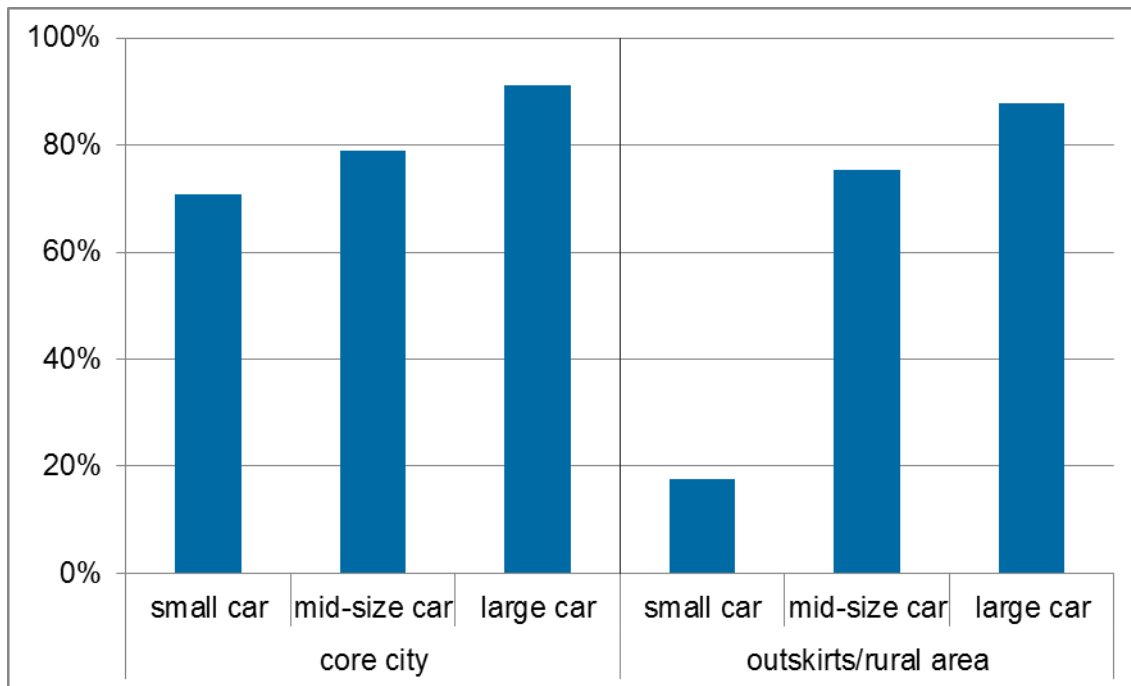


Source: Authors' own calculations, MiD 2008

The restrictions for BEVs relating to maximum mileage and the maximum trip length are extended by a special consideration of long trips. MiD 2008 only gives information on the car usage of one day and the usage restrictions that are imposed by long trips would be underestimated by evaluating only a single day. Therefore, the Poisson distribution is applied to the MiD 2008 database and the probability of the number of trips per year that exceed the maximum mileage of BEV is calculated. It is assumed that the car users accept less than five times per year that they are not able to use the BEV. The probability of the event (five or more trips a year that exceed the maximum mileage of BEV) is set as the maximum potential for BEV (Figure 3-3).

Figure 3-3 shows that the number of long trips imposes strong limitations on BEV car usage when it is assumed that there are no changes to the mobility demands and transport carrier selection. Trips exceeding the maximum mileage of BEVs occur more frequently for large cars and more often for car owners that are living in the city centre. It is noteworthy that the small probability of long trips for small cars by car owners living on the outskirts and in rural areas. The probability value is distinctively smaller than for the other groups of car owners.

**Figure 3-3: Probability of five or more trips per year that exceed the maximum mileage of BEV (150 km) – Poisson distribution**



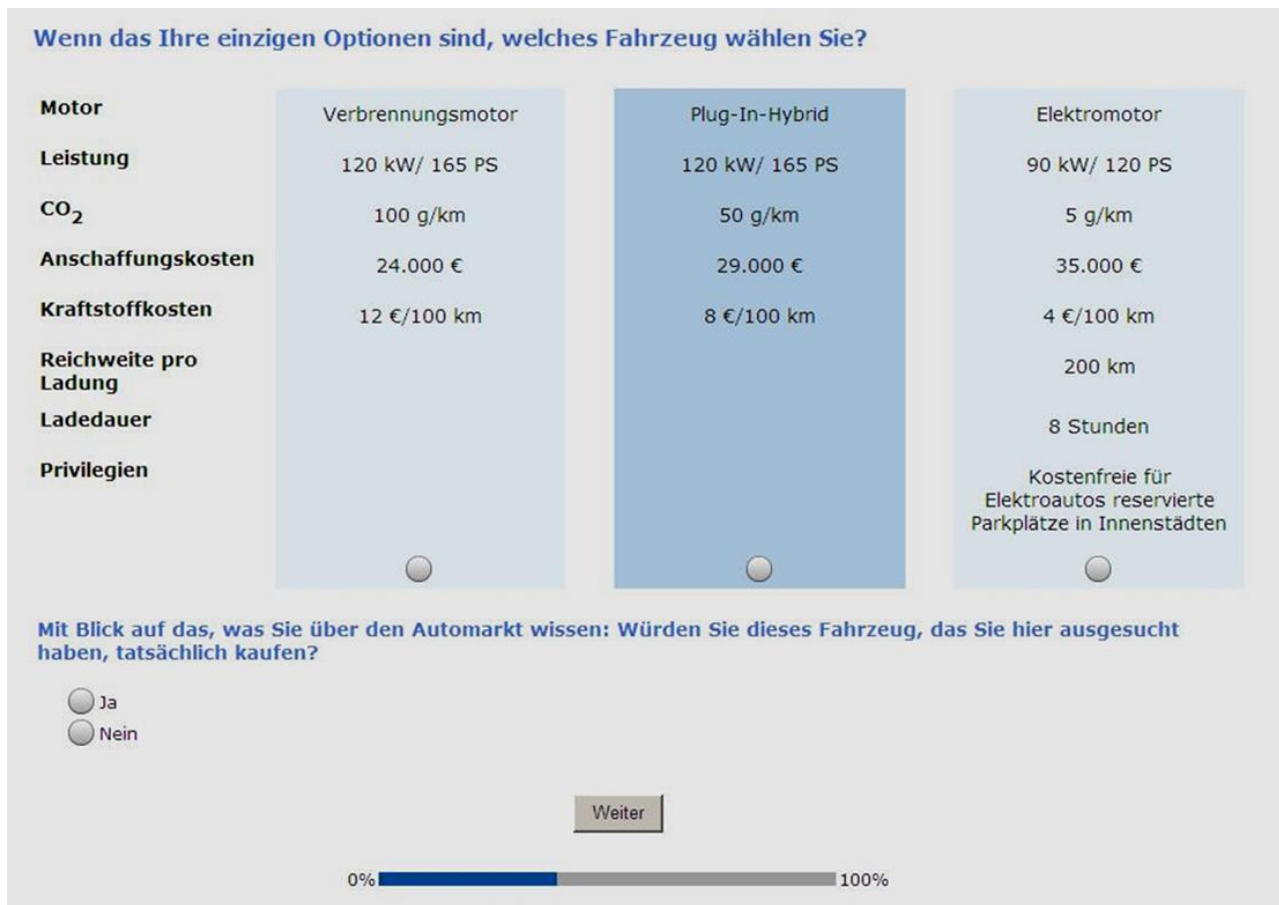
Source: Authors' own calculations, MiD 2008

The mentioned restrictions are applied to all cars of the car usage database that is derived from the mobility data of MiD 2008. The maximum potential for the market share of electric vehicles is determined and the share of new electric vehicle registrations cannot exceed the maximum potential value for each car buyer group.

### 3.1.2. Modelling the purchase decisions – conjoint analysis and potential market shares

The modelling of the purchase decisions between passenger cars that have different propulsion systems and different technology and cost characteristics is the main part of the approach used to derive the market penetration of electric vehicles in DEFINE. The purchase decisions of new car buyers depend on different technical features of the provided cars and other *soft* characteristics such as image and familiarity with new technologies. Pure cost analyses seem not to be sufficient to explain the car registration structure and a conjoint analysis is conducted to model the purchase decisions of new car buyers in 2020 and 2030. The conjoint analysis assumes that the purchase decisions are mainly based on a few relevant attributes and how the new car buyers evaluate different levels of these attributes.

Figure 3-4: Example of conjoint task



Source: Authors' own diagram

The survey used for purchase decision modelling was conducted as part of the OPTUM study that was realised by Oeko Institut and ISOE<sup>5</sup> in 2010 and 2011. Different levels of 7 attributes were randomly combined for a CV, a PHEV/REEV and a BEV to illustrate the purchase decisions between these three types of cars and each interviewee had to select one of the presented cars. The decision task was repeated 18 times by each interviewee with different sets of randomly selected attribute levels to guarantee enough data to enable a high quality estimation of the purchase decisions. Finally, the purchase decisions can be simulated by definition of *realistic* cars and regression methods that evaluate the answers of the interviewees. The attributes chosen for the conjoint analysis are the following (see Figure 3-4 for an example of a conjoint task):

- propulsion technology
- motor power (kW)
- retail price (€)
- fuel/electricity costs (€/km)
- type approval (NEDC) CO<sub>2</sub> emissions (g CO<sub>2</sub>/km)
- maximum mileage (km) – only applied in the case of BEVs

<sup>5</sup> Institut für sozial-ökologische Forschung.

- charging duration (h) – only applied in the case of BEVs
- privilege of free, reserved parking in city centres (yes/no) – only applied in the case of BEVs.

The conjoint analysis is divided into subgroups according to the size class of the cars and around 500 interviewees per size class participated in the survey. The participants were recruited as a representative sample according to the *Verbraucheranalyse 2010* (2010 Consumer Analysis), which handles analyses regarding new car buyers. The interviewees were also required to have stated the desire to buy a new car within two years after participating in the survey. More information about the approach and the methodology of the conjoint analysis is given in Götz et al. (2011).

The definition of a typical, average car per size class and propulsion technology is required for each modelling year to evaluate the survey. The technical configurations and the cost data of the vehicles are taken from the technology database of eMobil 2050 and the assumptions for energy costs and policy measures are applied in the case of the two scenarios (see chapter 2 for more information). An overview of the cars and their attribute levels used in DEFINE for the purchase decision modelling in 2020 and 2030 can be found in Table 3-2 and Table 3-3.

**Table 3-2: Characteristics of average passenger cars in the BAU scenario**

	small car			mid-size car			large car	
	BEV	PHEV	CV	BEV	PHEV	CV	PHEV	CV
2020								
Motor power [kW]	51	60	60	77	90	90	150	150
CO <sub>2</sub> emissions [g/km]	5	26	93	5	31	110	26	117
Retail price [€]	23.541	21.700	14.682	30.259	28.814	21.444	43.575	34.408
Fuel/electricity costs [€/100km]	4,07	5,36	7,52	4,64	6,49	8,94	6,05	8,07
Maximum mileage [km]	150			150				
Charging duration [h]	3			3,5				
Privilege	no			no				
2030								
Motor power [kW]	51	60	60	77	90	90	150	150
CO <sub>2</sub> emissions [g/km]	5	22	76	5	26	91	25	96
Retail price [€]	21.836	21.026	16.018	28.038	27.809	21.880	41.430	35.158
Fuel/electricity costs [€/ 100km]	4,60	5,87	6,95	5,64	7,05	8,26	7,39	7,52
Maximum mileage [km]	150			150				
Charging duration [h]	2,5			3,5				
Privilege	no			no				

Source: Authors' own assumptions (derived from Hülsmann et al. 2014)

Most characteristics of the average cars for conjoint analysis are the same or very similar for 2020 and 2030 and few changes are made between BAU and EM<sup>+</sup> scenario. Since the policy measures of EM<sup>+</sup> scenario aim to change the cost difference between electric and conventional cars, the greatest variation between the simulation years and the scenarios is assumed for the retail price and the specific fuel/electricity costs. In almost all cases, BEVs have the highest retail price of the different propulsion system options and conventional cars are the most favourable option with regard to the retail price. The retail price gap between electric driven vehicles and conventional cars is reduced in the EM<sup>+</sup> scenario by implementation of the feebate system and the higher cost of better energy efficiency level requirements of conventional cars to satisfy the stricter CO<sub>2</sub> regulation.

**Table 3-3: Characteristics of average passenger cars in EM<sup>+</sup> scenario**

	small car			mid-size car			large car	
	BEV	PHEV	CV	BEV	PHEV	CV	PHEV	CV
2020								
Motor power [kW]	51	60	60	77	90	90	150	150
CO <sub>2</sub> emissions [g/km]	5	26	93	5	31	110	26	117
Retail price [€]	21,402	20,631	15,250	28,120	27,744	22,068	42,505	35,106
Fuel/electricity costs [€/100km]	4.07	5.53	8.12	4.64	6.69	9.65	6.52	10.24
Maximum mileage [km]	150			150				
Charging duration [h]	3			3.5				
Privilege	no			no				
2030								
Motor power [kW]	51	60	60	77	90	90	150	150
CO <sub>2</sub> emissions [g/km]	5	21	67	5	22	80	22	85
Retail price [€]	21,274	21,011	17,712	27,461	28,080	23,094	41,909	38,505
Fuel/electricity costs [€/ 100km]	4.52	6.23	7.96	5.55	7.30	9.46	7.92	9.80
Maximum mileage [km]	150			150				
Charging duration [h]	2.5			3.5				
Privilege	no			no				

Source: Authors' own assumptions (derived from Hülsmann et al. 2014)

Electric driven vehicles have the considerable advantage of lower energy costs compared to conventional cars, but the difference between cars with different propulsion systems decreases from 2020 to 2030. The main factors are the additional taxation of electricity for car usage and the high efficiency gains of conventional cars that are enforced by CO<sub>2</sub> regulation. In fact, the fuel cost per mileage of conventional cars decreases from 2020 to 2030 in the BAU scenario due to their efficiency gains. The EM<sup>+</sup> scenario contains higher energy taxes on conventional fossil fuels and the specific energy price gap between electric driving and the use of the combustion engine increases compared to the BAU scenario. However, the even better energy efficiency level of conventional cars outweighs the higher energy taxation levels and specific energy costs of conventional cars decrease from 2020 to 2030 even in the EM<sup>+</sup> scenario.

The group of interviewees is divided further for the evaluation step of the conjoint analysis. The conjoint analysis is conducted separately for the three size classes of the DEFINE project. Additionally, the interviewees are divided with regard to the spatial planning classification of their home (core city and outskirts/rural areas) and with regard to the opportunity to charge the vehicle at the owner's property. These groups show different purchase decision behaviour and involve different restrictions due to their car usage and infrastructure requirements (see chapter 3.1.1).

The conjoint analysis shows that the market potential of electric vehicles is nearly as high as 50 % of all new car buyers and the acceptance of electric vehicles remains almost constant between 2020 and 2030 (Table 3-4). This is caused by the counteracting impact of lower electric vehicle retail prices and higher specific energy costs in 2030 when relating electric vehicles to conventional cars. The overall market potential increases to 58 % in the EM<sup>+</sup> scenario and remains nearly constant between 2020 and 2030. The reasoning for the equal acceptance of electric vehicles over time is the same as for the BAU scenario. The conjoint analysis also displays a higher market potential for PHEVs/REEVs in almost all car buyer groups.



**Table 3-4: Market potential of electric vehicles in 2020 and 2030 – divided into new car buyer groups (size class, spatial planning classification of car owners’ home and parking opportunity at their own property)**

	small car		mid-size car		large car
	BEV	PHEV/REEV	BEV	PHEV/REEV	PHEV/REEV
2020 - BAU - core city					
own property parking	13,5%	32,5%	26,1%	39,4%	61,5%
public space parking	21,1%	32,7%	20,5%	28,5%	50,9%
2020 - EM+ - core city					
own property parking	16,4%	35,9%	28,4%	41,1%	70,0%
public space parking	23,7%	35,5%	22,3%	30,1%	59,0%
2020 - BAU - outskirts/rural areas					
own property parking	18,1%	23,4%	8,3%	35,7%	32,9%
public space parking	30,6%	27,3%	29,0%	35,1%	57,4%
2020 - EM+ - outskirts/rural areas					
own property parking	20,2%	27,7%	9,1%	40,9%	42,7%
public space parking	33,1%	30,1%	30,4%	37,8%	64,0%
2030 - BAU - core city					
own property parking	14,6%	31,9%	24,2%	38,5%	56,3%
public space parking	21,9%	29,9%	19,6%	29,5%	48,2%
2030 - EM+ - core city					
own property parking	19,9%	35,0%	26,3%	40,2%	69,7%
public space parking	26,5%	32,5%	21,3%	31,8%	61,7%
2030 - BAU - outskirts/rural areas					
own property parking	19,4%	22,3%	7,4%	34,2%	29,7%
public space parking	31,5%	26,6%	28,4%	33,3%	56,0%
2030 - EM+ - outskirts/rural areas					
own property parking	21,3%	25,9%	8,4%	39,5%	43,0%
public space parking	34,7%	29,7%	30,1%	35,9%	63,5%

Source: Authors’ own calculations

The purchase behaviour of the different new car buyer groups varies quite strongly and is the highest with the car buyers of mid-size cars. Additionally, a clear trend is obvious with the car buyers that live in the core city and in the outskirts/rural areas. The acceptance of electric vehicles is considerably higher with car owners in core cities. The same counts – counter-intuitively – on average for car owners who do not have the option of parking their car at their own property and require (semi-)public infrastructure to use an electric driven vehicle. This trend is especially evident for car buyers who live in the outskirts/rural areas. The car buyers who live in city centres (smaller ratio of car owners with a parking opportunity at their own property) are more aware about the parking situation and the acceptance level is slightly higher with car owners who hold the opportunity to park at their own property.

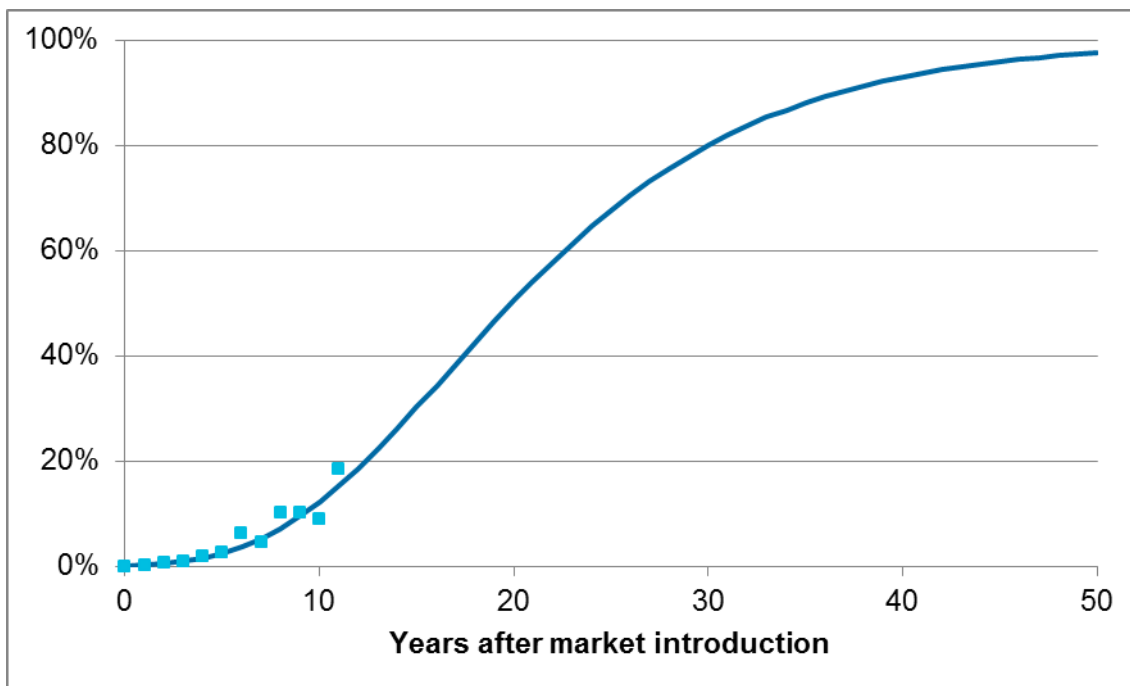
**3.1.3. Market diffusion – consideration of a diffusion factor**

A central assumption of the conjoint analysis is the comparability of the presented variety (models and design features) of electric and conventional cars. In reality, the comparability is not given since the car makers have different time schedules for the market introduction of electric vehicles and the number of electric vehicle models is smaller during the market penetration phase. Additionally, car makers need time to build up the car production facilities for electric vehicles and have to establish new processes to integrate batteries and other new technologies into the

manufacturing process. These factors are assumed to result in a lag of market penetration compared to the results of the conjoint analysis. Therefore, the acceptance level of electric vehicles from the conjoint analysis has to be reduced for the market penetration derivation.

A common approach to considering these barriers of market penetration is the use of a market diffusion factor. This factor estimates the ratio of the potential market share that can be obtained at a certain time period after the first market introduction of a new technology or a product. All factors that are mentioned in the previous paragraph are pooled together in this factor to facilitate consideration of the different barriers of market penetration.

**Figure 3-5: Market diffusion factor development for electric vehicles in DEFINE – ratio of potential market share**



Source: Hacker et al. 2011

A market diffusion factor can be determined in different ways. A very detailed approach would be the use of simulation models of changes in the production process and how the car makers adjust to changes in the vehicle market. This approach requires high resolution level models of the car production industry and seems too exaggerated for the modelling approach in DEFINE. A less detailed approach is the use of experiences from market penetration in the past. It was decided that the diffusion factor pathway derived in the OPTUM study (Hacker et al. 2011) would be used. This derivation of the diffusion factor uses historic data of market introduction of hybrid electric vehicles in the US market and a data fit to a Gompertz function is conducted (Figure 3-5). The base year of the market diffusion factor development is set as 2010 and 12 % and 50 % of the potential market share of electric vehicles are assumed as *real* market share in 2020 and 2030.

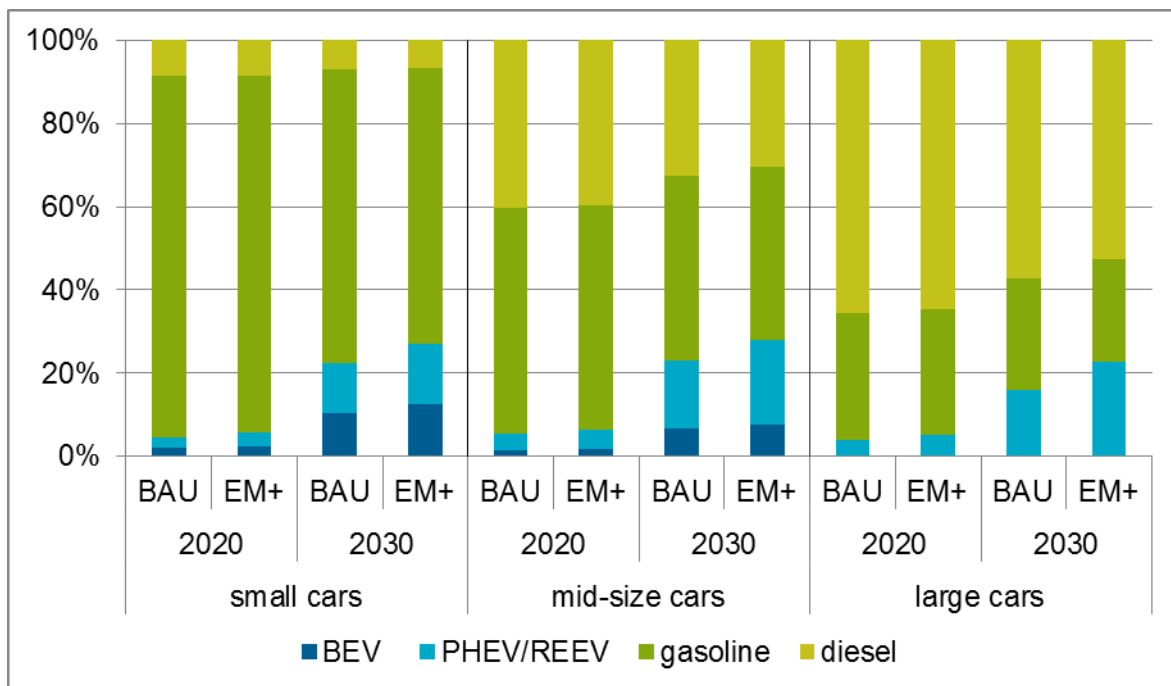
### 3.2. Market shares of electric vehicles

The market shares are derived in consideration of the mobility demands (see chapter 3.1.1), the purchase decisions of a representative group of new car buyers (see chapter 3.1.2) and the lack of

variety of electric vehicle models and the time that is needed to adapt the production processes to the requirements of electric vehicle production (see chapter 3.1.3). The modelling years for market penetration simulation are 2020 and 2030 and the electric vehicle registrations are set to zero in 2010. The market shares of years in between the modelling years (2010, 2020 and 2030) are not specifically simulated, but are needed for vehicle stock calculations. Therefore, the new registrations for these years are derived by using linear interpolation between the modelling years.

Figure 3-6 shows the market structure per size class as well as the input into the new car registration calculation with TEMPS.

**Figure 3-6: Passenger car market structure per size class in 2020 and 2030 – variation in propulsion system**



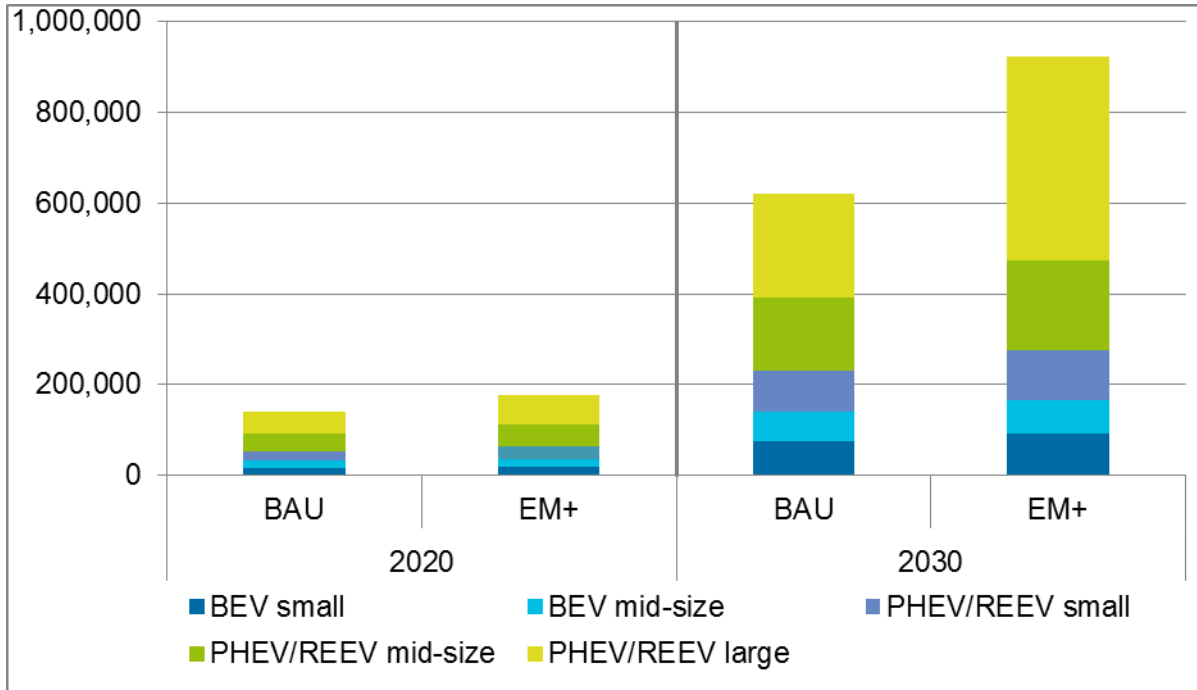
Source: Authors' own calculations

The market structure mirrors the results from the conjoint analysis and the differences between the two scenarios become evident only in 2030. The market share of electric vehicles increases over time from values of around 5 – 6 % (2020) to a market share of about 23 – 28 % (2030) in the EM<sup>+</sup> scenario. The market shares in the BAU scenario are significantly smaller in 2030 (16 – 23 %) and the difference between the two scenarios is the largest in the case of large cars since the acceptance level of electric vehicles increases the most in this size class. Pure electric vehicles (BEVs) gain the largest market shares in the small car segment and increase to 13 % of the new car registrations in 2030 in the EM<sup>+</sup> scenario.

The final distribution of new car registrations depends on the calculations of the total number of new cars per size class which is modelled using TEMPS. The total number of electric vehicle registrations in 2020 is around 150,000 cars, of which the larger share is PHEVs and REEVs. The difference between the two scenarios is rather small (around 35,000 cars). The difference between the scenarios adds up to 300,000 cars in 2030 and the number of electric vehicle registrations rises roughly by 50 % from BAU to EM<sup>+</sup> scenario. In total, 920,000 electric vehicles will be

registered in 2030 in the EM<sup>+</sup> scenario. The larger share of roughly 750,000 new registered cars is PHEVs and REEVs.

**Figure 3-7: Total number of electric vehicle new car registrations in 2020 and 2030**



Source: Authors' own calculations (TEMPS)

### 3.3. Vehicle stock of electric passenger cars

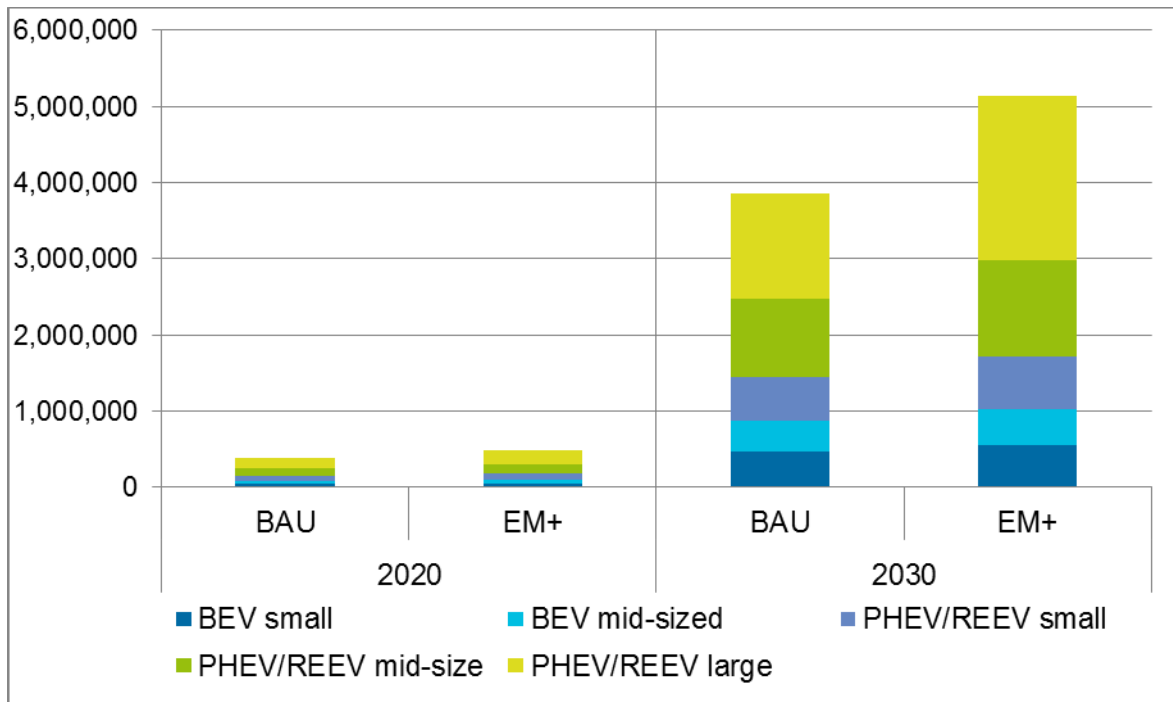
The relevant parameter for energy demand calculation and the analysis of interactions between the transport sector and the electricity dispatch is the vehicle stock. Oeko Institut's scenario modelling tool TEMPS is used for vehicle stock derivation and for the energy demand calculations. Assumptions of scrappage rates, annual mileage of cars and the total mileage of all cars are taken from Hacker et al. (2014) and can be found there.

The decisive parameters of the vehicle stock are the number and the corresponding specific energy demand and mileage. The total number and stock structure of electric vehicles are displayed in Figure 3-8. The total number of electric vehicles is distinctively higher in the EM<sup>+</sup> scenario than in the BAU scenario since the policy measures for electromobility support an increase in the attractiveness of electric driven cars. In this case, the vehicle stock holds close to 500,000 electric vehicles in 2020 and roughly 5.1 million electric vehicles in 2030. The larger share is PHEVs and REEVs (compare to the new registration in chapter 3.2). This amount represents close to 13 % of all passenger cars in 2030. The total number of electric vehicles decreases to approx. 400,000 in 2020 and 3.9 million electric vehicles when no policy measures are applied for the market penetration support of electromobility. The electric vehicle share is less than 10 % in this case.

The German government set a target of 1 million electric vehicles in 2020 and 6 million electric vehicles in 2030. These targets are not met in both scenarios. The EM<sup>+</sup> scenario meets the target

of 1 million electric vehicles in 2022 and 6 million electric vehicles would be reached in 2031. The calculations of DEFINE only consider passenger cars. Therefore, the targets for electric vehicles could potentially be reached earlier in the scenarios when taking into account other vehicles such as light commercial vehicles and/or microcars.

**Figure 3-8: Vehicle stock of electric cars in 2020 and 2030**



Source: Authors' own calculations (TEMPS)

#### 4. Electricity dispatch modelling and electric vehicle car usage patterns

High resolution electricity dispatch modelling simulates the operation of electricity production capacities with regard to a given electricity demand and a given set of electricity production facilities. The electricity demand of electric vehicles is different in the two scenarios and varying electricity dispatch and subsequently different CO<sub>2</sub> emissions of the electricity production sectors may arise. Thus, an electricity dispatch model of DIW Berlin is applied in DEFINE to show the effect of electric vehicles on the electricity production sector (see Gerbaulet and Schill, 2014).

The main concept of the electricity market is the matching of offered production capacities and the electricity demand at an hourly basis. Each hour, the offered capacities are stacked up according to increasing price (merit order) and the capacities up to the electricity demand are supposed to dispatch the electricity. Additionally, operation restrictions such as the start-up and the shut-down processes of power plants are to be considered. The decisive parameters for pricing at the electricity market are the short-term marginal costs of each electricity production capacity. Therefore, the electricity dispatch can be modelled by minimising the short-term marginal costs as well as start-up costs of the electricity production for a given electricity demand. The operation status and the start-up and shut-down requirements of each power plant are also included in the DIW model to minimise the costs of power production of the total modelling period. Restrictions

due to the electricity transmission and distribution grid are not considered in this study and electricity dispatch and electric vehicle charging depends wholly on the market scheme that is outlined above.

The framework conditions of the electricity market – electricity production capacities and electricity demand – are derived from the assumptions of the *Netzentwicklungsplan Strom 2013* (50 Hertz et al. 2013), which is used for transmission grid planning in Germany. Electricity consumption in Germany (without electricity demand from electric vehicles) is assumed to be around 560 TWh in both 2020 and 2030. Renewable generation capacities increase from 55 GW in 2010 to 121 GW in 2020 and 158 GW in 2030. Additionally, the energy demand of electromobility is required to simulate the impact of electric vehicles on the electricity production sector.

DIW Berlin developed a module for representation of electric vehicles in its electricity dispatch model in DEFINE. The input required for consideration of electric vehicles in electricity dispatch modelling is provided by Oeko Institut and consists of:

- energy consumption of the electric vehicles,
- the information of connectivity to a charging station/spot, and
- the information of maximum charging power at a charging station/spot.

This information is derived by combining the specific energy consumption data of electric vehicle stock development and car using patterns that are based on current passenger car use. Finally, 28 different electric car usage patterns (16 for BEV, 12 for PHEV/REEV) which have the required information for each hour of a year are applied in the electricity dispatch model for representation of the total electric vehicle stock.

#### 4.1. Electric vehicle car usage patterns

Representative mobility data of one day from all members of around 26,000 households is transformed from an individual level to a representation of car use in Germany (see chapter 3.1.1). This new database on car use in Germany is exploited to develop representative yearly car usage profiles that can be applied in electricity dispatch modelling. The electricity dispatch modelling requires the information of energy consumption and connectivity to a charging spot for the whole year and in hourly resolution, but the car usage data from MiD 2008 is given for one day. Thus, average car use profiles for weekdays, Saturday and Sunday are derived and combined to yearly car usage patterns.

As a first step, the whole database is divided with regard to the day of car use (weekday, Saturday and Sunday), the size class of the passenger car (small, mid-size and large) and the spatial planning category (core city and outskirts/rural areas) of where the car owner's household is located. These new datasets are the basis of the average car usage profiles that are derived for each category and all data is divided further into five car usage profiles:

- profile 1: no car use
- profile 2: first trip before 12 pm and daily mileage above 40 km
- profile 3: first trip before 12 pm, daily mileage less than 40 km and at least one trip to work
- profile 4: first trip before 12 pm, daily mileage less than 40 km and no trip to work, and
- profile 5: first trip after 12 pm.

The average car usage profiles consist of:

- the starting time of the first trip,
- the starting time of the longest parking period of the day,
- the duration and location of the longest parking period of the day, and
- the ending time of the last trip of the day.

It is assumed that all cars start their first trip from home and end their last trip at home and the cars are parked either at the car owner’s property or in the public space over night. It is also evident that only two trips per day are represented in the average car usage profiles and the daily mileage of the cars is divided into two trips according to the duration of these two trips. Thus, short trips and short parking periods are not incorporated in the average profiles, but the average mileage of all trips is considered in the profiles. Finally, the average of all datasets is specified for each category to obtain average car usage profiles. Average car usage profiles of mid-size cars are presented as an example in Table 4-1; all profiles are shown in Annex I.

**Table 4-1: Electric vehicle car usage pattern – weekday; mid-size cars**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>core city</b>									
1	0	-	-	-	-	-	-	11.361	42%
2	85	07:43	09:29	15:58	18:37	06:29	13:06	17.468	14%
3	21	07:17	07:57	16:10	17:40	08:13	13:37	14.427	18%
4	16	09:32	10:27	13:33	14:49	03:06	18:43	10.480	15%
5	25	15:39	16:14	18:18	18:53	02:04	20:46	12.222	12%
average	21							12.756	
<b>outskirts/rural area</b>									
1	0	-	-	-	-	-	-	14.026	39%
2	84	07:42	09:05	15:54	18:31	06:49	13:11	21.384	20%
3	21	07:16	08:08	15:55	17:40	07:47	13:36	15.541	16%
4	17	09:25	10:26	13:37	14:49	03:11	18:36	12.277	16%
5	28	15:24	16:02	18:25	19:02	02:23	20:22	14.989	10%
average	25							15.538	

Source: Authors’ own calculations (derived from MiD 2008)

As a second step, the average car use profiles of one day are combined to obtain weekly car use profiles. All databases were further divided by yearly mileage<sup>6</sup> and each car profile of a weekday is randomly connected to one profile of a Saturday and Sunday. Thus, only car usage profiles of the same size class, the same spatial planning classification of the car owner’s home and the same yearly mileage category are combined as weekly car usage profiles. The weekday car usage of this combination is applied for every day of the week and the weekly car usage profile is repeated each week of one year to obtain a yearly profile of car usage.

The MiD 2008 database underestimates – similar to other empirical mobility databases – long trips and the average yearly mileage cannot be described by the addition of daily mobility patterns that are given in MiD 2008. Additionally, some car usage profiles with no car use on the weekdays (see profile 1) are created by the approach used to derive yearly car usage. Therefore, the yearly profiles show less mileage on average than MiD 2008 and other empirical databases state for the entire vehicle stock.

<sup>6</sup> Small yearly mileage (< 10,000 km), average yearly mileage (10,000 to 20,000 km) and high yearly mileage (> 20,000 km).

Thus, trips are randomly added to the yearly profiles in a third step to achieve the average yearly mileage of each car profile category (size class and spatial planning category). Generally, long trips and short trips are added to the profiles. The data for short trips is taken from the profiles that are derived for weekdays, Saturday and Sunday. The data for long trips is MiD 2008 average data of all trips beyond a certain trip length. Car usage profiles are varied for BEVs and PHEVs/REEVs as more long trips are added to the yearly PHEV/REEV profiles compared to BEV profiles. In total, the added mileage of BEVs is the same as for PHEVs/REEVs and more short trips are added.

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PHEVs and REEVs contain an electric and an internal combustion engine for propulsion. The share of the electric driving mode depends on the car usage, the frequency of grid connectivity and the interaction of both propulsion systems. It seems probable that neither pure serial nor pure parallel drive train architectures will be applied in PHEVs and REEVs.

Thus, PHEVs and REEVs are considered in a simplified manner in electricity dispatch modelling. The electric engine is used primarily for driving and the internal combustion engine is exclusively started when the battery for electric driving is completely discharged. As a consequence, the share of electric driving mode merely depends on the car usage pattern and the frequency of charging station connectivity of each car.

The differences in the assumptions for connectivity to charging stations become evident when comparing the electric drive share of PHEVs/REEVs for 2020 and 2030. It increases from 55 % to over 60 % due to the higher frequency of grid connectivity and more frequent recharging procedures.

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The relevant information for electricity dispatch modelling is the energy consumption of the vehicles and the connectivity (time and maximum charging power) of the passenger cars to the charging station. The energy consumption is directly calculated by the combination of the specific energy consumption of the electric vehicle stock from TEMPS and the driving patterns and the trip lengths derived from MiD 2008. The information on the connectivity to charging stations and to the electricity grid is created by combining the parking (time and location) of the car usage profiles with the assumptions for charging infrastructure and the willingness of the car users to connect the electric car to the grid.

It is assumed that car owners have a charging spot at their property if they buy an electric vehicle and that they connect the car to the charging station at every possible time. An increase of (semi-)public infrastructure over time is adopted in both scenarios (see chapter 2.3). The assumption is that vehicles are connected to a charging station in 10 % of parking events in (semi-)public space (at work, during leisure time activities and shopping, (semi-)public parking overnight) in 2020. The share of connectivity in (semi-)public space increases to 30 % of (semi-)public parking events in 2030. Thus, the connectivity events are randomly distributed over all parking events and the plausibility of all profiles is checked by ensuring the satisfiability of the derived electric car usage and charging spot connectivity profiles.

Finally, 28 different electric vehicle profiles are selected to represent the total electric vehicle stock in the DIW Berlin dispatch model. Profiles of all categories (BEVs and PHEVs/REEVs; small, mid-size and large cars; core city and outskirts/rural areas; parking spot at own property and (semi-)public overnight parking) are selected and the dimension of the average yearly mileage of each size class is obtained on average by the chosen car usage profiles.



## 4.2. Electricity dispatch modelling – Two different modes of charging electric vehicles

Time-dependent power demand from electric vehicles and the interaction between electricity dispatch and electromobility are strongly linked to the mode of charging. Two extreme modes of charging can be distinguished: purely user-driven charging and purely cost-driven charging. Pure user-driven charging is characterised by:

- starting the charging process immediately after the connection to the charging station has been established and
- recharging the battery of the electric vehicles as fast as possible to its maximum capacity.

Pure cost-driven charging describes a different mode of recharging electric vehicles and it is characterised by:

- giving the electricity dispatch model full control over the time and power of the charging process on the condition that the vehicle is connected to the charging station and that all trips of the car usage profiles are compliant.

Both modes are analysed in DEFINE and the results with regard to electricity dispatch are presented for both charging modes (see chapter 5). User-driven charging is focusing on the demand of the electric car users and gives them control over the starting time of the recharging process of their cars. Cost-driven charging minimises the cost of the electricity production and potentially reduces power demand peaks of electric vehicles by shifting the charging process to low electricity price hours and by avoiding the power demand peak hours that are linked with high electricity prices. Additionally, transmission and particularly distribution grid bottlenecks may force the energy system operators to shift the charging process to off-peak hours or to reduce the power of the recharging process. This charging mode is not modelled in DEFINE since the applied electricity model of DIW Berlin does not integrate the electricity grid in their simulation runs.

It seems plausible that neither pure user-driven nor pure cost-driven charging will be applied in the case of electric vehicles in the real world. It appears more probable that some kind of hybrid charging mode will be established in which the vehicles are charged immediately to a certain capacity level and the charging process is driven by grid requirements and electricity dispatch prices after reaching this capacity level.

Nevertheless, the results of both charging modes that are presented in chapter 5 give valuable insight to the interactions of increasing shares of electric vehicles and the power market. However, it is important to keep in mind that the given results show both extremes of purely user and purely cost-driven electric vehicle charging.

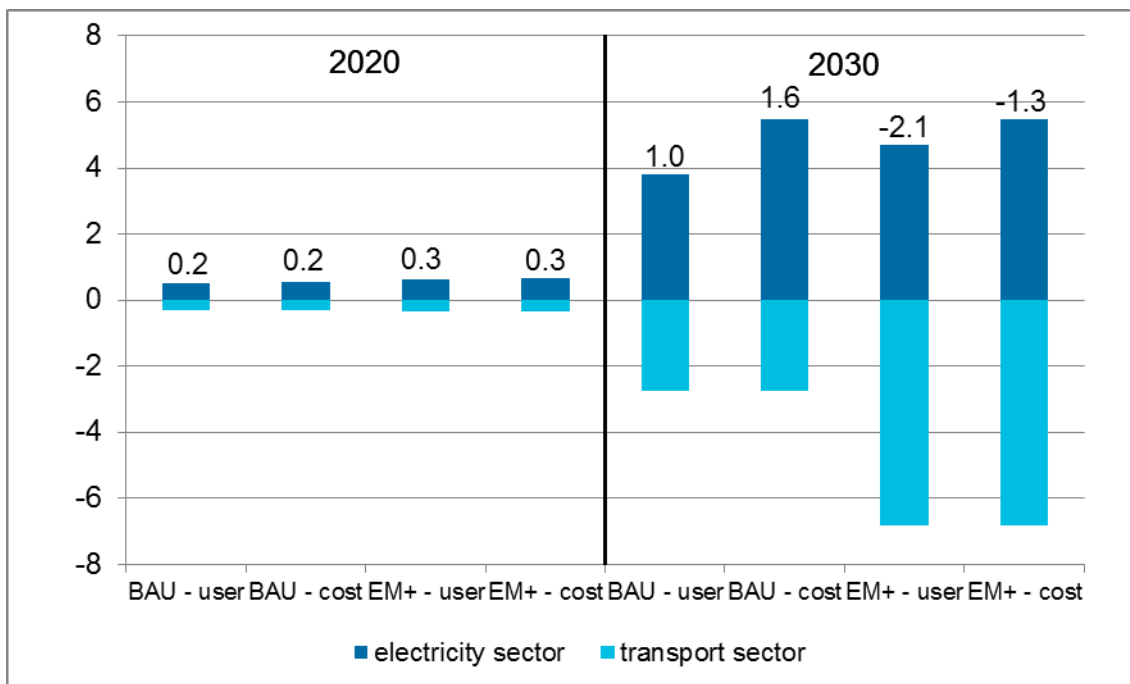
## 5. Electricity demand and CO<sub>2</sub> emissions of electric vehicles

Electric vehicles have a better energy efficiency than conventional vehicles and the final energy consumption can be reduced by market introduction of electric driven vehicles. The case is not straightforward for CO<sub>2</sub> emission mitigation. Obviously, the CO<sub>2</sub> emissions are reduced in the transport sector by zero emission driving of electric propulsion systems, but the additional power demand of the electric vehicles might increase the CO<sub>2</sub> emissions of the electricity production. However, the level of additional emissions of electricity production – when compared to an energy system without electromobility – can be traced back to electric vehicles alone. The emissions of electricity production depend on several factors, i.e. the flexibility of other electricity consumers, the

flexibility and controllability of the power production capacities, the market design. Therefore, the rationale of this study is to show the impacts of adding electromobility to the energy system and to understand if and how adjustments have to be made to achieve the full potential of the CO<sub>2</sub> mitigation of electric vehicles.

The CO<sub>2</sub> balance combines the transport sector modelling and the impact on total emissions in the transport sector (TEMPS) with the electricity dispatch modelling and the emissions from electricity production. The same mileage of the passenger cars is applied in all modelling runs and the electricity production capacities are fixed. The parameters that are changed between the modelling runs are the efficiency of conventional cars (see assumptions for CO<sub>2</sub> regulations in chapter 2.1) and the number of electric and conventional cars (see chapter 3.3). Thus, changes in the CO<sub>2</sub> balance are caused by the varying energy consumption of conventional cars (efficiency and number of cars) and by different operation of electricity production capacities. The base case that is used for comparison of CO<sub>2</sub> emissions in all the following diagrams is a scenario in which the energy efficiency values of the BAU scenario are applied to the transport sector and no electric vehicles are integrated in the vehicle stock.

**Figure 5-1: CO<sub>2</sub> impact of electric vehicles to transport sector and electricity sector in 2020 and 2030 (M t CO<sub>2</sub>) – user = user-driven charging; cost = cost-driven charging**



Source: Authors' own calculations (TEMPS, Schill et al. 2014)

Figure 5-1 displays the CO<sub>2</sub> impact of the two market scenarios (BAU and EM<sup>+</sup>) of electric vehicles and the different charging modes (user-driven and cost-driven) that are applied in electricity dispatch modelling. Therefore, the mitigated CO<sub>2</sub> emissions of the transport sector are set against the additional CO<sub>2</sub> emissions of the electricity generation and the net CO<sub>2</sub> balance in comparison to the scenario without electromobility is calculated. It is not surprising that the impact on CO<sub>2</sub> emissions (and energy demand) is still very small in 2020. The electricity consumption of electric

passenger cars accounts for less than 0.2 % of total electricity consumption in 2020. The electromobility share of total electricity consumption increases to roughly 1.2 – 1.6 % in 2030.

As a consequence of the small electric vehicle stock, the effect on CO<sub>2</sub> emissions is also very small in 2020. The emissions of the transport sector decrease by 0.3 to 0.4 M t CO<sub>2</sub>, but the CO<sub>2</sub> balance shows a net gain of CO<sub>2</sub> emissions due to the rising emissions of the electricity sector. The same holds for the BAU scenario in 2030. The net increase of CO<sub>2</sub> emissions is roughly 1.0 – 1.6 M t CO<sub>2</sub> even if the transport sector emissions are mitigated by roughly 3 M t CO<sub>2</sub>. A different result arises for the EM<sup>+</sup> scenario. The net CO<sub>2</sub> emissions are lower than in the base case and the emission reduction in the transport sector (6.8 M t CO<sub>2</sub>) outweighs the additional emissions of electricity production. However, the transport sector emission reduction cannot be attributed merely to electromobility since the EM<sup>+</sup> scenario also illustrates the effect of the better energy efficiency of conventional cars in comparison to the BAU scenario and a higher share of electric vehicles. Approx. 70 %<sup>7</sup> of the additional CO<sub>2</sub> emission mitigation of the transport sector from BAU to EM<sup>+</sup> scenario can be ascribed to the lower energy consumption of conventional cars. This high amount is when considering that even in 2030 the larger part of new registrations are conventional cars and the full non-emission driving accounts only for BEVs.

The emissions of the electricity sector differ clearly between the user-driven and the cost-driven charging mode. This can be explained by changes in power plant dispatch. The user-driven charging mode involves a time-independent additional electricity load to the energy system since it is caused only by the car users and the time period of connectivity to the charging stations. Thus, the additional electricity demand starts the electricity production from capacities that have been slightly above the marginal power plant of the merit order curve. At times, this additional electricity production capacity might be surplus renewable energy that remained non-usable before adding electromobility. At other times – especially in the evening hours and in hours of low renewable energy production – the additional operating capacity might be from fossil power plants. Since high grid connectivity of electric vehicles is expected in evening hours, this additional fossil power generation is often provided by peak gas power plants (see Schill et al. 2014).

The cost-driven charging enables the electricity dispatch model to shift the charging to hours of low short-term marginal costs. Renewable production capacities have the lowest marginal costs, followed by lignite and hard-coal power plants. As a consequence, the charging is shifted as much as possible to hours of renewable surplus production and to the night when the electricity load is lower and lignite and hard-coal power plants are the typical marginal power plants. Thus, the CO<sub>2</sub> mitigation effect of better integration of renewable electricity into the energy system is combined with electricity production from high-emission production capacities such as lignite and hard-coal power plants. Overall, the cost-driven charging thus shows a higher CO<sub>2</sub> intensity of the additional electricity consumption with the given assumptions for electricity production capacities and electricity consumption derived from the *Netzentwicklungsplan Strom 2013*.

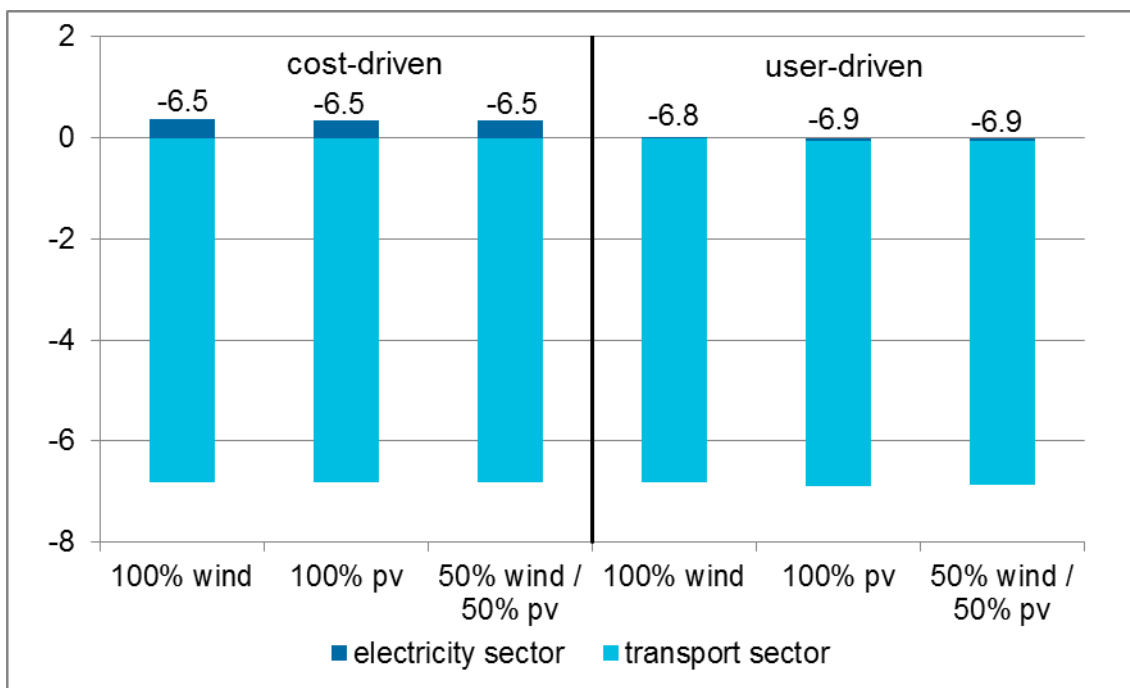
Cost-driven charging also results in optimal integration of renewable energy capacities since their marginal costs are lower compared to all other electricity production options. The electricity dispatch model uses perfect foresight and can shift the charging hours in an optimal manner to renewable electricity production hours. The share of renewable curtailment in 2030 is around 0.65% (relative to the total potential feed-in of onshore wind, offshore wind, and PV) in the scenario that does not include electricity demand from electromobility. It decreases to 0.55% in the user-driven charging mode and even further to 0.29% when the cost-driven charging is applied. In

<sup>7</sup> The number is calculated by comparing the difference between BAU and EM<sup>+</sup> scenario with the difference between the BAU and sensitivity scenario that holds the conventional car energy efficiency of BAU scenario and the new registration data of EM<sup>+</sup> scenario.

reality, this optimal use of renewables might be hampered by the unwillingness of car users to enable the energy supplier to shift charging hours as well as by restrictions and requirements due to the transmission and distribution grid.

It might be concluded that electromobility does not yield a benefit with regard to CO<sub>2</sub> emissions when considering Figure 5-1. This seems to be true with the framework conditions of the power market that are assumed as the base case. A strategy to better exploit the CO<sub>2</sub> mitigation potential of electric vehicles would be to add renewable capacities to the electricity system. Therefore, additional electricity dispatch model runs are conducted with additional renewable capacities (RE<sup>+</sup>) that produce as much electricity as is demanded by electric vehicles are added to the power production system (see Schill et al. 2014). Three sub-scenario model runs for the EM<sup>+</sup> scenario in 2030 are conducted by a) using only wind power plants (100 % wind), b) using only photovoltaics (100 % pv) and c) using wind power plants and photovoltaics (50 % wind / 50 % pv) as additional electricity production capacities.

**Figure 5-2: CO<sub>2</sub> impact of electric vehicles on transport sector and electricity sector in 2030 (M t CO<sub>2</sub>) – RE<sup>+</sup> scenario (added renewable electricity production capacities)**



Source: Authors' own calculations (TEMPS, Schill et al. 2014)

Figure 5-2 shows the net CO<sub>2</sub> balance of the transport and the electricity generation sector of the EM<sup>+</sup> scenario with the added renewable production capacities. On this account, the emissions of the EM<sup>+</sup> scenario are compared to the emissions of the scenario without electric vehicles. It is not surprising that the addition of renewable capacities results in less CO<sub>2</sub> emissions in comparison to the previous model runs. The new renewable capacities are almost completely integrated into the power system when applying the cost-driven charging mode. The charging hours are shifted very rarely to hours of additional operation of lignite and hard-coal power plants and the additional emissions of the electricity sector are limited to 0.3 to 0.4 M t CO<sub>2</sub>. The net CO<sub>2</sub> mitigation of electricity sector and transport sector is increased to 6.5 M t CO<sub>2</sub> and the mitigation potential is

almost fully exploited. The net CO<sub>2</sub> balance is even better when applying the user-driven charging mode in electricity dispatch modelling as the utilization of lignite and hard-coal power plants is decreased. The emissions of the electricity system can even be reduced compared to the case without electric vehicles and without additional renewables in two sub-scenarios, since hydro pump storage power plants can integrate the added capacities and replace lignite and hard-coal power plant operation.

Although the added renewable capacities are very well integrated, it might come about that potential renewable electricity is curtailed in some hours due to a lack of load consumers. The renewable curtailment rate is between 0.29 % and 0.55 % in the model runs without additional renewable capacities. This rate increases to 0.4 % - 0.91 % after adding renewable capacities. Since the potential renewable feed is almost completely integrated into the system, these curtailment rates are regarded as remaining very low even after adding renewable capacities to the system.

However, it can be concluded that electric vehicles have the potential to reduce CO<sub>2</sub> emissions that are caused by motorised transport. It has also been illustrated that the energy system might be adapted to the added electricity demand from the electric vehicles to achieve the CO<sub>2</sub> mitigation to the fullest.

## 6. Conclusion

The market penetration of electric vehicles and the vehicle stock in Germany up to 2030 are derived as part of the modelling framework developed in DEFINE that analyses the emission and economic effects of the market introduction of electromobility. The vehicle stock data serves as an input parameter for DIW Berlin's dispatch model, which illustrates the interactions of electric vehicles and the electricity production. The dispatch model also determines the CO<sub>2</sub> emissions of the power sector. Finally, the CO<sub>2</sub> emissions of transport and electricity sector are compared in order to show the net CO<sub>2</sub> impact of electromobility.

Two scenarios are developed to compare the impact of different electric vehicle market developments and to better understand the impact of policy measures for supporting the electromobility market. Three policy measures that improve the economics of electric vehicle usage in comparison to conventional car usage are applied in the EM<sup>+</sup> scenario. Continuation of current policies is assumed in BAU scenario.

The market penetration of electric vehicles and electric vehicle stock are derived by considering restrictions of electric vehicles and analysing acceptance data of electromobility. The impact of the applied supporting policy measure (EM<sup>+</sup> scenario) is clear and the electric vehicle stock increases to 5.1 million passenger cars in 2030. The electric vehicle stock is made up of approx. 3.9 million passenger cars in 2030 if no additional policy measures are implemented (BAU scenario). The major share of the electric car stock is PHEVs/REEVs.

The net CO<sub>2</sub> emission balance of CO<sub>2</sub> mitigation in the transport sector and the potential CO<sub>2</sub> emission increase in the electricity sector is analysed. A net gain in CO<sub>2</sub> emission is evident in the BAU scenario. The EM<sup>+</sup> scenario shows a small CO<sub>2</sub> benefit in 2030 which is attributed to lower energy consumption levels of conventional cars. If additional renewable capacities are added to the power plant fleet that has been derived before from the *Netzentwicklungsplan Strom 2013*, it can be seen that the CO<sub>2</sub> mitigation potential of electromobility can be (almost) completely exploited and the emission reduction is as high as 6.8 M t CO<sub>2</sub> in 2030.

It is evident from the work conducted for this study that electromobility contains the potential for CO<sub>2</sub> emission mitigation of the transport sector, but this potential is not exploited automatically. The electricity production capacities have to be carefully assessed in order to not add CO<sub>2</sub> emissions in the electricity production sector compared to a scenario without electromobility. In the case of the assumptions derived from the *Netzentwicklungsplan Strom 2013*, the electricity model runs show higher CO<sub>2</sub> emissions and additional renewable capacities are required to prevent an increase in GHG emissions due to electromobility. However, it is also illustrated that it is possible to achieve the full potential of GHG emission mitigation of electric vehicles and that electric vehicles are able to fulfil their role as one part of a GHG emission mitigation strategy for the transport sector.

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## Annex

### Annex I. Electric vehicle car usage pattern

**Table I-1: Electric vehicle car usage pattern – weekday; core city**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	10.119	42%
2	85	07:35	09:22	16:21	18:57	06:59	12:38	17.173	11%
3	20	07:24	08:08	16:11	17:34	08:03	13:50	11.774	19%
4	16	09:17	10:11	13:56	15:04	03:45	18:13	9.954	16%
5	33	15:08	15:54	18:55	19:38	03:01	19:30	10.692	12%
average	20							11.245	
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	11.361	41%
2	85	07:43	09:29	15:58	18:37	06:29	13:06	17.468	14%
3	21	07:17	07:57	16:10	17:40	08:13	13:37	14.427	18%
4	16	09:32	10:27	13:33	14:49	03:06	18:43	10.480	15%
5	25	15:39	16:14	18:18	18:53	02:04	20:46	12.222	12%
average	21								
<b>large cars</b>									
1	0	-	-	-	-	-	-	12.497	43%
2	110	08:15	10:11	16:21	18:59	06:10	0,55	24.586	14%
3	21	07:20	08:01	16:24	17:49	08:23	0,56	14.118	17%
4	17	09:41	10:45	14:04	15:29	03:19	0,76	12.827	14%
5	27	15:31	16:09	18:30	19:14	02:21	0,85	13.298	11%
average	24							14.573	

Source: own assumptions (derived from MiD 2008)

**Table I-2: Electric vehicle car usage pattern – weekday; outskirts/rural area**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	9.768	39%
2	84	07:27	08:48	15:50	18:18	07:02	13:09	16.921	17%
3	21	07:21	08:01	15:41	17:25	07:40	13:56	11.262	18%
4	18	09:10	10:05	13:39	14:55	03:34	18:15	10.492	15%
5	23	15:16	15:50	18:30	19:04	02:40	20:12	11.731	11%
average	23							11.582	
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	14.026	39%
2	84	07:42	09:05	15:54	18:31	06:49	13:11	21.384	20%
3	21	07:16	08:08	15:55	17:40	07:47	13:36	15.541	16%
4	17	09:25	10:26	13:37	14:49	03:11	18:36	12.277	16%
5	28	15:24	16:02	18:25	19:02	02:23	20:22	14.989	10%
average	25							15.538	
<b>large cars</b>									
1	0	-	-	-	-	-	-	12.883	38%
2	91	07:36	09:01	15:55	18:17	06:54	13:19	21.891	20%
3	21	07:14	08:04	16:08	17:42	08:04	13:32	16.558	15%
4	17	09:18	10:11	13:16	14:19	03:05	18:59	13.129	15%
5	27	15:07	15:41	17:57	18:34	02:16	20:33	15.007	11%
average	27							15.563	

Source: Authors' own assumptions (derived from MiD 2008)



**Table I-3: Electric vehicle car usage pattern – Saturday; core city**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	9.976	57%
2	133	07:27	10:12	17:20	19:60	07:08	11:27	17.370	7%
3	19	07:17	07:46	14:30	15:42	06:44	15:35	8.255	5%
4	16	09:21	10:17	14:00	14:48	03:43	18:33	11.598	17%
5	39	14:60	15:35	17:54	18:50	02:19	20:10	13.003	15%
average	19								
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	8.458	48%
2	108	09:09	10:42	15:27	17:20	04:45	15:49	16.877	11%
3	13	09:15	09:43	15:10	16:18	05:27	16:57	12.761	3%
4	15	10:07	10:60	13:49	14:39	02:49	19:28	13.988	25%
5	25	15:44	16:24	18:27	19:02	02:03	20:42	12.174	13%
average	19							11.384	
<b>large cars</b>									
1	0	-	-	-	-	-	-	8.368	48%
2	81	09:20	12:13	16:08	19:23	03:55	13:57	22.454	12%
3	18	06:21	06:53	13:06	15:42	06:13	14:39	18.058	3%
4	19	09:57	10:53	13:49	15:04	02:56	18:53	14.535	25%
5	19	15:16	16:12	19:21	19:52	03:09	19:24	12.812	12%
average	17							12.461	

Source: Authors' own assumptions (derived from MiD 2008)

**Table I-4: Electric vehicle car usage pattern – Saturday; outskirts/rural area**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	9.291	49%
2	92	08:32	10:44	15:50	18:54	05:06	13:38	15.345	10%
3	20	06:59	07:43	15:11	16:57	07:28	14:02	10.703	5%
4	16	09:59	10:51	13:58	14:39	03:07	19:20	10.821	20%
5	21	14:26	14:56	16:53	17:21	01:57	21:05	10.408	16%
average	17								
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	14.355	49%
2	115	09:01	11:36	16:39	18:56	05:03	14:05	18.836	13%
3	21	07:32	08:20	14:33	17:21	06:13	14:11	14.317	3%
4	15	09:32	10:23	13:27	14:13	03:04	19:19	12.270	22%
5	30	14:38	15:25	17:57	18:44	02:32	19:54	17.005	13%
average	23								
<b>large cars</b>									
1	0	-	-	-	-	-	-	14.592	46%
2	103	08:32	10:32	15:42	18:07	05:10	14:25	18.793	14%
3	20	07:50	08:59	14:49	15:50	05:50	16:00	14.438	3%
4	16	09:32	10:31	13:35	14:34	03:04	18:58	14.390	24%
5	34	14:29	15:12	17:41	18:26	02:29	20:03	15.983	13%
average	23							15.305	0%

Source: Authors' own assumptions (derived from MiD 2008)

**Table I-5: Electric vehicle car usage pattern – Sunday; core city**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	7.857	65%
2	98	08:52	09:47	14:56	16:22	05:09	16:30	11.372	6%
3	11	08:18	08:43	14:38	14:51	05:55	17:27	9.919	1%
4	18	08:51	09:36	14:55	15:49	05:19	17:02	13.663	10%
5	31	15:02	15:30	17:41	18:16	02:11	20:46	11.201	18%
average	13								
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	9.825	65%
2	195	09:53	11:10	15:42	18:11	04:32	15:42	20.430	8%
3	16	09:51	11:50	17:42	18:13	05:52	15:38	13.363	1%
4	17	10:06	10:46	14:12	14:55	03:26	19:11	12.531	14%
5	37	14:58	15:54	18:42	19:17	02:48	19:41	14.763	12%
average	23							11.672	
<b>large cars</b>									
1	0	-	-	-	-	-	-	9.646	62%
2	155	10:14	11:56	16:37	18:49	04:41	15:25	14.713	6%
3	28	06:53	08:38	15:16	16:54	06:38	13:59	16.603	1%
4	21	08:46	10:03	14:40	15:53	04:37	16:53	19.557	14%
5	31	14:20	15:11	17:29	18:04	02:18	20:16	14.487	17%
average	18							12.259	

Source: Authors' own assumptions (derived from MiD 2008)

**Table I-6: Electric vehicle car usage pattern – Sunday; outskirts/rural area**

profile	daily mileage (km)	first trip (hh:mm)		second trip (hh:mm)		parking (hh:mm)		yearly mileage (km)	share
		start	end	start	end	day	night		
<b>small cars</b>									
1	0	-	-	-	-	-	-	11.405	68%
2	96	08:46	11:24	16:51	18:37	05:27	14:09	21.818	5%
3	22	07:21	07:33	14:23	15:50	06:50	15:31	8.362	2%
4	17	10:03	10:44	14:14	14:45	03:30	19:18	14.140	11%
5	28	15:02	15:26	18:08	18:46	02:42	20:16	13.011	14%
average	11							12.422	
<b>mid-size cars</b>									
1	0	-	-	-	-	-	-	15.445	65%
2	137	09:27	11:18	16:12	18:33	04:54	14:54	16.711	7%
3	16	09:14	09:56	16:43	17:35	06:47	15:39	12.713	1%
4	17	09:29	10:38	14:05	15:15	03:27	18:14	14.479	13%
5	31	14:45	15:29	18:14	18:46	02:45	19:59	17.699	14%
average	16							15.693	
<b>large cars</b>									
1	0	-	-	-	-	-	-	14.092	60%
2	95	09:26	10:47	15:13	17:10	04:26	16:16	17.424	9%
3	21	07:48	08:14	16:42	17:18	08:28	14:30	13.054	2%
4	16	09:58	10:43	14:17	15:02	03:34	18:56	15.278	13%
5	43	15:03	15:44	18:13	18:53	02:29	20:10	17.156	15%
average	18							15.013	

Source: Authors' own assumptions (derived from MiD 2008)