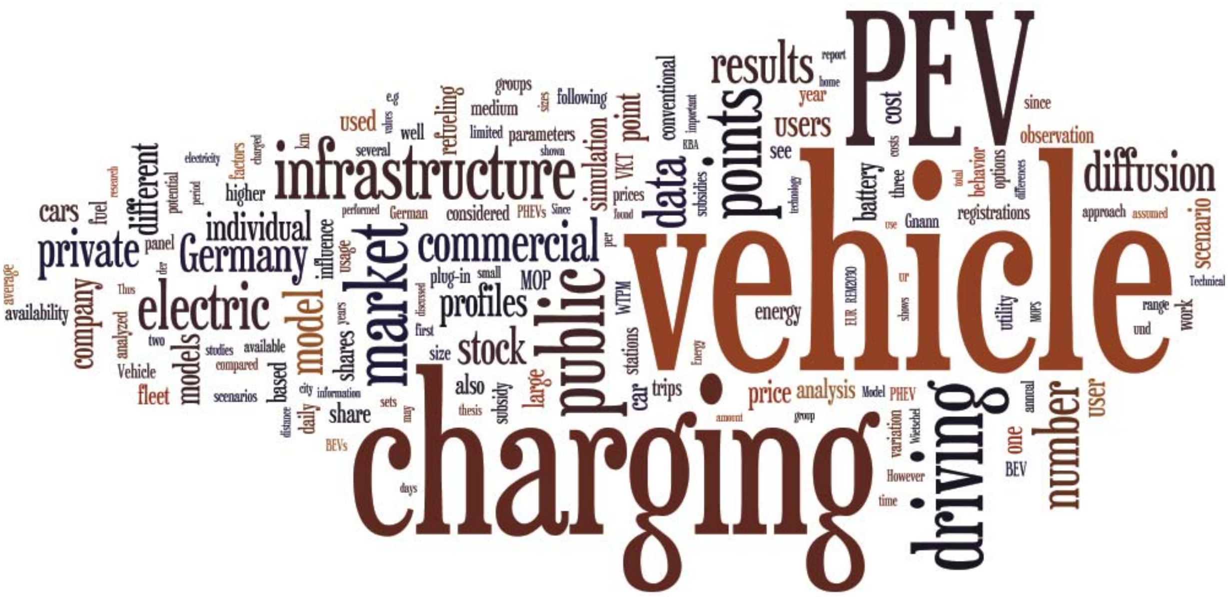
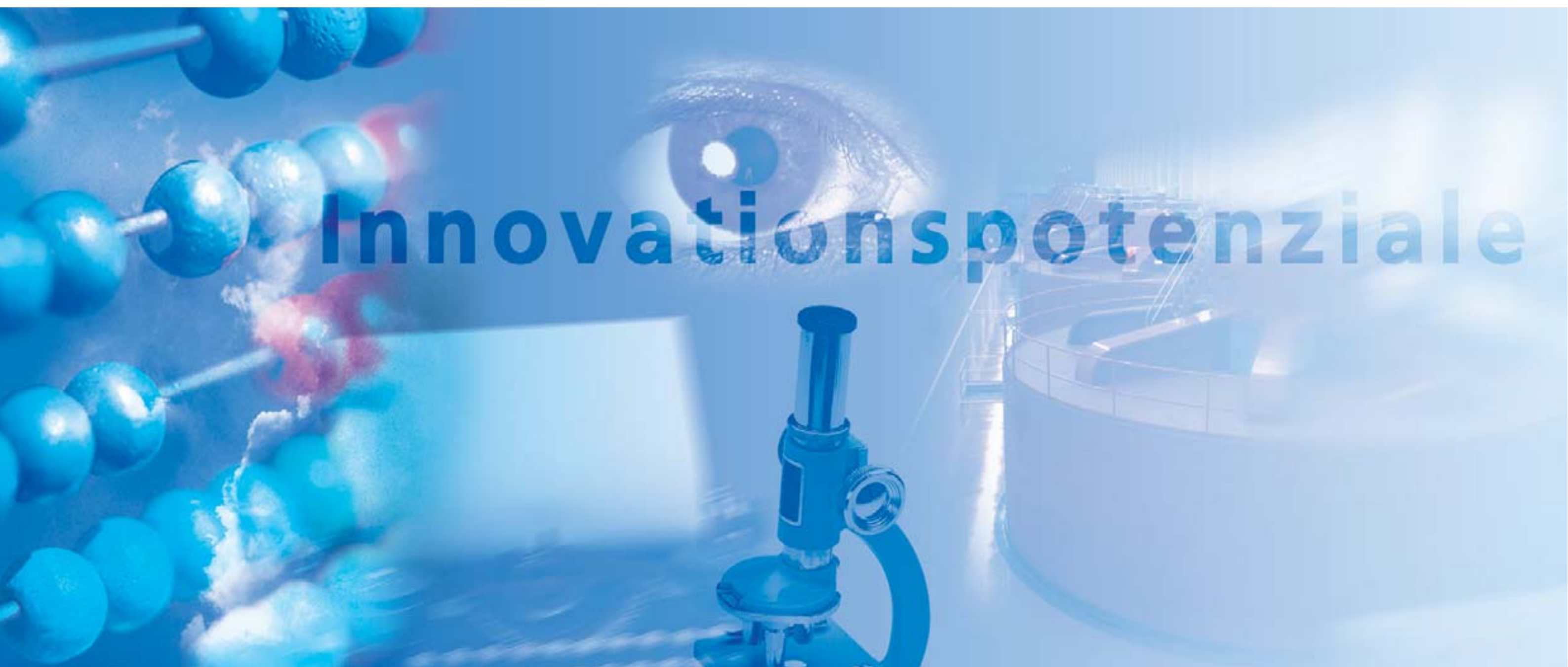
Market Diffusion of Plug-in Electric Vehicles and their Charging Infrastructure

Till Gnann





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Till Gnann

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Market diffusion of plug-in electric vehicles and their charging infrastructure

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Für meinen Vater

Abstract

Plug-in electric vehicles (PEVs) are a means to reduce greenhouse gas emissions from the transportation sector and diminish the dependency on fossil fuels. An often stated barrier to the diffusion of PEVs is the lack of charging options which prevents potential users from purchasing PEVs. However, the limited number of PEV users impedes a profitable operation of public charging points and thus their installation and roll-out. This thesis analyzes this potential lock-in effect for PEVs.

An agent-based model is developed to simulate the joint diffusion of PEVs and their charging infrastructure in Germany until 2030. An individual analysis of several thousand real-world driving profiles from the private sector and several hundred from commercial vehicles collected for this thesis allows to determine the individual utility optimizing drive train. The utility of each drive train is calculated based on its total costs of ownership, favoring and obstructing factors of PEVs, and takes the current charging infrastructure into account. The subsequent joint simulation of PEV users' driving and charging at public charging points permits to decide on the profitability of public charging stations and a potential further construction.

The results show that the dissemination of public slow-charging options has no influence on the diffusion of PEVs in Germany until 2030 from a techno-economical point of view. Instead, domestic charging points are a prerequisite for private PEVs and commercial charging points for commercial PEVs. These charging facilities already cover the charging needs of most vehicles, while additional charging points at work could further increase the number of private PEVs. Furthermore, the annual PEV registrations are dominated by commercial plug-in hybrid electric vehicles which only occasionally recharge public slow-charging facilities. Hence, public slow-charging options cannot become economically viable until 2030 – even with a growing number of PEVs. Further research is needed to quantify the psychological need of public charging points and their implications for the diffusion of PEVs.

This thesis is based on my research conducted at the Fraunhofer Institute for Systems and Innovation Research ISI under the supervision of Professor Dr. Martin Wietschel at the Institute for Industrial Production (IIP) at the Karlsruhe Institute of Technology.

Kurzfassung

Elektrofahrzeuge können einen Beitrag leisten, den Ausstoß von Treibhausgasen und die Abhängigkeit von fossilen Brennstoffen im Transportsektor zu reduzieren. Häufig wird dabei die fehlende Ladeinfrastruktur als Hemmnis für die Verbreitung von Elektrofahrzeugen genannt, das potenzielle Nutzer davon abhält, Elektrofahrzeuge zu kaufen. Jedoch verhindert die beschränkte Anzahl an Elektrofahrzeugen einen profitablen Betrieb öffentlicher Ladepunkte und einen damit verbundenen Auf- und Ausbau. In dieser Arbeit wird dieser potenzielle Lock-in-Effekt untersucht.

Für die gekoppelte Diffusion von Elektrofahrzeugen und ihrer Ladeinfrastruktur wird ein agentenbasiertes Modell entwickelt, das Deutschland bis 2030 betrachtet. Mithilfe einer individuellen Analyse von mehreren tausend privaten und einigen hundert, eigens für diese Arbeit erhobenen, gewerblichen Fahrprofilen von Fahrzeugen, wird die nutzenoptimale Antriebsart für jedes Fahrzeug bestimmt. Der Nutzen wird auf Basis der Total Cost of Ownership des Fahrzeugs, sowie hemmenden und fördernden Faktoren berechnet, wobei die gegebene Ladeinfrastruktur berücksichtigt wird. Anschließend wird eine simultane Ladesimulation der Elektrofahrzeuge durchgeführt, welche eine Rentabilitätsrechnung für öffentliche Ladepunkte und die Entscheidung über einen Ausbau ermöglicht.

Die Ergebnisse zeigen, dass die Verbreitung öffentlicher Langsamladepunkte in Deutschland aus techno-ökonomischer Sicht keinen Einfluss auf die Marktdiffusion von Elektrofahrzeugen bis 2030 hat. Ladepunkte an privaten Stellplätzen für Privatfahrzeuge oder auf dem Firmengelände für gewerbliche Fahrzeuge sind eine Voraussetzung für die Verbreitung von Elektrofahrzeugen. Diese Lademöglichkeiten decken den Ladeinfrastrukturbedarf für die meisten Fahrzeuge ab; eine zusätzliche Lademöglich-keit für Privatfahrzeuge am Arbeitsplatz kann die Nutzerzahl zudem erhöhen. In den simulierten Neuzulassungen der Elektrofahrzeuge überwiegen jedoch gewerbliche Plug-in Hybridfahrzeuge, die nur in selten öffentlich laden. Aus diesen Gründen können sich öffentliche Ladepunkte bis 2030 nicht amortisieren – auch nicht mit einer zunehmenden Zahl an Elektrofahrzeugen. Weiterer Forschungsbedarf ist notwendig, um den psychologischen Bedarf an öffentlicher Ladeinfrastruktur zu quantifizieren und dessen Implikation auf die Diffusion von Elektrofahrzeugen zu bestimmen.

Diese Arbeit wurde im Rahmen meiner Forschungsarbeit am Fraunhofer-Institut für System- und Innovationsforschung ISI erstellt und betreut von Prof. Dr. Martin Wietschel am Institut für industrielle Produktion (IIP) am Karlsruher Institut für Technologie (KIT).

Contents

Chapter 1

Introduction

1.1 Motivation

The reduction of greenhouse gas (GHG) emissions and the dependency on fossil fuels are two of the most fundamental challenges of the 21st century [Kahn Ribeiro et al., 2007,IEA, 2010]. This is particularly important for the transport sector which is a major contributor to global GHG emissions (23% of global GHG emissions in 2004 [Kahn Ribeiro et al., 2007], 22% of global CO_2 emissions in 2012 [IEA, 2014]). For this reason, the European Union has set the goal for a reduction of 60% of all GHG emissions from the transportation sector by 2050, compared to 1990 [Peters et al., 2013], and the European Commission (EC) reacted with EC directive 443/2009 [EC, 2009]. This directive forces car makers to reach an average CO_2 emission of 95 g CO_2/km by 2020 in all European markets. Especially long-term goals, like a reduction of vehicle emissions to 20 g CO_2/km necessary to reach the 2°C goal in 2050, are not attainable with conventional fuels [McKinsey, 2009,Schade, W., 2010,Skinner et al., 2010,Peters et al., 2013]. Alternative fuel vehicles (AFVs) in general and plug-in electric vehicles (PEVs) or fuel cell electric vehicles (FCEVs) in particular could provide a means to reduce emissions from the transportation sector. Although the new attention paid to alternative fuels is often considered as a new peak of Gartner's hype cycle [Bakker, 2010, Jun, 2012, Konrad et al., 2012], the situation for PEVs is different compared to the 1980's in California or 1990's in Germany [Chan, 2007]. Apart from the political interest and rising prices for fossil energy [IEA, 2014][1], PEVs are expected to become technically and economically competitive to conventional fuel vehicles in the near future due to technological improvements, like rising energy densities, and falling prices of Lithium-ion batteries [Nykvist and Nilsson, 2015, Thielmann, 2011, Thielmann et al., 2012].

Germany as one major car market and supplier of vehicles [OICA, 2014] is particularly interested in future technological improvements. German car makers want to obtain their position on the global car market, while policy makers aim at maintaining jobs in the automotive industry and at keeping up with developments in "green" technologies.[2] Hence, the German government has set a goal has set a goal of reaching a stock of one million plug-in electric vehicles by 2020 and 6 million by 2030 [NEP, 2009,RegProg, 2011,BMWi

[1]Although currently the oil price is at a five-year-minimum, the long-term growth rate has been positive for several decades [IEA, 2014].

[2]Green technologies are sometimes denoted as the sixth Kondratieff wave [Naumer et al., 2010,Naumer et al., 2013].

and BMU, 2010]. Further, Germany intends to become a lead market and lead supplier of PEVs [NEP, 2009,RegProg, 2011,BMWi and BMU, 2010]. In order to monitor these goals and to propose further courses of action in Germany, the National Platform for Electric Mobility has been installed, consisting of policy makers, scientists as well as representatives from non-governmental organizations and the automobile industry (see [NPE, 2014] for their latest report). At the moment, the market for PEVs, in Germany and worldwide, is at an early stage and several scientific studies have been carried out to forecast their future market development.[3] A common way to model the future evolution of PEVs is based on the total cost of ownership (TCO) of a vehicle[4] and vehicle usage data as user behavior[5]. Yet, studies in this area of research incorporate several insufficiencies: (1) the commercial vehicle sector which accounts for more than half of all vehicle registrations in several major car markets[6] is often neglected in scientific studies [Hacker et al., 2011b, Redelbach et al., 2013, Schühle, 2014]. (2) Also the vehicle buying decision is not solely based on cost[7], but also on attributes like vehicle size, brand or safety, and cost-based analyses should be extended (see e.g. [Eppstein et al., 2011]). Further, (3) most models use average driving patterns[8] although driving varies largely between drivers and days[9]. When modeling the market diffusion of PEVs (and their charging infrastructure), shortcomings 2 and 3, and for Germany also shortcoming 1, should be reflected.

In addition to other factors, an important barrier to the adoption of PEVs is the so-called limited range anxiety [Tate et al., 2008], partly caused by the current lack of charging infrastructure [Dütschke et al., 2011b, Egbue and Long, 2012, Steinhilber et al., 2013]. Users wish to have a sufficient charging infrastructure before they buy a plug-in electric vehicle [Dütschke et al., 2011b, Egbue and Long, 2012, Steinhilber et al., 2013]. For this reason, the European Directive on the deployment of alternative fuels infrastructure [EC, 2014] forces member states to propose a national action plan on public charging infrastructure development and set up a minimum amount of public charging points. For Germany, the directive suggests 150,000 public charging points by 2020 [EC, 2014]. First actions in Germany have been taken by the Federal Ministry of Economic and Energy (BMWE) by defining the power levels and suggesting a first number of charging spots that should be publicly available (35,000 public charging points by 2020) [BMWE, 2015]. These amounts differ significantly, since there is no commonly accepted approach to determine the number of charging points needed and most scientific studies focus on the placement of charging points [Lam et al., 2013, Dong et al., 2014, Namdeo et al., 2014, Sathaye and Kelley, 2013]. Studies analyzing the economy or use of charging points often find that extensive usage is necessary to make charging points economically viable [Kley, 2011] while usage in several model projects is comparatively low [Ecotality and INL, 2012, Bruce et al., 2012]. Occupancy rates depend on the number of PEVs in the vehicle stock and should thus be analyzed jointly to overcome a potential lock-in [Lin and Greene, 2011, Dong et al., 2014, NPE, 2012, Kalhammer et al., 2007, BCG, 2009, Ma et al., 2014, Chen et al., 2013].

[3] See [Al-Alawi and Bradley, 2013] for a review on market diffusion models of electric vehicles.

[4] See e.g. [Thiel et al., 2010, McKinsey, 2011, Pfahl et al., 2013, Wu et al., 2015].

[5] See e.g. [Dagsvik et al., 2002, Santini and Vyas, 2005, Keles et al., 2008, Lamberson, 2008, Mock et al., 2009, Nemry and Brons, 2010, Wansart and Schnieder, 2010, Shepherd et al., 2012].

[6] See e.g. [KBA, 2014b, UK DoT, 2013, JP-StatBureau, 2013].

[7] See e.g. [Mueller and de Haan, 2009, de Haan et al., 2009].

[8] See e.g. [Dagsvik et al., 2002, Santini and Vyas, 2005, Lamberson, 2008, Mock et al., 2009, Wansart and Schnieder, 2010, Shepherd et al., 2012].

[9] See e.g. [Smith et al., 2011, Amjad et al., 2011, Neubauer et al., 2012].

This interaction and co-diffusion of AFVs and their refueling infrastructure is a field of research for several types of vehicles[10], yet it has not been comprehensively analyzed for PEVs and their charging infrastructure.

1.2 Research question and course of action

Based on the three identified research gaps, (i) insuffiencies in PEV market diffusion modeling, (ii) missing quantitative simulation results for public charging options and (iii) lack of a joint analysis for PEVs and charging infrastructure diffusion, the main research question of this thesis is:

How do the diffusion of plug-in electric vehicles and the diffusion of their charging infrastructure mutually influence each other?

This research question has, to the best of the author's knowledge, not yet been comprehensively analyzed. Since PEVs are a new technology and data about vehicle registrations or the charging infrastructure stock is rare, a modeling approach shall be developed to answer the research question for Germany until 2030. This implies several consecutive questions:

Can the co-diffusion of PEVs be modeled in the same way as for other alternative fuel vehicles? Since the introduction of automobiles, several types of vehicles have diffused into vehicle stocks worldwide. A refueling infrastructure was set up for the gasoline vehicle as the first mass market vehicle. The first mass market alternative fuel vehicle[11] - the diesel vehicle - profited from the gasoline infrastructure that could be extended to diesel [Karlsch and Stokes, 2003, Grube, 2004]. The same holds for other fuels, for which refueling stations could be expanded. However, for PEVs, currently planned charging facilities exceed the number of refueling stations largely [BMWE, 2015, EC, 2014] because of technical limitations of the vehicles. Thus, when analyzing the co-diffusion of PEVs and their charging infrastructure, modeling approaches have to be investigated and extended for PEV specialties.

What are adequate data sources to model the driving and charging behavior of private and commercial PEVs? The technical limitations of PEVs necessitate a detailed analysis of driving behavior to estimate their market potential. Such analyses are often performed with vehicle usage data of conventional vehicles[12]. As vehicle usage data is publicly available in many countries [US-DoT, 2009, ENTD, 2009, MOP, 2010, Auto21, 2011, Karlsson, 2013], adequate German data sets for the analysis of PEVs have to be determined that cover private and commercial vehicles. The latter is important so that the high share of commercial vehicle registration can be considered.

What influences the adoption of PEVs apart from (public) charging infrastructure? The market diffusion of PEVs is not only influenced by the diffusion of charging infrastructure, but also by a variety of other factors like energy or vehicle prices, the availability

[10] See e.g. [Huétink et al., 2010, Janssen et al., 2006, Melaina, 2003, Meyer and Winebrake, 2009, Schwoon, 2006, Stephan and Sullivan, 2004, van der Vooren and Alkemade, 2010].

[11] Plug-in electric vehicles were available already in 1830, yet they could not compete with the mass production of gasoline vehicles in the early 1900's [Chan, 2007].

[12] See e.g. [Dagsvik et al., 2002, Santini and Vyas, 2005, Mock et al., 2009, Nemry and Brons, 2010, Shepherd et al., 2012].

of PEVs on the market or common parking spots. These should be retrieved and analyzed to put the influence of charging infrastructure into context. This allows to answer a last relevant question for policy makers: *What should an adequate charging infrastructure construction look like from a technical, economical and user behavioral point of view?*

In this thesis, the focus on Germany until 2030 allows to determine the early evolution of PEVs in a major market, after which a critical mass should be reached and the co-diffusion should have become self-sustaining [Allen, 1988, Mahler and Rogers, 1999]. Results in this area may be generalized and transferred to other countries. The outline of this thesis runs as follows: Chapter 2 contains a brief overview of plug-in electric vehicles and their charging infrastructure which points out the main differences to conventional vehicles and refueling stations (2.1). Thereafter existing studies on the co-diffusion of AFVs and their refueling infrastructure are reviewed to retrieve stylized facts that models should cope with and best fitting modeling approaches for the co-diffusion (2.2). Chapter 3 contains a presentation of vehicle driving data sets of private and commercial vehicles. The driving profiles later used for simulation are compared to other data sets and tested for their representativity. In Chapter 4 the agent-based simulation model ALADIN (Alternative Automobiles Diffusion and Infrastructure) is developed (Sections 4.1 and 4.2). Scenarios for the simulation are presented and all techno-economical assumptions, e.g. for vehicle characteristics, vehicle market or energy prices, are described (Section 4.3). The results of the simulations are presented in Chapter 5 which is divided into three parts: First, the market potential of commercial fleet vehicles is determined to show the differences of private and commercial vehicle driving and purchasing behavior (Section 5.1). Second, the market diffusion of PEVs with non-public charging infrastructure is determined. Here, special focus is put on the influence of framework conditions to show their impact on the PEV market diffusion (Section 5.2). Lastly, the joint diffusion of public charging points and PEVs is determined. Here, several variations of infrastructure configurations and subsidies are analyzed (Section 5.3). Finally, the thesis is summarized, conclusions are drawn and suggestions for further research are made in Chapter 6.

Chapter 2

Diffusion models of alternative fuel vehicles and their refueling infrastructures

Introduction

This chapter aims at demonstrating the need for research in the field of PEVs and their charging infrastructure diffusion and serves to point out what can be learned from earlier works when modeling the interaction of PEVs and charging infrastructure. It contains two sections: The first Section 2.1 holds a brief overview of AFVs and defines the distinctions of PEVs to other AFVs which are considered in this work. In addition, the differences of charging infrastructure of PEVs compared to refueling stations of conventional fuels are shortly described. In the second Section (2.2) a structured literature review of AFV and refueling infrastructure diffusion models is performed to gain insights from current modeling approaches.[13]

2.1 Background of alternative fuel vehicles

2.1.1 Overview of alternative fuel vehicles

Alternative fuel vehicles have been a field of research for several decades (see e.g. [Greene, 1985, Sperling and Kurani, 1987, Greene, 1996, Chan, 2007]). Research on PEVs started in the 1980's in California, while fuel cell electric vehicles (FCEVs) came into focus of research and politics in the 1990's. Since 2000 both vehicle groups have gained worldwide attention by car makers, politicians and the media, especially because of rising emissions and the dependency on fossil fuels in the transport sector [IEA, 2010, Kahn Ribeiro et al., 2007]. Besides these two vehicle groups, there are three more types of AFVs that have already gained significant market shares in some national vehicle markets: vehicles powered with biofuels, natural or synthetic gas vehicles and hybrid electric vehicles, although the latter are often not considered as AFV but as a further development of conventional vehicles (CV).

[13] Literature reviews are often performed to identify research gaps and before the starting new modeling processes [Doebling et al., 1996, Garcia and Calantone, 2002, Kemp and Volpi, 2008, Hacker et al., 2009].

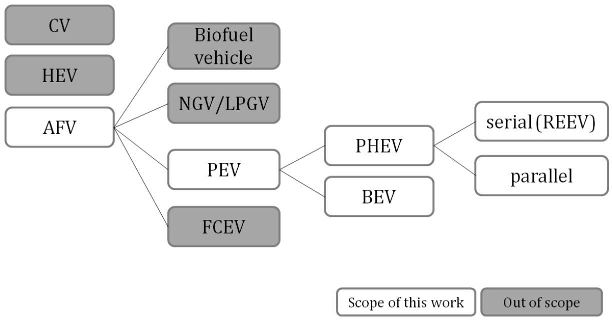

Figure 2.1: Alternative fuel vehicles considered in this thesis. CV=conventional vehicle, HEV=hybrid electric vehicle, AFV=alternative fuel vehicle, NGV=natural gas vehicle, LPGV=liquefied petroleum gas vehicle, PEV=plug-in electric vehicle, FCEV=fuel cell electric vehicle, PHEV=plug-in hybrid electric vehicle, BEV=battery electric vehicle.

The largest group of alternative fuel vehicles of the worldwide vehicle stock is flex-fuel vehicles with about 35 million vehicles and more than 23 million vehicles in Brazil. They can burn gasoline, ethanol and methanol or any mixture of them in an internal combustion engine. Since the latter two fuels are mostly produced from biomass, flex-fuel vehicles can be counted to biofuel powered vehicles. Vehicles solely fueled by ethanol are mainly registered on the Brazilian vehicle market and account for about six million vehicles worldwide.[14] Natural gas vehicles (NGVs) are propelled by an internal combustion engine that burns gaseous or compressed liquid natural gas (CNG). Together with vehicles that consume liquefied petroleum gas (liquefied petroleum gas vehicles (LPGVs)) or any other synthetic gas, they make up about 35 million vehicles powered with gases worldwide. About 20 million are NGVs with the largest markets in Iran (3.5m), China (3.3m), Pakistan (2.8m) and Argentina (2.5m), while LPGVs' largest markets are Turkey (3.9m), Russia (3m), Poland (2.8m) and South Korea (2.4m) totaling to 25 million LPGVs registered until 2014 [NGV-Journal, 2015, WLPGA, 2014]. Hybrid electric vehicles (HEVs) use an internal combustion engine for propulsion. In addition, a small battery is used for start-stop operation and recovers the energy from braking in a battery which is called recuperation. The energy that can be used for an additional stimulus of propulsion determines whether the vehicle is a mild (battery is only used for start-stop operation) or a full hybrid (battery is also used for "boosting"). Up to now, about 8.2 million hybrids have been sold worldwide with Japan (4m) and the US (3.4m) as their major markets [Marklines, 2015]. Fuel cell electric vehicles contain an electric drive train that is powered by a fuel cell unit where hydrogen is converted into electricity. A small buffer battery cannot be recharged at the electricity grid, but permits recuperation of braking energy. Currently, FCEVs are not recorded in any sales statistic since only very few FCEVs are available on the vehicle market at the moment, yet they may gain importance in the future.[15]

PEVs can be divided into three subgroups that are distinguished according to their level of electrification (see Figure 2.1 for distinctions and e.g. [Michaelis et al., 2013b, Wietschel et al., 2011] for definitions). Battery electric vehicles (BEVs) work completely

[14]Since there is no publicly available data on the registrations and sales of biofuels, which may stem from varying definitions about the mix of fuels, these registrations are based on press releases [Calmon, F., 2013, Motavalli, J., 2012].

[15]According to [Marklines, 2015] there are 135 FCEVs registered in stock in Japan and the US as of 1st of January 2015.

electric and store their propulsion energy in a Lithium-Ion battery.[16] They can only be charged via the electricity grid and thus their tank-to-wheel emissions depend on the electricity mix charged. The second option of PEVs is the plug-in hybrid electric vehicle (PHEV) which can also be refueled at conventional refueling stations. PHEVs can be subdivided into parallel and serial hybrids, while the position of the fuel-powered and electric machine determine the distinction. Parallel PHEVs contain two drive trains that can be used independently or at the same time. An independent discharge of the battery is called charge-depleting mode, whereas during a joint use of both drive trains the vehicle is driven in charge-sustaining mode. In serial PHEVs, the vehicle comprises only the electric drive train that discharges the battery which can be recharged through a fuel-powered generator during driving. Serial PHEVs are often called range-extended electric vehicles (REEV) or extended range electric vehicles (EREV).[17] Table 2.1 shows the market shares of PEVs in the major car markets in 2013 as well as their stock in 2014. Currently, PEVs do not account for a significant market share in any major car market, although smaller markets like Norway or the Netherlands reach up to 6% [Mock and Yang, 2014]. Today, the largest car market for PEVs are the US (223,000 PEVs) whereof the majority is driven in California.

Table 2.1: International PEV adoption in major car markets.

Country	DE	US	JP	FR	CN
PEV market shares 2013 (new car sales)^a	0.2%	1.3 %	0.6 %	0.8 %	0.1 %
PEV new car sales 2013^{a,b}	7,000	95,000	25,000	9,000	12,000
PEV stock 01/01/2014^c	24,000	223,600	88,500	37,100	29,100
PEV charging stations during 2014^{c,d}	4,800	15,200	5,000	8,000	8,100

a: [Mock and Yang, 2014]; b: [ICCT, 2014]; c: [NPE, 2014]; d: Public & semipublic charging points for Germany; DE=Germany, US=United States, JP=Japan, FR=France, CN=China

This thesis focuses on PEVs and their charging infrastructure, since, together with FCEVs, they are the only means to reach EU and national emission targets for 2050 [McKinsey, 2009, Schade, W., 2010, Skinner et al., 2010]. With a certain number of PEVs available on the vehicle market, PEVs will be the near-term solution to cope with these targets [NPE, 2014]. To reach the current limit values for CO_2 emissions in 2020, however, a certain number of PEVs is necessary [Peters et al., 2013]. Apart from emission targets, plug-in electric vehicles could help to integrate intermittent renewable energies into the energy system [Dallinger and Wietschel, 2012, Dallinger et al., 2013]. The most important characteristics of PEVs and their charging infrastructure that are different from other (alternative) fuel vehicles are pointed out in the following section.

2.1.2 Charging infrastructure needs of plug-in electric vehicles

The major barriers for a large adoption of PEVs are their cost, their limited range and their associated insufficient charging infrastructure [Dütschke et al., 2011b, Götz et al., 2011, Globisch et al., 2013]. While PEV price reductions can be expected by economies

[16]Earlier PEVs were also based on nickel metal hydrid batteries (see e.g. [Watabe and Mori, 2011]).

[17]Serial and parallel hybrid electric vehicles are not distinguished in this thesis since their recharging or refueling behavior can hardly be distinguished. When both vehicle options are considered in the further analyses, they only vary in technical and economical parameters.

of scale, the limited range of PEVs is a matter of battery technology. Currently, batteries have an energy density that is about 50 times lower than for conventional fuels (see e.g. [Fischer et al., 2009]). R&D activities focus on improving the energy density of battery technologies, e.g. with new materials, but current Lithium-ion technology will be used in PEVs until at least 2025 [Thielmann et al., 2012, Thielmann et al., 2014]. The lower energy density of Lithium-ion batteries necessitates higher recharging frequencies for PEV users if today's driving behavior should be maintained.

The insufficiency of charging infrastructure seems to be unproblematic when comparing the current PEV stock and PEV charging stations in Table 2.1. The ratio of PEVs per (public) PEV charging stations (5-20) is much lower than the average ratio of vehicles per refueling stations for NGV suggested by [Janssen et al., 2006] (1,000). However, apart from the higher recharging frequency, the observed necessity of additional charging stations arises from their technical restraints.

Charging facilities can be described according to a number of attributes (see [Kley et al., 2011] and Figure 2.2). In this work, only conductive (wired) charging facilities are considered since inductive and charging options as well as battery exchange systems are very expensive [Kley, 2011]. Inductive charging facilities suffer from high energy losses when the vehicle and charging facility are not very close to each other [Schraven et al., 2011]. Also investments of charging facilities integrated into streets or parkings are significantly higher than for conductive charging points [Wietschel et al., 2009, Kley et al., 2010]. Investments for battery exchange stations would be even higher [Kley et al., 2010] and would force car makers to standardize their batteries. Apart from that, insurance policies for batteries are one more issue to solve which was not feasible for the only company offering this service [manager magazin, 2013]. For load shifting and the storage of intermittent renewable energies, a significant number of PEVs is required for a cost efficient operation. Only the power and capacity of a vehicle fleet is comparable to power or energy for needed for load shifting on a national level [Dallinger and Wietschel, 2012, Heinrichs, 2014, Babrowski et al., 2014]. Hence, only unidirectional connections without information flow are considered. This work focuses on very simple charging facilities to determine the amount of charging infrastructure for an early market evolution. For simplicity, pay per use is considered for billing which is metered at the charging station. To sum up, in this thesis, charging facilities are only distinguished by their accessibility and their power.

Four different types of accessibility of charging infrastructure are distinguished: domestic, commercial, semipublic and public charging facilities. Private or domestic locations are only accessible to private cars of one household. Commercial charging facilities offer the possibility to recharge commercial vehicles at the company site and are thus a pendant to domestic charging points. Semipublic charging facilities offer access to a limited number of people[18], e.g. the members of a sports club or the workplace, whereas public charging options are available to everyone [Becker, 2009, Kley et al., 2010]. A lot of charging facilities are already available to potential PEV users with domestic charging spots, although at low power rates (level 1 and 2 (see below)). According to [infas and DLR, 2002, MOP, 2010, Behrends and Kott, 2009] about 60% of private vehicles in

[18] In [Reinke, 2014], semipublic charging facilities belong to a private owner, but offer access to the public, while publicly owned charging facilities with access to a limited number of people are special cases of public charging infrastructure. In this thesis, the definition for semipublic places is consistent with [Reinke, 2014] while the latter is considered as public charging infrastructure.

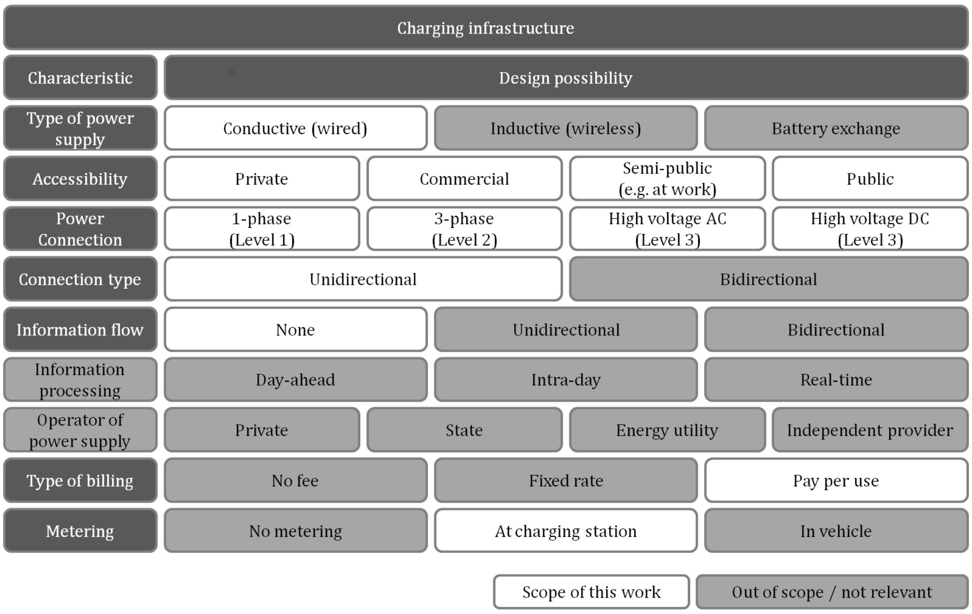

Figure 2.2: Characteristics of charging infrastructure considered in this thesis. Illustration based on [Kley et al., 2011].

Germany are parked in garages overnight (see also Section 3.3.2 and Figure 2.3).[19] Also commercial charging facilities could most often be easily installed for vehicles belonging to a company.

The power at the charging facilities determines the time for recharging. Usually three levels of alternating current (AC) power connections are distinguished which depend on each country's electricity grid. In Germany these are 3.7 kW at level 1, 11–22 kW at level 2 and above 22 kW at level 3. A fourth level allows on high-voltage direct current (DC) power above 50 kW [Kley et al., 2011, Kley, 2011, Jochem et al., 2014]. Hence, charging a battery with a capacity of 25 kWh completely would take almost 7 hours at the lowest power level 1 in Germany. Higher power reduces the time to charge, yet also with a 100 kW charger it would take 15 minutes to recharge and thus longer than with conventional fuels.[20] With higher accessibility and power, the technical and organizational requirements of setting up charging facilities rise [Kley et al., 2011] and therewith the costs to install charging facilities.

Thus, the following major differences for the charging infrastructure of PEVs to other propulsion technologies can be identified:

- The technical limitations of current batteries and charging stations lead to higher refueling frequencies and durations compared to conventional fuels and to a higher need of charging facilities.
- However, the availability of some charging facilities in private, commercial or semipublic places reduces the necessity of a massive public charging station roll-out. This distinction of charging access types is different from conventional fuels.

Hence, models that focus the co-diffusion of PEVs and their charging infrastructure should consider these specialties.

[19] Similar shares of garages are also found for the US [Lin and Greene, 2011, Vyas et al., 2009].

[20] Costs for these charging options will be presented in Section 4.3.

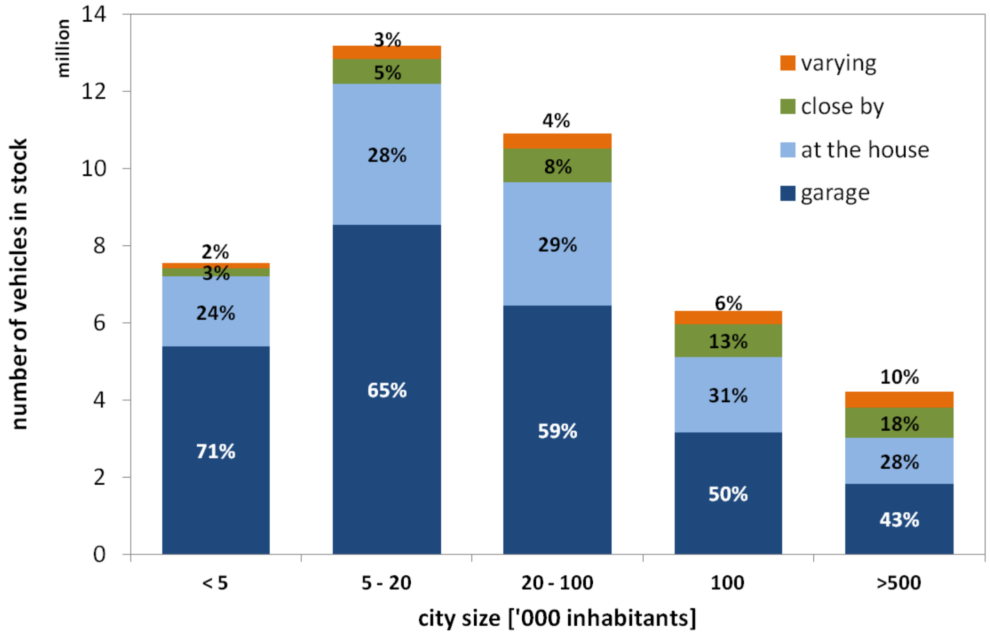

Figure 2.3: Availability of garages in German vehicle stock. Garage availability and city sizes from [infas and DLR, 2002], total number of vehicles from [KBA, 2014a].

2.2 Literature review of previous modeling approaches[21]

Modeling the interaction in diffusion of AFVs and their refueling infrastructure has been a field of research for some decades, yet PEVs and their charging infrastructure interaction has not received much attention up to now. Therefore, this literature review of AFVs aims at identifying important factors and insights for further modeling undertakings. The following subsection identifies stylized facts and requests to models that should be considered when the co-diffusion of AFVs and their refueling infrastructure is analyzed in general (2.2.1). Models that treat the co-diffusion for different AFVs are presented and classified in Section 2.2.2. Their research questions and coverage of stylized facts are discussed in Section 2.2.3, while conclusions for further research are drawn at the end of this chapter.

2.2.1 Stylized facts of vehicle and infrastructure market diffusion

In the following, stylized facts of AFV market diffusion that should be included in models are identified. It is common practice in economical research to analyze important empirical regularities that are stable across different studies, markets or sectors [Kaldor, 1957, Easterly and Levine, 2001, Cont, 2001]. These empirical regularities are coined stylized facts [Kaldor, 1957] and helpful to summarize the present state of knowledge as well as to identify directions of further research [Easterly and Levine, 2001]. This subsection is

[21]This section is based on [Gnann and Plötz, 2015].

structured as follows: The background analysis starts with a review of empirical studies of NGVs as an AFV type that has diffused into markets in several countries in order to derive general stylized facts for AFV modeling. Thereafter user acceptance studies on AFVs and their refueling infrastructure are regarded to retrieve how potential users evaluate vehicles propelled by new fuels. These findings are summed up as factors that should be considered by models in the last part of this subsection. They build the basis for the model that is described in Chapter 4.

Empirical studies on natural gas vehicles and their refueling infrastructure

While for gasoline an initial infrastructure built-up was necessary, it was different for diesel vehicles and NGVs, since gasoline refueling stations were already in place and could be extended for these fuel types with minor modifications. For a comparison of several countries, their adoption of NGVs and their refueling infrastructure Janssen et al. (2006) introduced the so-called vehicle to refueling station index (VRI), defined as the number of refueling stations times 1,000 divided by the number of vehicles [Janssen et al., 2006]. The index shows the market development phases with the ratio being below one for early markets and above one for more mature markets (see [Janssen et al., 2006]).

Extending the work of Janssen et al. (2006) with newer data [VDA, 2010, eldia.com, 2011, BFS, 2013, ANP, 2012, KBA, 2013b, KBA, 2013a, MWV, 2013, Eurostat, 2013, GVR, 2012, Erdöl-Vereinigung der Schweiz, 2008, europia, 2012, UP, 2012], the historical evolution of NGV stocks is illustrated in Figure 2.4 while NGVs comprise vehicles propelled with liquefied petroleum gas (LPG) or CNG and their charging infrastructure for six different countries. Abscissa and ordinate show the market shares of stocks of NGVs (number of NGVs in stock divided by total number of vehicles in stock) and of refueling stations respectively (as number of refueling stations selling gas for these vehicles divided by the total number of refueling stations for CVs). Displayed are market shares for NGVs and CNG refueling stations for Argentina (AG), Brazil (BR), Germany (DE), Italy (IT), Sweden (SE) and Switzerland (CH) as well as LPGVs and LPG refueling stations for Germany and the Netherlands (NL). The blue line indicates equal market shares of vehicles and refueling stations. The diagram has two logarithmic axes to compare large values, e.g. of Brazilian market shares (share of CNG vehicles 2009: 7.5%), to small ones, e.g. in Switzerland (share of CNG 1999: 0.002%). Here, market shares are used instead of absolute values in order to be independent of the factor that has to be multiplied by vehicles (1,000 in [Janssen et al., 2006]), which allows a direct comparison of different vehicle markets.[22] Although this illustration does not consider the charging station capacities (in terms of nozzles or amount of fuel sold) it serves as a proxy for the development of early markets.

All countries except Brazil show a share of NGV refueling stations higher than the share of NGVs. The Netherlands, Brazil and Argentina are more mature markets (more on the upper right corner) and seem to develop an initial refueling infrastructure before vehicles gain larger market shares. All countries' developments have positive slopes and for all countries except Brazil, the slopes are smaller than one, i.e. the stock share of vehicles is growing faster than the market share of refueling stations; for Brazil the slope is almost one. This might derive from the market maturity: younger markets with little

[22] Since the ratio of refueling stations selling gas and the total number of refueling stations is displayed, the density of the refueling station network of CVs for each country is implicitly considered as well.

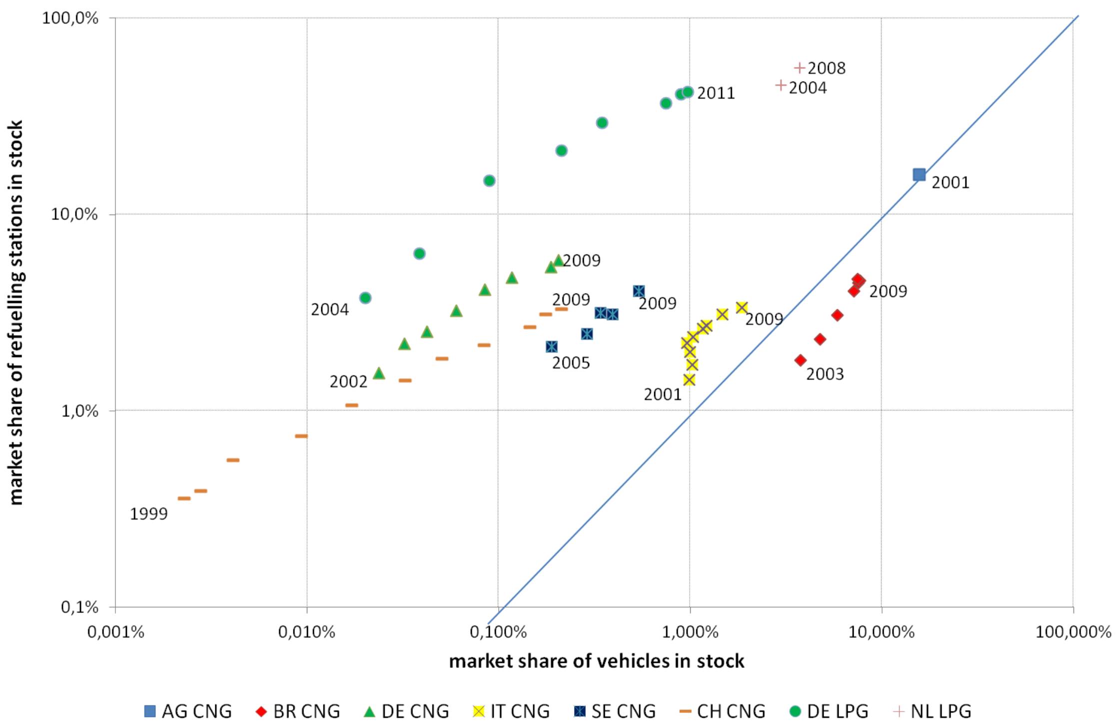

Figure 2.4: Stock market share of different gas vehicles and corresponding refueling stations for different countries and years. Data from [VDA, 2010, eldia.com, 2011, BFS, 2013, ANP, 2012, KBA, 2013b, KBA, 2013a, MWV, 2013, Eurostat, 2013, GVR, 2012, Erdöl-Vereinigung der Schweiz, 2008, europia, 2012, UP, 2012].

market shares for vehicles seem to converge to equal market shares of vehicles and refueling stations.

This illustrative example suggests the following relationships:

- Market shares for NGV refueling infrastructure are higher than market shares for NGVs in the beginning of a market diffusion.
- The ratio of both market shares tends to develop to one for early markets and to higher market shares for vehicles for more mature markets.

These findings are confirmed by studies on NGVs in several countries. Flynn (2002) analyzed NGVs in Canada in the years 1984 to 1986 [Flynn, 2002]. He studied policy measures, focusing on the barriers to adoption. His main findings with respect to the interaction of vehicle and infrastructure were that (1) infrastructure has to be available to customers as soon as there are vehicles on the market and (2) refueling stations have to become profitable soon to sustain investments into a further infrastructure development. Yeh (2007) studied the adoption of NGVs in Argentina, China, Italy, Pakistan, Brazil, India, New Zealand and the United States [Yeh, 2007], using the vehicle-to-refueling-station index VRI suggested in [Janssen et al., 2006]. In her work she found that the following conditions were decisive for a market diffusion of NGVs in all countries: (1) The prices for natural gas should be 40-50% lower than for conventional fuels, (2) the average payback period should not be more than 3-4 years, and (3) "that successful NGV markets have the tendency to gravitate toward a VRI of 1" [Yeh, 2007], which supports the findings of the example on NGVs. Collantes and Melaina (2011) studied the co-evolution of NGVs and their refueling infrastructure in Argentina [Collantes and Melaina, 2011]. They used a quantitative and qualitative approach and concluded that there was little political influence in the build-up of refueling infrastructure and private users invested when vehicles entered the market. However, they stated that lower fuel prices and several infrastructure standards were the main drivers for adoption.

From the evidences collected by these studies, the following findings can be added:

- There has to be some infrastructure as soon as there are vehicles on the market which approves the first observation in this subsection.
- Refueling stations have to economize in the short to medium term, so a model should reflect their profitability.
- Fuel prices for AFVs should be lower than for conventional vehicles.

For modeling the co-diffusion of PEVs and their charging infrastructure, this means that an initial amount of charging infrastructure has to be in place, while the profitability of charging stations should be included in the model. Also the profitability of electric versus conventional driving will be reflected in the model introduced in Chapter 4.

How does refueling infrastructure influence the adoption of AFVs?

Several studies analyze the adoption of AFVs and their refueling infrastructure in general whereof some are presented in the following.

Sperling and Kurani (1987) investigated diesel vehicles and their corresponding refueling network in California [Sperling and Kurani, 1987]. They conducted a survey of diesel vehicle buyers in 1986 that addressed the influence of fuel availability in the vehicle buying decision. They compared buyers that bought their vehicles prior to or after 1982 and tested whether those buyers were less concerned about finding refueling stations who bought their car in later years. All interviewees were asked after they bought their car. From the responding 535 participants of this study they concluded that: (1) diesel car owners had the same or less difficulty finding refueling sites than expected, (2) the level of concern was about the same for earlier and later buyers. (3) Furthermore the authors stated that a minimum level of 15-20 % of all refueling stations has to offer the "new" fuel to meet users' needs [Sperling and Kurani, 1987]. Another survey performed by Sperling and Kitamura (1986) showed that an initial refueling network should be "about 1/10th of the size of the gasoline retail network [...] to relegate refueling concerns to a relatively insignificant role in the vehicle-purchase decision" [Sperling and Kitamura, 1986]. Greene (1996) supports the results of [Sperling and Kurani, 1987] regarding the minimum percentage of refueling coverage in a US-wide survey about flex-fuel vehicles conducted in 1996 with about 2,000 participants interviewed by phone [Greene, 1996]. He also found that if 15-20% of conventional refueling stations offered the new fuels, it would be sufficient to remove the adoption barrier of fuel availability.

Dütschke et al. (2011) reviewed user acceptance studies on natural gas vehicles in Germany and put them into international context to find out how acceptance for plug-in electric vehicles could be increased [Dütschke et al., 2011a]. Additionally, they conducted a survey of 142 NGV drivers in Germany in 2010. The main barriers to NGV adoption identified in this comprehensive analysis were cost and the lack of infrastructure, although the infrastructure concern "was not referred to very often by the interviewees" [Dütschke et al., 2011a]. Furthermore, concerns about lacking infrastructure for NGV-interested people were lower than for non-interested car drivers [Dütschke et al., 2011a].

Peters et al. (2011) studied plug-in electric vehicles and their possible early adopters with an online survey including 969 participants and tried to find out how Rogers' consumer groups [Rogers, 1962] could be characterized and identified for PEVs [Peters et al., 2011b]. They pointed out that consumers regard conventional infrastructure as highly superior to PEV charging infrastructure, but a significant influence of infrastructure in the purchase decision was not observed [Peters et al., 2011b]. The largest user acceptance study for PEVs in Germany up to now was conducted in the German pilot regions of E-mobility with more than 2,300 participants [Dütschke et al., 2011b]. According to Dütschke et al. (2012) the main factors consumers wish to be focused on for plug-in electric vehicles and charging infrastructure are to increase the vehicle range and to decrease their charging duration [Dütschke et al., 2011b]. Users also wish that public charging infrastructure is set up by companies or public authorities which is supported by a study of Continental (2011) [Continental, 2011]. Götz et al. (2011) also identified the missing charging infrastructure as one of the major barriers to adoption [Götz et al., 2011]. Globisch et al. (2013) detected that charging their vehicles at home is perceived as positive by users of PEVs while charging duration and frequency of PEVs are clear disadvantages [Globisch et al., 2013]. With a questionnaire distributed in the German pilot regions, they compared private and commercial users and found that the availability of charging infrastructure is perceived as insufficient, while commercial users rate charging infrastructure as even less sufficient [Globisch et al., 2013].

The evidence presented in this section suggests that:

- There has to be a minimum level of infrastructure for first users to adopt (15-20 % of conventional refueling stations for fuels similar to conventional fuels). This confirms the first finding in the empirical studies section.

- Concerns about infrastructure of non-interested people are higher than for interested ones (or early adopters) who tend to have almost no concerns. Thus, a model for AFV and infrastructure adoption should be able to distinguish different user groups.

- Actual users of AFVs have less difficulty to find refueling stations than they thought prior to purchase. Hence, decreasing concerns with AFV use should be reflected by models as well.

- As political action for refueling infrastructure construction is demanded by users, the integration of policy options into models should be considered.

Transferring these findings to PEVs, the initial charging infrastructure that has to be in place are domestic charging facilities in garages, which can already be used. Further, the model described in Chapter 4 will distinguish user groups with large sets of vehicle driving profiles. Also decreasing concerns regarding the use of PEVs as well as the integration of policy options will be considered in the model.

Summary of stylized facts

In this subsection a number of stylized facts from empirical and user acceptance studies on AFVs are identified that should be considered in models for vehicle and refueling infrastructure diffusion. From the evidence collected in this subsection, it can be concluded that the following general factors should be integrated into models of combined AFV and AFV refueling infrastructure market diffusion:

(A) An initial amount of AFV refueling or recharging infrastructure

(B) AFV and AFV refueling infrastructure market shares

(C) profitability of refueling or charging stations

(D) fuel prices for conventional and alternative fuels

(E) different user groups

(F) decreasing user concerns with AFV use

(G) potential policy measures

In Section 2.1.2 some specialties of PEVs and their charging infrastructure were pointed out that should be incorporated by models for PEV and charging infrastructure diffusion. Thus, apart from the general factors models should integrate, there are two specific factors relevant for PEV and infrastructure market diffusion models:

(H) refueling duration and frequencies can differ between PEV and conventional vehicles

(I) multiple types of infrastructure have to be differentiated by accessibility

Thus, nine factors are proposed which should be considered by models treating the interaction PEV and charging infrastructure diffusion (see also Table 2.3, first column). In the following section, existing models of AFV and AFV refueling infrastructure are tested whether they obey to these requests and find out if their modeling approach should be adopted. The requests to the model proposed in this thesis will be discussed in Section 4.4.

2.2.2 Review of models for joint vehicle and infrastructure diffusion

The studies presented thus far provide evidence that there is an interaction between AFV market diffusion and AFV refueling infrastructure market diffusion. This subsection holds a general scheme of model classification followed by a summary of model approaches used in literature to evaluate the interaction between AFV and AFV infrastructure.

Classification of models for vehicle and infrastructure diffusion

Generally, models can be clustered in many different ways and there is no common classification for all types of models (see e.g. [Zeigler, 1976, Geroski, 2000, Fleiter et al., 2011, Al-Alawi and Bradley, 2013, Jebaraj and Iniyan, 2006, Tran and Daim, 2008]). For the present case of models for AFV and their infrastructure market diffusion, model classification schemes from the market diffusion literature (such as [Geroski, 2000, Al-Alawi

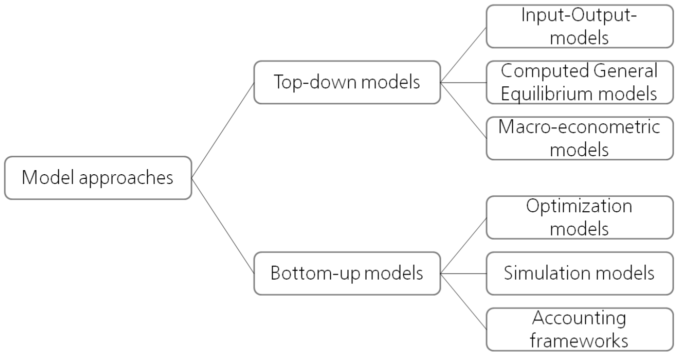

Figure 2.5: Classification of models based on [Dreher, 2001, Sensfuss, 2008, Fleiter et al., 2011]

and Bradley, 2013]) could be used as well as model classification schemes from energy economics (such as [Fleiter et al., 2011, Ventosa et al., 2005]) for energy-related infrastructures such as refueling stations networks.

In the following, a classification based on [Dreher, 2001, Sensfuss, 2008, Fleiter et al., 2011] is used (Figure 2.5). This is a common classification for energy system models which copes with dynamic effects such as the interaction of vehicle and refueling infrastructure market diffusion (see also [Dreher, 2001, Ventosa et al., 2005, Sensfuss, 2008]).[23] This classification distinguishes between two model philosophies: bottom-up and top-down models. These model philosophies and subordinated model classes are briefly described in the following for a better understanding.

Top-down models are based on at least one main assumption or development which is decomposed in the analysis. They are generally used for macroeconomic coherences which study industries in relation to national economies [Dreher, 2001, Sensfuss, 2008]. Top-down models can be further subdivided into three model classes: input-output models, general-equilibrium models and macro-econometric models. *Input-Output models* are adapted to evaluate changes in economy through exogenous changes in the sectoral demand [Kemfert, 1998, Sensfuss, 2008] while *Computable General Equilibrium* models assume long-term equilibria and model the economy based on equations. They are frequently used to analyze policies and their impacts [Sensfuss, 2008]. *Macro-econometric models* are often applied to evaluate past events empirically and derive prognoses thereof. For that reason imperfect market behavior is estimated based on economic data [Sensfuss, 2008, Kemfert, 1998].

Bottom-up models combine several detailed assumptions which are composed to an overall picture. They are used if detailed technological and economical information about all necessary subgroups is available [Sensfuss, 2008, Fleiter et al., 2011]. Bottom-up models can be further divided into optimization models, simulation models and accounting frameworks [Fleiter et al., 2011]. *Optimization models* perform a demand and supply matching and often try to maximize the economic surplus. While the maximization can derive from all factors in the objective function there is always a number of constraints that have to be respected [Sensfuss, 2008, Fleiter et al., 2011]. *Simulation models* are not based on equilibria. Instead, a set of rules is applied for mechanisms that define behavioral processes in the model which return a step wise development of the whole system [Sensfuss, 2008]. Sensfuss (2008) also subdivides simulation models into *agent-based models* and

[23]For a more general approach on the diffusion of innovations, refer to [Rogers, 1962, Geels, 2002]. In this study, a classification based on mathematical solution methods is preferred.

system dynamics models [Sensfuss, 2008]. *Accounting frameworks* model several sectoral outcomes and aggregate them for a full development [Fleiter et al., 2011].

With this classification, model approaches may be categorized and evaluated by their quality in fitting to the interaction of vehicle and refueling infrastructure diffusion for AFVs in general and PEVs in particular. This classification is used to categorize models from literature in the following.

Models for AFV and AFV infrastructure diffusion

In a literature review, ten studies were identified that jointly analyze the market diffusion of AFVs and their refueling infrastructure. An overview is given in Table 2.2, their approaches and main findings are presented in the following and summarized in Table 2.4 and Table 2.5.

Table 2.2: Overview of analyzed models for AFVs and their refueling infrastructure

Reference	AFV-type	Country	Time horizon*
[Hu and Green, 2011]	LPGV, FCEV	several	2000–2030
[Huétink et al., 2010]	FCEV	Netherlands	2010–2100
[Janssen et al., 2006]	NGV	Switzerland	2000–2030
[Köhler et al., 2010]	FCEV	EU27+2	2010–2040
[Melaina, 2003]	FCEV	United States	2010–2030
[Meyer and Winebrake, 2009]	FCEV	none	0–50
[Schwoon, 2006]	FCEV	Germany	2010–2030
[Schwoon, 2007]	FCEV	Germany	0–20
[Stephan and Sullivan, 2004]	FCEV	none	0–20
[van der Vooren and Alkemade, 2010]	LPGV	none	0–200

*years or time steps

Hu and Green (2011) examined the co-diffusion of LPGVs and their infrastructure and drew conclusions for FCEVs in a macro-econometric approach [Hu and Green, 2011]. In a multi-national analysis, country-specific break-even-distances for LPGVs[24] were analyzed in an elasticity model and several break-even-distances were calculated to find out if the system could become self-sustaining. After this ex-post analysis on LPGVs, findings were transferred to FCEVs keeping as many aspects from LPGVs as possible. The main conclusions were that (1) there is a strong connection between market penetration and break-even-distance of LPGVs, (2) infrastructure increases trigger market penetration of vehicles and vice versa, not enough, however, for a self-sustaining growth. Moreover, (3) a mix of financial and non-financial support policies is required for a market penetration of FCEVs.

Huétink et al. (2010) investigated FCEVs and their refueling infrastructure in the Netherlands [Huétink et al., 2010]. An agent-based simulation model was used to study the "relation between initial refueling infrastructure and [...] hydrogen vehicles" with special focus on user behavior [Huétink et al., 2010]. In their work Huétink et al. (2010) applied

[24]In [Hu and Green, 2011], the break-even-distance is defined as the distance after which a LPGV is more economic than a CV.

Rogers' perceived innovation attributes (relative advantage, compatibility, complexity, trialability and observability [Rogers, 1962]) to FCEVs. They derived the FCEV purchase price, the availability of hydrogen and social learning as main drivers for FCEV and infrastructure diffusion. Based on these drivers Huétink et al. (2010) formed consumer and refueling station agents that interact in a predefined fictive area which allowed to test different initial infrastructure set-ups. This led to the overall result that network effects have a significant impact with three consecutive findings: (1) diffusion is slower than in benchmark patterns if network effects are considered, (2) a nationwide infrastructure roll-out is better for diffusion than an urban strategy and (3) the social network structure also has an influence, i.e. small networks have favorable conditions.

Janssen et al. (2006) studied natural gas vehicles with a focus on policy development in a system dynamics approach [Janssen et al., 2006]. After an examination of previous international experiences, a system dynamics model with three reinforcing loops (emerging market loops for vehicles and fueling stations as well as a market forecasting loop) and two balancing loops (market saturation loops of vehicles and fueling stations) was established. Several policies were compared to a base scenario for the Swiss vehicle market in order to test the possibility of stimulating the latter. They found five indicators for a degree of market penetration that were drawn from the analysis: (1) the ratio between NGVs per CNG refueling station, (2) the type coverage, which is the offer of vehicle models presented to potential customers, (3) the NGV investment pay-back time, (4) the sales per NGV type and (5) the subsidies per vehicle.

Köhler et al. (2010) examined FCEVs and their refueling infrastructure in Germany using a system dynamics approach to retrieve the initial amount of infrastructure needed and its political and macroeconomic implications [Köhler et al., 2010]. They extended an existing transportation model by an economic policy analysis within the transition towards hydrogen in the transport sector. The main findings were that (1) there is only a small subsidy needed for the initial set-up of refueling infrastructure, (2) "the overall impact on the economy is positive", and (3) both FCEVs and their infrastructure need political support during its introduction while a full transition to FCEVs will take a long time [Köhler et al., 2010]. Besides, the "provision of a hydrogen distribution (as well as production) is not a major economic barrier to the adoption of hydrogen vehicles" [Köhler et al., 2010, p.1238], which is not in line with findings of other studies [Ball et al., 2009, Offer et al., 2010].

Melaina (2003) analyzed FCEVs in the US [Melaina, 2003]. A threefold simulation approach was used to determine the initial number of hydrogen stations necessary to trigger a self-sustaining market diffusion for the US market. In the first approach, he determined the number of hydrogen stations as a percentage of gasoline stations based on [Sperling and Kurani, 1987] and found 4,600 to 17,700 stations. The second approach divided metropolitan land areas into parts which resulted into 1,600 to 4,500 stations. The third and finally preferred approach regarded arterial roads in the US with corresponding 4,500 to 9,200 hydrogen stations. With these estimated numbers he explored the cost of hydrogen infrastructure in the early FCEV adoption process and found that a highly coordinated political effort would generate the lowest cost.

Meyer and Whinebrake (2009) also investigated FCEVs and their infrastructure in the US [Meyer and Winebrake, 2009]. Based on the theory of complementary goods, a system dynamics model was created on three attributes: the FCEV adoption, FCEV refueling stations and hydrogen market conditions with four reinforcing and two balancing loops.

Unlike [Janssen et al., 2006] Meyer and Whinebrake (2009) used a reinforcing loop for the causal combination of FCEVs and hydrogen stations and one for conventional vehicles and their refueling stations. Two more reinforcing loops covered the scrapping of FCEVs and conventional vehicles. The balancing loops covered the construction of hydrogen and conventional stations. Like in [Köhler et al., 2010], the individual user decides whether to buy a FCEV based on a utility function in which the station density attractiveness is included. They found that scenarios in which both vehicles and infrastructure were subsidized, markets could reach momentum and become self-sustaining, while focusing on one market only would not. Hence, they concluded that policies would have to consider both complementary goods.

Schwoon (2006) analyzed hydrogen vehicles in Germany with a multi-agent simulation approach and differentiated between three types of interacting agents: consumers, car producers and refueling station owners [Schwoon, 2006]. Moreover, he used a utility function for each consumer which was extended by a term for the fuel availability. Unlike in system dynamic approaches, weights for the infrastructure values individually change over time due to network effects. In his work Schwoon (2006) focused on different taxing and refueling station set-up scenarios with the following findings: (1) a diffusion of FCEVs can take place without a dense infrastructure if conventional vehicle owners pay taxes for their driving and (2) car manufacturers could benefit from own investments in infrastructure or cooperation with its constructors.

Schwoon (2007) studied hydrogen vehicles and refueling infrastructure in an agent-based simulation model combined with a spatial GIS-model for Germany [Schwoon, 2007]. Extending his previous work, which dealt with the adoption and also regarded the car producers explicitly, [Schwoon, 2007] focused on the initial infrastructure development based on geographic information. For each individual driver a certain "don't worry distance" was introduced, which is the distance between two refueling stations that is enough for the user, and tested in several scenarios if the infrastructure development was sufficient to reach the tipping point[25]. He concluded that (1) there have to be some initial hydrogen refueling stations for a market penetration kick-off, (2) the German HyWay-ring may be a good starting point, but (3) the optimal setting of the initial refueling stations depends on the "don't worry distance".

Stephan and Sullivan (2004) used an agent-based approach in a fictive area (central business district and surrounding rural area) for hydrogen vehicle and infrastructure market penetration [Stephan and Sullivan, 2004]. Two types of agents were considered: hydrogen retailers and (about 400) vehicle owners. Like most of the other agent-based approaches, consumers in [Stephan and Sullivan, 2004] also optimized a utility function, which in this case includes a worry factor for the availability of hydrogen like in [Schwoon, 2007]. They found that (1) cost for vehicles and infrastructure is an important factor and (2) the initial placement of refueling stations is crucial.

Van der Vooren and Alkemade (2010) had a more general approach to large technological systems in an accounting model [van der Vooren and Alkemade, 2010]. Their main research question was how the rise and fall of technologies that depend on infrastructure could be explained (cf. [Grübler, 1990]). They concluded: (1) the timing of a competing system has a large influence on the technological diffusion of the regarded system, (2) reaching momentum with infrastructure does not necessarily mean that the

[25] When the co-diffusion system has reached the tipping point or critical mass, it becomes self-sustaining and no more external stimuli are needed [Allen, 1988, Mahler and Rogers, 1999].

corresponding technology has to reach momentum and (3) lock-in occurs only when both reach momentum.

When comparing the results of these ten studies, there are three main findings which several studies support: (1) political support is needed for the initial infrastructure set-up [Hu and Green, 2011, Köhler et al., 2010, Melaina, 2003, Meyer and Winebrake, 2009]. (2) According to several studies the system can become self-sustaining [Köhler et al., 2010, van der Vooren and Alkemade, 2010], although some studies disagree [Hu and Green, 2011]. (3) An initial amount of refueling infrastructure is necessary for a self-sustaining system [Köhler et al., 2010, Schwoon, 2007, Stephan and Sullivan, 2004] which supports request A from the previous subsection. Furthermore, a variety of factors are identified which confirm the previously conducted requests.

While these models are compared according to the coverage of the extracted factors in the following section, their findings will be discussed with model results in Chapter 5. These findings are summed up in Table 2.4 and Table 2.5 at the end of this chapter.

2.2.3 Discussion of presented co-diffusion models

General discussion

Some models analyze vehicles powered by natural gas (three out of ten), while most analyze FCEVs (eight out of ten). To the best of the author's knowledge, there is no diffusion model that explicitly models the interaction of PEVs and their charging infrastructure. The large number of models considering FCEVs on the one hand and only a few with NGV on the other indicate the novelty of a combined diffusion approach in this field.

Beside the various results and implementation ideas covered by the models, there is a clear focus on bottom-up (nine out of ten) and simulation models (eight out of ten). Within the simulation models there are four agent-based approaches and three system dynamics models. While the bottom-up approaches require a large effort for data collection, top-down models do not operate on a similar level of detail. Of course, the required level of detail in modeling depends to a certain extend on the specific research question of each study.

There are three groups of research questions which are investigated by the models: (I) Is there a tipping point or how high is the tipping point? The majority of models tries to answer this question by estimating the number of refueling stations and users that have to adopt [Hu and Green, 2011, Köhler et al., 2010, Melaina, 2003, Meyer and Winebrake, 2009, Schwoon, 2007, Stephan and Sullivan, 2004]. (II) The second group of research questions focuses on policy options and infrastructure roll-out strategies that are often compared to the number of refueling stations [Huétink et al., 2010, Janssen et al., 2006, Schwoon, 2006]. (III) Finally, the last group of studies aims for theoretical insights [Hu and Green, 2011, van der Vooren and Alkemade, 2010]. When model classes and research questions are compared, no model class seems to be particularly well suited for one specific research question. Still, since the majority of the observed models favors simulation approaches, this model class seems appropriate for the specific requests in the papers.

Coverage of stylized facts

Table 2.3 summarizes which factors identified in Section 2.2.1 are covered by the ten models from literature. The symbol '✓' indicates whether a specific factor is integrated in a model, '–' if it is not and '(✓)' when the integration is not clear, but is presumed.

Table 2.3: Analysis of different models for AFVs and their refueling infrastructure. Indication if request is reflected in the model with '✓', if not with '–', otherwise with '(✓)' and footnote.

Factors to be modeled / Author(s) (Year)	[Hu and Green, 2011]	[Huétink et al., 2010]	[Janssen et al., 2006]	[Köhler et al., 2010]	[Melaina, 2003]	[Meyer and Winebrake, 2009]	[Schwoon, 2006]	[Schwoon, 2007]	[Stephan and Sullivan, 2004]	[van der Vooren and Alkemade, 2010]
(A) Consideration of initial refueling infrastructure	✓	✓	✓	✓	✓	✓	✓	✓	✓	–
(B) Eval. of market shares for AFVs and infrastructure	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(C) Observation of profitability of charging stations	–	✓	✓	✓	✓	(✓)^a	–	–	–	(✓)^b
(D) Reflection of ratio of fuel prices	✓	✓	(✓)^c	(✓)^a	(✓)^a	✓	✓	(✓)^d	✓	(✓)^b
(E) Contemplation of different user groups	–	✓	(✓)^f	(✓)^f	–	✓	✓	✓	✓	(✓)^b
(F) Integration of decreasing user concerns with use	–	✓	–	–	–	✓	✓	–	(✓)^a	–
(G) Modeling of policy options	(✓)^e	✓	✓	✓	–	(✓)^a	✓	–	–	–
(H) Consideration of refueling time and frequency	–	–	–	–	–	–	–	–	–	–
(I) Reflection of different infrastructure owners	–	–	–	–	–	–	–	–	–	–

a: unclear, but supposedly yes; *b*: unclear, since too general; *c*: externally defined; *d*: supposedly individual reflection; *e*: policy recommendation, calculation unclear; *f*: logit for user differentiation

None of the models covers all aspects derived from the literature in Section 2.2.1. While all general AFV questions may be answered with 'yes' for [Huétink et al., 2010], there is one model where only once can be affirmed for sure and three times with doubts [van der Vooren and Alkemade, 2010]. Thus, if the affirmations are summed up, all models are within a narrow range and this comparison is not considered to be quantitative. However, (1) bottom-up simulation models answer more questions with 'yes' than top-down models and (2) there is no difference in coverage between system-dynamics and agent-based models. Hence, this indicates that a bottom-up simulation approach is not only the most frequently used but also the most promising one to reproduce the stylized facts from Section 2.2.1.

Taking a closer look at the at the previously determined general factors, it can be stated that most models cover the general factors quite well, while user behavioral aspects (E and F) are best-covered by simulation models. Different user groups (E) are a basic ingredient of agent-based models and the integration of decreasing user concerns with time of use (F) is often covered by neighboring effects or social interaction [Bonabeau, 2002]. In the system dynamics models, users are often differentiated with logit-functions ([Janssen et al., 2006], in the part concerning the model ASTRA in [Köhler et al., 2010]) while in other models users individually decide on the basis of the logit-function [Meyer and Winebrake, 2009]. However, no correlation is to be found between factors and research questions.

Concerning the specific factors of PEVs there is no model covering any of the two aspects. Neither refueling duration and frequency (H), nor the different infrastructure owners (I) are covered. This might correspond to the fact that these two aspects result from technical and organizational challenges linked to PEV requirements which are not analyzed in these studies. Yet, this also means that current approaches cannot be transferred to plug-in electric vehicles without adaptations. For this reason, a new model approach is proposed in Chapter 4 that covers the extracted stylized facts as well as special PEV requests.

Summary and conclusions for further research

In this chapter, plug-in electric vehicles (PEVs) were defined and differentiated against other alternative fuel vehicles (AFVs). In addition, their differences concerning refueling behavior compared to conventional fuels were pointed out (Section 2.1). Thereafter, models for the interaction of the market diffusion of AFVs and their refueling infrastructure were analyzed in a structured literature review (Section 2.2). Stylized facts and factors to be integrated into models were retrieved from empirical analyses, studies on user behavior of AFVs and the specific characteristics of PEVs of Section 2.1. The identified factors were discussed for ten models. This collection comprises, to the best of the author's knowledge, the current models that cope with combined AFVs and refueling infrastructure market diffusion. Three conclusions and suggestions for the further procedure of this thesis can be condensed:

1. There is a chicken-and-egg-problem for AFVs, i. e. a lock-in effect where potential consumers do not buy vehicles when there is no refueling infrastructure and designated refueling infrastructure suppliers do not set up facilities as there are no customers. To overcome this situation, some initial refueling infrastructure has to be installed. Then the system may reach a tipping point from which on it can become self-sustaining. The tipping point is the most frequent research topic in this field. In the further proceeding of this work, this tipping point for PEVs will be analyzed.

2. Existing models on NGVs and FCEVs can reproduce historical market evolutions. The demands from the stylized facts where covered by most models analyzed (2.2.3).

Most of them are able to answer economical questions and to analyze some policy options. However, user adoption behavior and its change over time could be better integrated. The most common approaches are system dynamics or agent-based simulations. Hence, in Chapter 4, a simulation model for the co-diffusion of PEV and their charging infrastructure is proposed which is based on real-world driving profiles presented in Chapter 3.

3. The co-diffusion models analyzed in this section have to be strongly adapted for an integration of currently uncovered PEVs. With a widely available electricity grid and a large number of domestic charging facilities (at home in many major car markets) the chicken-egg-problem is different for potential PEV users that could recharge their vehicles at home. The longer charging duration and higher frequency as well as the lack of public charging options probably leads to a higher psychological need for charging facilities than the proposed 15–20% of conventional refueling stations. Currently, there is no model that treats the co-diffusion of plug-in electric vehicles and their charging infrastructure and none of the models analyzed here could be used to integrate PEVs without major adaptations. This attests the necessity of a new model for PEVs and their charging infrastructure which explicitly considers the charging duration, frequency and ownership (see Chapter 4).

Table 2.4: Analysis of models for AFVs and their refueling infrastructure - part 1

Author(s) (Year)	Model class	Research question	Novelty / Highlights	Major findings
Hu and Green (2011)	Macro-Econometric Model	existence or height of tipping point (I), theoretical insights (III)	break-even-distances from LPGV transferred to FCEV	- market penetration and break-even-distance connected - system not self-sustaining - mix of support policies required
Huétink et al. (2010)	Agent-based Simulation	policy options and infrastructure roll-out strategies (II)	application of Rogers' perceived innovation attributes to FCEVs and derivation of main drivers for FCEV and infrastructure diffusion	- inclusion of network effects leads to slower diffusion - nationwide roll-out preferable to urban strategy - structure of social network influences results
Janssen et al. (2006)	System Dynamics Simulation	policy options and infrastructure roll-out strategies (II)	development of policy options and indicators for degree of market penetration	indicators: - ratio between vehicles and refueling stations - offer of models presented to customers - vehicle investment pay-back time - sales per vehicle type - subsidies per vehicle
Köhler et al. (2010)	System Dynamics Simulation	existence or height of tipping point (I)	combination of existing transport model with model for economic policy analysis	- only small subsidy needed for initial hydrogen infrastructure - overall economy impact is positive - political support for vehicles and infrastructure needed - infrastructure not a major barrier for vehicle diffusion
Melaina (2003)	Various Simulations	existence or height of tipping point (I)	threefold approach for determination of initial charging infrastructure amount	- number of refueling stations varies with approach (1,600 to 17,700 hydrogen refueling stations for the US) - coordinated political set-up with lowest costs

Table 2.5: Analysis of models for AFVs and their refueling infrastructure - part 2

Author(s) (Year)	Model class	Research question	Novelty / Highlights	Major findings
Meyer and Whinebrake (2009)	System Dynamics Simulation	existence or height of tipping point (I)	model based on theory of complementary goods	both vehicles and infrastructure have to be financially supported
Schwoon (2006)	Agent-based Simulation	policy options and infrastructure roll-out strategies (II)	changing weight for infrastructure in individual utility function due to network effects	- FCEV diffusion possible without dense infrastructure network if conventional cars are additionally taxed - car manufacturers could benefit from investments in infrastructure
Schwoon (2007)	Agent-based Simulation	existence or height of tipping point (I)	combination of agent-based model and GIS-simulation and introduction of "don't worry distance"	- initial amount of filling stations necessary - HyWay-ring in Germany as starting point - optimal initial network depends on "don't worry distance"
Stephan and Sullivan (2004)	Agent-based Simulation	existence or height of tipping point (I)	combination of agent-based model and geographic information aspects	- cost is an important factor in vehicle and refueling infrastructure diffusion modeling - initial placement is crucial for successful market penetration
van der Vooren and Alkemade (2010)	Accounting Model	theoretical insights (III)	general view on large technological systems	- timing has a large influence on technology diffusion - co-diffusing technologies do not have to reach momentum at the same time - lock-in only occurs when both reach momentum

Chapter 3

Vehicle usage data

Introduction

The aim of this chapter is to describe and compare the main German vehicle usage data sets and to determine the ones to use in this thesis. First, the term driving profile is defined, then, the importance of a long observation period for an analysis of PEVs is shown and the differences of user groups are displayed (3.1). In the following, different data sets of private and commercial driving behavior are presented and analyzed whether they are representative for German vehicle registrations (Sections 3.2 and 3.3). While private driving profiles with a long observation period are publicly available for Germany, there are no commercial driving profiles with an observation period of more than one day. For this reason, a data collection of commercial vehicle usage data with an average observation period of three weeks has been performed by the author which is described in Section 3.3 as well.

3.1 Long observation periods for individual PEV analyses and the distinction of user groups

Vehicle usage data is an important means to study the driving behavior of persons and vehicles and are used for several detailed analyses (see e.g. [Santini and Vyas, 2005, Kley, 2011, Amjad et al., 2011, Smith et al., 2011, Plötz et al., 2014a]). In this thesis, the term driving profile (often also referred to as driving pattern) comprises all trips of one vehicle within a certain time horizon and will be used equivalently to vehicle usage data. While several studies use average vehicle usage data [Dagsvik et al., 2002, Santini and Vyas, 2005, Keles et al., 2008, Köhler et al., 2010, Meyer and Winebrake, 2009, Nemry and Brons, 2010, Schade, 2008, Lamberson, 2008, Shepherd et al., 2012, Wansart and Schnieder, 2010, Orbach and Fruchter, 2011], they neglect the large variations in driving between drivers or between days of individual drivers [Amjad et al., 2011, Smith et al., 2011, Neubauer et al., 2012]. The inclusion of individual user behavior is relevant to identify niches (see also Section 2.2.1) and is particularly important for PEVs since their ability to perform their driving profile completely with a BEV or with high amounts of electric driving in a PHEV strongly depends on the individual vehicle usage and the regularity of his driving behavior [Karlsson and Kullingsjö, 2013, Plötz et al., 2014a]. The electric driving share of PHEVs essentially determines a its TCO. For example, if there are two vehicles whose driving profiles have been collected for two days, and vehicle A drove 10 km the first and 130 km the second day while vehicle B drove 70 km on both days. The average daily mileage is 70 km for both vehicles, however a BEV with an electric range of 100 km would only be able to perform driving profile B without recharging during the day. If a PHEV with an electric range of 50 km is assumed to be able to recharge once per day, its electric driving share would be 71% for profile B, but only 43% for driving profile A.

The connection between technical PEV potentials and observation period was analyzed systematically in [Gnann et al., 2012a], where driving profiles with an observation period of seven days were tested in order to determine whether BEVs could perform them completely with varying battery capacities. The simulation of seven days was compared to the feasibility of every single day in the driving profiles while the latter showed a higher share of profiles that could performed with a BEV. Thus, the feasibility of a driving profile can be largely overestimated if short time driving profiles are used. Furthermore, an analysis of the influence of the observation period on electric driving shares was performed in which the confidence band of each vehicles' electric driving share with respect to the number of observation days was examined [Plötz et al., 2014a].[26] With an observation period of five days the 95%-confidence band of the individual electric driving shares showed a median at 19.1%, i. e. the error (due to observation period) on the electric driving share of half of the users was larger than 19.1%. This error decreased with 20 days of observation where the median of the 95%-confidence bands was at 9.5%. Hence, a precise determination of an individual's electric driving share requires a long observation period. If BEV feasibility and PHEV electric driving share are considered in a market potential analysis, results are affected by the observation period as well [Gnann et al., 2012c]. Since in this thesis the market diffusion of PEVs and their charging infrastructure is analyzed, the usage of driving profiles with a long observation period is mandatory (see also [Greene, 1985,Neubauer et al., 2012]). Yet, only a few models consider this premise (see e.g. [Pearre et al., 2011,Khan and Kockelman, 2012]).

As a matter of fact, data collections are designed for special purposes and are subject to limited funding. So, data collections very often focus either on a long observation period to the account of the number of observations or on a large number of observations at the expense of a shorter observation period. Figure 3.1 shows the number of observations and the observation period of several international driving profile data sets [US-DoT, 2009,ENTD, 2009,WVI et al., 2010,MOP, 2010,Auto21, 2011,Karlsson, 2013,Fraunhofer ISI, 2014]. While there are some data sets with more than 30,000 individual driving profiles (NHTS (United States): 180,000; KiD2010 (Germany): 47,114; MiD2008 (Germany): 34,601), they were collected for only one day to provide cross-sectional data of the national driving behavior. However, as described earlier, an analysis of individual profiles is accompanied by errors if only one day is used. An analysis of individual driving behavior without large errors due to variation between days can be performed with very long observation periods like in [Auto21, 2011](see e.g. [Blum, 2014]). Yet, the small sample of 75 vehicles in [Auto21, 2011] does not allow to generalize results for any subgroup. Hence, this thesis uses driving profiles of a certain length and a relevant number of observations which allows to use both advantages (individual analysis and possibility to generalize). These will be described and their characteristics will be discussed in the following sections.

[26] For this analysis the electric driving share of each individual profile was assumed to be Gaussian distributed, so that the confidence interval was given by $\Delta s_i(T) = t_{(1-\alpha/2,T-1)} \cdot \sigma_i(T)/\sqrt{T}$ with T being the number of observation days and $t_{(x,n)}$ the Student's t-distribution for n degrees of freedom.

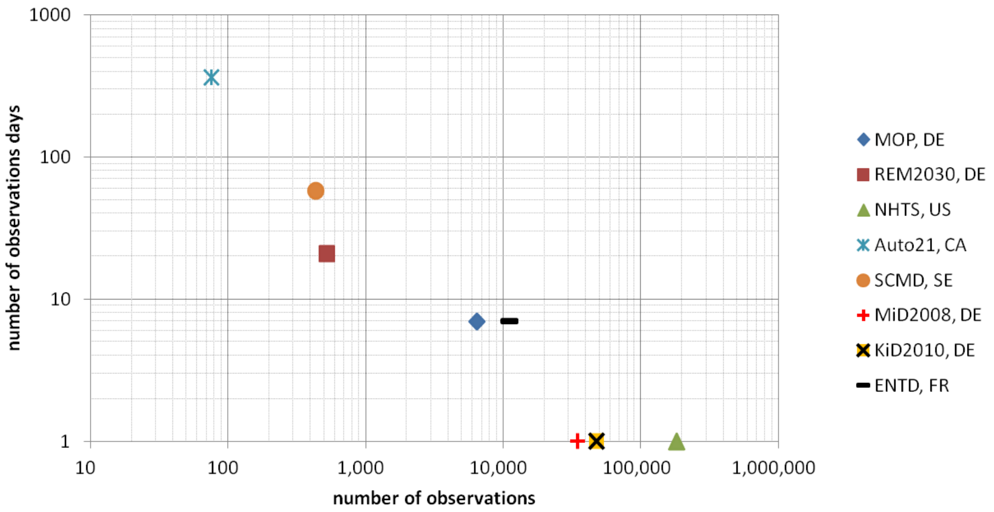

Figure 3.1: Comparison of different driving profile data sets with respect to observation period and number of observations. Data from [US-DoT, 2009, ENTD, 2009, WVI et al., 2010, MOP, 2010, Auto21, 2011, Karlsson, 2013, Fraunhofer ISI, 2014]

Furthermore, this work distinguishes between private and commercial driving profiles. This is important to mention since several studies neglect commercial vehicle owners (see e.g. [Schühle, 2014, Santini and Vyas, 2005, Kley, 2011, Shafiei et al., 2012, Hacker et al., 2011b]), although they account for more than 60% of annual passenger car registrations in Germany [KBA, 2014b].[27] German commercial and private vehicles differ in a number of characteristics (cf. Table 3.1). In contrast to vehicle registrations, the German vehicle stock is dominated by private vehicles which results from a shorter holding period of commercial vehicles and a large second-hand car market where mainly private users buy the used vehicles. Table 3.1 also shows that the average driving distance of commercial cars is larger than for private vehicles which, paired with a regular driving, is favorable for PEVs. The statistical significance of differences of average distance and regularity of driving will be analyzed in Section 5.1.1.

However, the group of commercial users has to be further subdivided, since it comprises vehicles which are only used for commercial purposes as well as vehicles with mixed (private and commercial) use. In the following, the solely commercially used vehicles are called fleet vehicles, while vehicles with mixed use are so-called company cars. According to [Pfahl, 2013], the total number of company car registrations is about the same as for fleet vehicles [Pfahl, 2013]. Yet, the exact number of company cars is difficult to determine, since the German Federal Motor Authority does only distinguish natural and legal car holders, i. e. the distinction in Table 3.1. For the further procedure of this work, the following is assumed: The commercial vehicle stock is distributed equally to fleet vehicles and company cars based on [Pfahl, 2013].

Summing up, this section showed that (1) a long observation period is decisive for the analysis of PEVs and (2) the commercial vehicle sector has to be considered separately.

[27] The commercial passenger car sector is very heterogeneous and no unique definition exists for it [Steinmeyer, 2007, Deneke, 2005]. Here, a commercial vehicle is defined to be licensed to a legal person or public entity, while a private vehicle is licensed to a private person.

Table 3.1: Privately and commercially licensed passenger cars in Germany

criteria	private	commercial	reference
Stock (2014-01-01)	39,363,889	4,487,341	[KBA, 2014a]
Share of stock	89.8%	10.2%	[KBA, 2014a]
Registrations (2013)	1,120,125	1,832,306	[KBA, 2014b]
Share of registrations	37.9%	62.1%	[KBA, 2014b]
Avg. vehicle holding period [a]	6.2	3.8	[VCD, 2008, DAT, 2011]
Avg. motor size [ccm]	1,638	1,994	[KBA, 2014a]
Avg. VKT on weekday [km]	40.1	76.8	[IVS et al., 2002]
Avg. VKT on Sat./Sun. [km]	28.8	29.3	[IVS et al., 2002]

These two conditions are considered when the driving profiles for the further analysis are determined in the following.

3.2 Private vehicle usage data

3.2.1 Overview of private vehicle usage data sets

In Germany, there are two large studies on the travel behavior of households publicly available: Mobility in Germany (MiD, [infas and DLR, 2002, infas and DLR, 2008]) and the German Mobility Panel (MOP, [MOP, 2010]). A third study on travel behavior (not publicly available) is similar to MOP yet restricted to the region of Stuttgart in southern Germany (MOPS, [Hautzinger et al., 2013]). These data sets are shown in Table 3.2.

Table 3.2: Overview of private driving profiles for Germany

Attribute	MiD2002	MiD2008	MOP	MOPS
Reference	[infas and DLR, 2002]	[infas and DLR, 2008]	[MOP, 2010]	[Hautzinger et al., 2013]
Data collection design	Questionnaire	Questionnaire	Questionnaire	Questionnaire
Time of collection	2002	2008	1994–2010[a]	2012
Number of households	26,848	25,922	12,812	992,584
Number of vehicle profiles	33,293 (17,773)[b]	34,601 (20,927)[b]	6,339	1,312,817
Number of vehicle trips	61,645	73,552	172,978	19,100,429

a: collection is still ongoing, b: vehicles with movement

The data collection for MiD was performed twice in 2002 and 2008 and MiD is a household travel survey. Thus, not only trips with vehicles were collected, but also trips by foot, bike or public transport were recorded. The collection of 2002 was performed for 26,848 households (2008: 25,922) which had to report all their trips on one reporting day. Trips were collected during the whole year 2002 (and partially in 2003) whereof 33,293 vehicles can be extracted (2008: 34,601). Apart from the travel behavior, there is a large number of socio-demographic information about the households and drivers (e.g. income, education, sex) as well as the vehicles (e.g. vehicle size, fuel type, brand).

MOP is an ongoing household travel survey that has been performed since 1994 with

1,000 households every year.[28] Users report all their trips during one week which also include trips by foot, bike or public transport. By using information from 1994 until 2010, data of 12,812 households can be analyzed. In contrast to MiD, the allocation of trips to vehicles is not available in the initial data set. Thus, this allocation has to be performed where unambiguously possible based on the following assumptions (see also [Kley, 2011, Chlond et al., 2014]):

- If there is only one vehicle in the household, trips of all household members as vehicle driver are assigned to the vehicle. In this case the socio-demographic information of the first driver is assigned to the vehicle profile.

- If the number of vehicles exceeds the number of drivers, the trips of the first household member are assigned to the first vehicle, those of the second driver to the second vehicle until the last driver's trips are assigned. This might overestimate the driving of single vehicles.

- If the number of vehicles is smaller than the number of household members, the vehicles will be exempted from the further analysis, since the allocation of trips to vehicles is unknown.

Since the data structure changes over the years, an allocation algorithm has to be adapted for every year (cf. A.1 for details). This returns 6,339 vehicle driving profiles with about 170,000 single trips. Apart from the trip distances, the purposes of all trips are collected, which allows to distinguish between trips to private locations[29], to the work place[30] and trips with public destinations (other purposes) equal to the accessibility types of charging infrastructures in Section 2.1.2. Also, socio-demographic and vehicle information is available for this data set, such as the vehicle ownership which distinguishes natural and legal persons. Thus, this data set does not only contain private vehicles, but also company cars which are analyzed separately in the following.

For the MOPS-data, a seven-day mobility survey was performed with about 5,000 households in the region of Stuttgart (i.e. the six districts: Stuttgart, Göppingen, Ludwigsburg, Rems-Murr-Kreis, Esslingen and Böblingen – see Figure 3.2). Based on this survey, socio-demographic data of the region and trip matrices, the data set was extrapolated to the whole region of Stuttgart. Thus, this sample contains trips for 2.7 million persons, including all trips by foot, public transport or bike including their starting and stopping zones. Those zones are different in size and smaller the closer they are to the city center (central station of Stuttgart). There are also zones outside the observation area with starting and stopping points of trips, although the home of all users is within the observation area (see right panel of Figure 2). For more details on these zones refer to Table 3.3 and Figure A.1.

As only vehicle trips are of interest in this study, an allocation of personal trips to vehicles is performed where unambiguously possible (same assumptions as for MOP). A focus on 15 min-intervals further reduces the sample size and complexity. Socio-demographic information of vehicle owners and vehicles is rare in this data set since it is synthetically

[28]Some households are chosen to participate multiple, yet not more than three, times.

[29]Purposes 7 and 77 according to the codebook of MOP.

[30]Purposes 2 and 4 according to the codebook of MOP.

Figure 3.2: Observation area of MOPS on German map (left), in detail (center) and divided into zones including surrounding outer area (right). Own display with data from [Hautzinger et al., 2013].

generated. Yet, the information about trip locations permits simulating the driving of PEVs simultaneously and geographically and testing whether charging points could be occupied by other PEVs in a charging simulation [Kuby et al., 2013]. The additional information available besides the trip distances, times, and purposes are the household sizes, age, sex and occupation of the driver as well as the locations of their homes and work places.

Table 3.3: Geographic zones of observation area of MOPS.

Attribute	Value
Surface of inner area	3,652 km^2 (1% of Germany)
Zones in inner area	1,014
Average surface of inner area zones	3.8 km^2 (SD=6.1 km^2)
Surface of outer area	13,186 km^2
Zones in outer area	140 (+20 distant zones)
Average surface of outer area zones	97.0 km^2 (SD=92.9 km^2)

3.2.2 Comparison of private vehicle usage data sets

In this thesis, each driving profile is analyzed separately to test whether it is technically feasible and economically sensible as PEV. As explained in Section 3.1 this requires an observation period of multiple days. Hence, the data sets MOP and MOPS are used for further analyses. However, the information of MiD serves for validation of the other data sets in terms of driving behavior, vehicle sizes and garage availability.

Figure 3.3 shows the distributions of daily and annual vehicle kilometers traveled (VKT) in the data sets. On the left panel, the cumulative distribution functions of the daily trips are displayed. Shown are the data sets MiD2002 (dotted green) and MiD2008 (dotted black) with their mileage on the day of observation. Thus, only the vehicles with movement are displayed here. For MOP and MOPS two curves are displayed: the average daily distance for all drivers (i. e. the sum of the trips during the observation week divided by seven; displayed in dashed blue for MOP and dash-dotted black for MOPS) and the daily distances of all drivers on all driving days (dashed red for MOP and dash-dotted yellow for MOPS). By dividing the sample sizes, it is visible that a vehicle is moved on

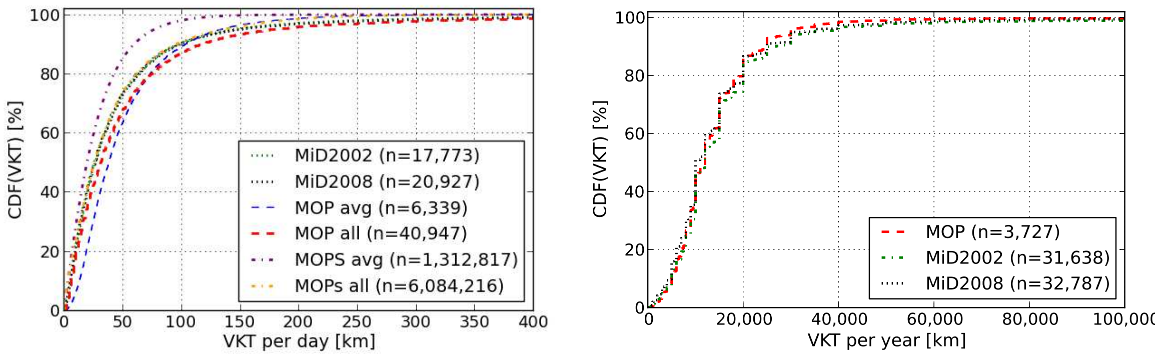

Figure 3.3: Comparison of daily and annual VKT in different private driving profile data sets. *Left panel:* Cumulative distribution function of daily VKT. *Right panel:* Cumulative distribution function of annual VKT. Data from [infas and DLR, 2002, infas and DLR, 2008, MOP, 2010, Hautzinger et al., 2013].

6.46 days on average in MOP and on 4.63 days in MOPS.[31] The figure contains four interesting findings: (1) The distribution daily VKTs of MiD2002 and MiD2008 is almost equal. This confirms the robustness of samples with a large number of observations when analyzing the whole sample. (2) When all individual daily distances of MOP or MOPS are compared to MiD, the shares of MOP and MOPS are slightly lower for shorter distances (73% of all vehicle trips in MiD and 67% of all vehicle trips in MOP are lower than 50 km). Thus, daily driving distances may be slightly overestimated by using the MOP data. (3) The share of users with an average daily vehicle distance below 120 km is lower in MOP than in MiD and higher above 120 km. This confirms the slight overestimation of driving distances when using the MOP data. (4) Driving distances for MOPS are lower than in all other data samples, especially long-distance trips are not included in the sample. These findings suggest a careful interpretation of results.

The right panel of Figure 3.3 uses the same display as the left panel, although here the cumulative distributions of the annual VKT are displayed. Shown are the reported annual VKT for MiD2002 (dash-dotted green), MiD2008 (dotted black) and MOP (dashed red). Due to incomplete responses in the questionnaires, the sample sizes are reduced here. Two main findings can be extracted: (1) The three curves are almost equal to each other, thus the sample size of MOP is sufficient for the further analysis of the VKT. (2) Several steps can be found which can be explained by the estimated annual VKT in the questionnaires. The statistical relevance of these differences will be analyzed hereafter.

Since driving behavior is connected with vehicle size, Table 3.5 shows the mean annual VKT, their standard deviations and subsample sizes of the three data sets MiD2002, MiD2008 and MOP distinguished by car sizes. For this distinction, a small vehicle is defined to have a motor with a cubic capacity of less than 1,400 ccm, a medium sized vehicle between 1,400 ccm and 2,000 ccm and a large vehicle with 2,000 ccm and more. As MOPS does not contain any information about car sizes it is not displayed in this table.

[31] This is not comparable to the share of vehicles in motion in MiD since not all trips in MOP could be allocated to vehicles and vehicles without movements were extracted.

Table 3.4: Annual VKT in different vehicle sizes of private driving profiles for Germany. Data from [infas and DLR, 2002, infas and DLR, 2008, MOP, 2010]

Vehicle size	attribute	MiD2002	MiD2008	MOP
small	mean [km]	11,280	11,826	10,466
	stdev [km]	9,910	13,384	9,020
	number	5,442	6,751	966
medium	mean [km]	14,791	14,805	14,676
	stdev [km]	11,759	15,209	11,199
	number	13,222	20,517	2,165
large	mean [km]	17,839	15,965	16,204
	stdev [km]	16,637	16,912	11,746
	number	5,536	5,519	596

In all three data sets medium sized vehicles' means are equal at an annual mileage of about 14,700 km per year with statistically insignificant differences.[32] For small and large vehicles the average annual VKT differs slightly more. Based on statistical tests, only large vehicles of MiD2008 and MOP are in good accordance while all other samples are significantly different.[33] Significant differences are found between all three data sets. As all three data sets comprise a large number of participants, it is unclear which one is best. Thus, MOP is considered representative for private driving behavior.

Apart from driving behavior the availability of garages or a parking close to the own grounds is important when analyzing PEVs with respect to their charging infrastructure. As mentioned in Section 2.1.2 the availability of a garage could simplify the (individual) infrastructure set up largely. The questionnaires of MiD and MOP contain questions regarding this topic. However, their formulation is slightly different for all three. In MiD2002 users were asked for the common parking spot of every vehicle with the following responses: in a garage (58.5% of all vehicles), at a parking on own property (29.2%), at parking close to own property or apartment (7.9%) and at varying parking spots (3.9%)(see also Figure 2.3 and [Gnann et al., 2013] for a further distinction of city sizes). For MiD2008, responses were changed to the question of the common parking spot: on the own property (71.3%), at parking directly close to own property or apartment (25.2%), farther away from own property or apartment (1.0%) and at varying parking spots (2.3%). In MOP the share of vehicles with garages is 66.2%. Thus, the responses in MiD2008 do not allow to determine if the vehicle parking spot is a garage, and it is only possible to compare the garage availability from MOP to MiD2002 finding it slightly higher in MOP. Yet, the availability of garages in both samples is around 60%, which is confirmed by [Behrends and Kott, 2009].

In summary, MOP and MOPS will be used for further analyses because of their long observation period. Furthermore, in terms of driving behavior and garage availability there are small differences in the data sets. Their influence on results will be discussed in the further proceeding of this work.

[32] A two-sided t-test with unequal sample sizes and unequal variances rejects the null hypothesis with p=66.0% for a comparison of MiD2002 and MOP, p=62.3% when MiD2008 and MOP are compared and p=92.4% for MiD2002 and MiD2008 (see e.g. [Fahrmeir et al., 2011]).

[33] A two-sided t-test with unequal sample sizes and unequal variances rejects the null hypothesis for small vehicles with p=1.1% (MiD2002-MOP), p <0.01% (MiD2008-MOP) and p=0.97% (MiD2002-MiD2008). For large vehicles p=0.21% (MiD2002-MOP), p=65.3% (MiD2008-MOP) and p <0.01% (MiD2002-MiD2008) are found.

Table 3.5: Common parking spot of private vehicles for Germany based on [infas and DLR, 2002, infas and DLR, 2008, MOP, 2010].

Response option	MiD2002	MiD2008	MOP
Garage	58,8%	-	66.2%
on the own property	29.2%	71.3%	-
on parking directly close to own property or apartment	-	25.2%	-
on parking close to own property or apartment	7.9%	-	-
farther away from own property or apartment	-	1.0%	-
at varying parking spots	3.9%	2.3%	33.8%

3.3 Commercial vehicle usage data[34]

Commercial vehicles comprise about 60% of annual German vehicle registrations and are thus a relevant market for PEVs. Available vehicle usage data sets are discussed in this section.

3.3.1 Overview of commercial vehicle usage data sets

Until 2011, the only publicly available vehicle usage data set for German commercial vehicles was "Motor Traffic in Germany" (KiD, [IVS et al., 2002, WVI et al., 2010]). This data set only comprises vehicle driving profiles with an observation period of one day. For this reason a data collection for commercial vehicles has been designed and performed by the author in the ongoing project "Regional Eco Mobility 2030" resulting in the "REM2030 driving profiles" (REM2030, [Fraunhofer ISI, 2014]).[35] A subsample for the region of Stuttgart is named REM2030S and Table 3.6 gives an overview of the commercial data sets.

Table 3.6: Overview of commercial driving profiles for Germany

Criteria	KiD2002	KiD2010	REM2030	REM2030S
Reference	[IVS et al., 2002]	[WVI et al., 2010]	[Fraunhofer ISI, 2014]	
Collection design	Questionnaire		GPS-tracking	
Time of collection	2001-2002	2010	2011-2014^a	
Observation period	1 day		21.0 days	
Number of vehicles (profiles)^b	76,797 (32,171)^b	70,249 (24,958)^b	522 (498)^c	164
Total number of vehicle trips	163,108	330,293	71,338	13,374

a: data collection ongoing; b: profiles with movement; c: profiles with at least seven days of observation

KiD was collected twice, in 2002 and 2010. The design of the study was similar to MiD, although no household records but only those of company vehicles were collected in KiD. A questionnaire was distributed for about one year and vehicle trips were reported

[34]This section which is based on [Gnann et al., 2015a].
[35]For a description of their collection and preparation refer to Section A.3.

on one observation day. KiD2002 comprises the information of 76,797 passenger cars of which 32,171 were in motion on the observation day. In total, the data set comprises 163,108 vehicle trips. In the 2010 edition of KiD 330,293 vehicle trips of 25,958 vehicles in motion were collected. However, the observation period in KiD is only one day per vehicle. Since the time horizon of the used data collection has a significant influence on the upscale to VKT as well as on the technical feasibility and potential electric driving share, a single day data base might result in a strong bias (see e.g. [Gnann et al., 2012a, Plötz et al., 2014a] and Section 3.1).

For this reason, a data collection of conventional vehicle profiles with a time horizon of about three weeks was performed by the author in the on-going project "REM2030" [Fraunhofer ISI, 2014]. The REM2030 data was collected with GPS-trackers over 21 days on average and currently contains 522 vehicle driving profiles of which 498 have an observation period more than six days and are analyzed in the following.[36] The 373 passenger cars and 125 light commercial vehicles (LCVs) in REM2030 with an observation period of at least one week perform about 53,000 or 19,000 trips respectively. This yields a daily average of 6.7 trips and 73 km per day for passenger cars and 6.8 daily trips and 67 km on average for LCVs which is in line with [WVI et al., 2010]. Regarding the distinction of solely commercially used (fleet vehicles) and partly privately used commercial vehicles (company cars), the REM2030 data mainly contains company fleet vehicles which are used for commercial purposes only.[37]

Since the collection design does not allow to distinguish vehicle trip purposes, the average beeline to the company site is calculated to determine a trip to the company site. With this calculation a stopping point is assumed to be commercial when the distance of the beeline is lower than 500 meters and public otherwise. This follows the distinction of possible charging facilities in Section 2.1.2 and allows to determine commercial and public locations in which potential PEVs could be charged. Furthermore, since an annual mileage is not part of the small questionnaire distributed with the GPS-trackers, it is calculated by the mean of the daily distance means times 365[38].

REM2030S is a subsample of profiles and comprises 164 profiles whose company sites are in the region of Stuttgart. This subsample is extracted to maintain a data set with the same spatial focus as MOPS. MOPS and REM2030S are used for the simultaneous simulation of users at charging locations. Their representativity is discussed in the following, while their impact on results will be discussed in Section 5.3.5.

3.3.2 Comparison of commercial vehicle usage data sets

Like for private vehicles the arguments of a long observation period also hold for commercial driving profiles. Thus, the REM2030 and REM2030S profiles will be used in the further analyses, while KiD2002 and KiD2010 are exploited for comparison of driving behavior, vehicle sizes and affiliation to commercial branches.

[36] For a description of their collection and preparation refer to Section A.3.

[37] Although the vehicle usage is only available for data collected as of 1st of January 2014, it shows a majority of fleet vehicles. Prior to to 2014, companies were requested to put the GPS-trackers in fleet vehicles.

[38] $VKT^a = 365 \cdot 1/7 \cdot 1/K_i \sum_{i=mon}^{sun} \sum_{k=1}^{K_i} VKT_{ik}$ with i as weekday, VKT_{ik} as the vehicle kilometers traveled on the kth weekday of i and K_i as frequency of this weekday in the driving profile.

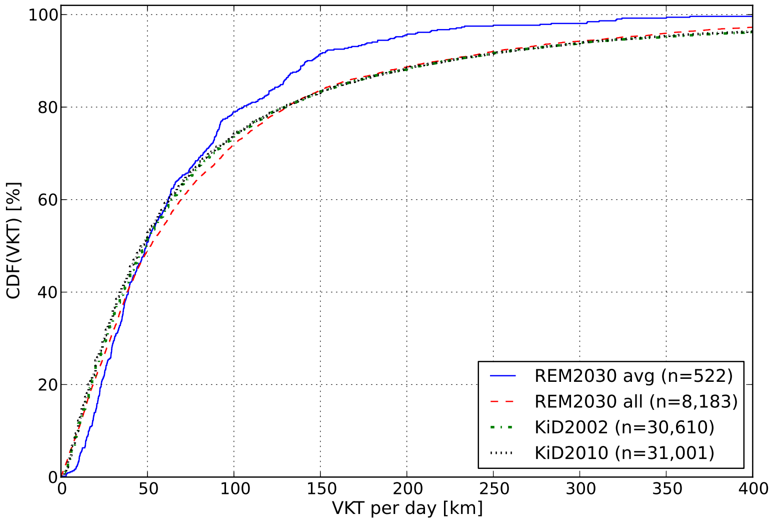

Figure 3.4: Comparison of daily VKT in different commercial driving profile data sets. Data from [IVS et al., 2002, WVI et al., 2010, Fraunhofer ISI, 2014]

Figure 3.4 shows the cumulative distribution functions of daily VKT for these commercial driving profiles. Like for MiD2002 and MiD2008 in the left panel of Figure 3.3 for private users, the daily VKT for KiD2002 (green dash-dotted) and KiD2010 (black dotted) are the reported driving distances on the day of observation. Hence, the number of daily VKT corresponds to the number of vehicles with movement on the day of observation. For this figure only passenger cars and LCVs are considered.[39] Like MOP for private vehicles, the REM2030 data is displayed in two ways: the average daily driving as explained earlier in this section (solid blue) is displayed as well as the single driving days (red dashed). For an average number of 21.0 days with observation in REM2030, an average number of 15.7 days with driving can be determined which could result from five working days per week for most commercial branches. There are three points to retain for discussion in the following analyses: (1) The distributions for KiD2002 and KiD2010 are almost equal to each other. (2) The distribution of the single days of observation of REM2030 is also very close to the distributions of KiD2002 and KiD2010. (3) However, the distribution of calculated average daily distances for REM2030 shows less long distances (above 100 km) than the other distributions. An interpretation may be that the low frequency of long-distances per vehicle is compensated by a high frequency of shorter trips within a profile. For the following analyses the similarity of single daily VKT in REM2030 to KiD2002 and KiD2010 suggests that the REM2030 profiles are an adequate choice for commercial driving behavior.

Further, the differences in driving between vehicle sizes in KiD2002, KiD2010 and REM2030 are evaluated. Table 3.7 shows the mean daily VKT, its standard deviation and number of driving profiles for the four sizes classes: small (cubic capacity (CC)<1,400 ccm), medium (1,400 ccm≤CC<2,000 ccm), large (2,000≤CC) and LCVs (weight below 3.5 tons).

[39]The SQL code for this query runs as follows: *SELECT * FROM pkw WHERE v01 IN (2,3).*

Table 3.7: Average daily driving of commercial driving profiles for Germany differentiated by vehicle sizes. Data from [IVS et al., 2002, WVI et al., 2010, Fraunhofer ISI, 2014].

Vehicle size	attribute	KiD2002	KiD2010	REM2030
Small	mean [km]	28.27	31.34	42.00
	stdev [km]	63.87	62.06	29.01
	number of profiles	4,551	5,076	113
Medium	mean [km]	53.22	60.73	82.32
	stdev [km]	112.31	123.59	63.24
	number of profiles	14,570	14,427	198
Large	mean [km]	54.62	60.73	104.05
	stdev [km]	123.85	117.70	94.89
	number of profiles	9,958	8,716	56
LCV	mean [km]	33.67	42.33	66.68
	stdev [km]	84.21	98.81	64.37
	number of profiles	40,851	25,573	131

While the daily VKT is always larger in REM2030, insignificant differences of daily VKT are found among almost all subsamples.[40] Moreover, the overestimation of driving behavior could result from the different calculations of average daily VKT (as explained earlier in this section) as well as from the collection design. Companies that took part in the data collection of REM2030 were allowed to choose the vehicles whose driving was recorded. While standard deviations are almost twice the mean values for KiD2002 and KiD2010, mean and standard deviation are about equal for REM2030 within a subsample. Thus, the sample values are broader distributed for KiD than for REM2030 (which also stems from the inclusion of several vehicles that are not moved during the day of observation in KiD). For the further proceeding of this work, the tendency of REM2030 to overestimate driving will be kept in mind.

Another important distinction of driving profiles in the commercial passenger car sector is the commercial branch [Ketelaer et al., 2014]. The commercial branches are clustered according to [Eurostat, 2008]. Since the REM2030 data collection is intended to be representative for commercial registrations regarding commercial branches, this premise is tested in the following. In Table 3.8 the number of annual vehicle registrations [KBA, 2014b], the average daily VKT, its standard deviation and the number of driving profiles within a commercial branch for data sets REM2030 and KiD2010 are presented. Further, the p-value of a two-sided t-test for mean values with unequal sample sizes and unequal variances is shown in the last column.

First, it has to be mentioned that about 90% of all commercially licensed vehicles are newly registered in four groups: G (Wholesale and Trade), C (Manufacturing), N (Administrative services), and S (Other services).[41] About 89% of vehicles within section G (Wholesale and Trade) are licensed to companies that work within vehicle trade, with

[40] A two-sided t-test with unequal sample size and unequal variances rejects the null hypothesis at p=7.1% for large vehicles and p=1.7% for small vehicles when KiD2002 and KiD2010 are compared and p <1% for all other comparisons.

[41] When comparing registrations with vehicle stock, it is found that the holding periods in sectors G (Wholesale and Trade), C (Manufacturing) and N (Administrative services) are much lower than average (1.1 to 1.7 years compared to 3.8 years).

Table 3.8: Driving distances distinguished by commercial branches

NACE section	annual registrations[a]	KiD2010[b] sample size	KiD2010[b] avg. daily VKT	KiD2010[b] st.dev. daily VKT	REM2030[c] sample size	REM2030[c] avg. daily VKT	REM2030[c] st.dev. daily VKT	p-value[d]
G - Wholesale and trade	699,506	3,068	45.20	106.10	45	64.19	34.83	0.00
C - Manufacturing	380,367	2,559	70.11	142.13	101	78.67	45.66	0.11
N - Administrative and support service activities	357,835	958	56.09	108.51	43	78.61	66.09	0.04
S - Other service activities	265,926	8,457	60.06	129.09	51	62.09	43.81	0.75
Q - Human health and social work activities	33,391	1,064	42.39	79.86	67	51.74	31.52	0.04
F - Construction	31,150	2,559	59.00	121.25	38	47.13	29.23	0.03
O - Public administration, defense, social security	28,546	1,910	41.46	93.67	66	29.05	18.15	0.00
H - Transportation and storage	27,269	890	52.31	103.38	45	202.84	96.92	0.00
K - Financial and insurance activities	18,582	238	59.61	98.83	5	48.83	25.53	0.44
J - Information and communication	16,271	146	47.41	92.45	10	65.56	37.51	0.22
M - Professional, scientific, technical activities	12,065	10	95.46	82.55	4	60.20	20.94	0.24
D - Electricity, gas, steam, air conditioning	7,452	376	52.52	99.66	16	32.47	21.63	0.01
I - Accommodation and food service	5,495	226	43.16	110.73	0	0.00	n.n.	n.n.
L - Real estate activities	4,419	1	0.00	n.n.	0	0.00	n.n.	n.n.
E - Water, sewery, waste, remediation	3,938	419	59.24	119.85	7	37.81	38.89	0.21
R - Arts, entertainment and recreation	3,541	119	36.67	79.55	0	0.00	n.n.	n.n.
A - Agriculture, forestry, shipping	2,963	543	39.96	98.57	0	0.00	n.n.	n.n.
P - Education	2,134	61	60.64	93.95	0	0.00	n.n.	n.n.
U - Extraterritorial organizations and bodies	1,418	33	75.33	232.21	0	0.00	n.n.	n.n.
B - Mining and quarrying	1,192	100	61.60	118.62	0	0.00	n.n.	n.n.
Total	1,903,460	23,737	55.46	119.10	498	71.50	65.00	0.00

a: [KBA, 2014b]; b: [WVI et al., 2010]; c: [Fraunhofer ISI, 2014]; d: p-value for two-sided t-test of difference of means with unequal sample sizes and unequal variances.

vehicle parts and vehicle maintenance [KBA, 2013]. In section C (Manufacturing) another 74% of vehicles are registered to vehicle construction while car rentals sum up to 85% of vehicles in section N (Administrative services) [KBA, 2013]. Thus, in total 63% of all commercial passenger car registrations are directly related to the automotive industry. This is important to know since a large number of these vehicles might be showroom cars that are hardly driven during first registration or company cars with a high amount of driving. The fourth largest car registration group is section S (Other services) which contains about 14% of all commercial registrations. 99% of the vehicles in this group comprise membership organizations, trade unions as well as political and religious organizations [KBA, 2013]. In the further analysis special emphasis will be put on these four vehicle groups.

Furthermore, some branches within the single data sets show high daily VKT, for example the branches H (Transport), C (Manufacturing) and N (Administrative services). These average daily VKT between the different commercial branches can be compared by a t-test assuming log-normal distributed daily VKT.[42] Statistical tests for two data sets of commercial driving show the average daily VKT in branches H (Transport), O (Public administration), A (Agriculture, forestry, shipping), and D (Energy) to differ from at least two third of the other branches within one data set.[43]

However, for the representativity for driving in commercial branches, the average daily VKT between REM2030 and KiD2010 within each branch is tested (p-values in the last column). The null hypothesis (values differ from each other) is rejected with the probability p, thus small p-values can be interpreted as significant differences while large p-values show statistically insignificant differences. p-values smaller than 1% are found for commercial branches G (Wholesale and Trade), O (Public administration) and H (Transport). Since branch G (Wholesale and Trade) accounts for about 30% of annual registrations this does not favor a detailed analysis of driving behavior within commercial branches. However, the differences between REM2030 and KiD concerning driving behavior are insignificant for commercial branches that are responsible for two thirds of annual registrations. For the further procedure of this work, the REM2030 data can be considered representative for annual registrations in large parts, however, conclusions for single commercial branches will be drawn carefully.

For this work, the following conclusions for commercial driving behavior can be drawn: Since there was no data set with more than one day of observation for commercial vehicles, the REM2030 driving profiles have been collected for this purpose and will be used for the further analyses. A comparison of driving distances distinguished by vehicle size, by commercial branch, and without distinction shows that the REM2030 profiles tend to slightly overestimate driving distances. However, a comparison of the other available data sources does not show good accordance either. Thus, for the following, analyses concerning vehicle sizes, commercial branches, and commercial driving will be discussed in light of these findings.

[42] The distribution of daily driving distances in the samples is right-skewed. Thus, using the logarithms of the daily VKT, the normality premise for a t-test is approximately fulfilled. This corresponds to the assumption that average daily driving distances of randomly chosen vehicles are log-normal distributed (see [Greene, 1985, Lin et al., 2012, Dong et al., 2014, Kagerbauer, 2010] for a similar discussion.

[43] A two-sided t-test for mean annual VKT with unequal variances and unequal sample sizes is significant at $p < 1\%$.

Summary

The aim of this chapter was to present the main data sources for this thesis and to discuss their main characteristics with respect to other data sets. The main data source is vehicle driving profiles which comprise all vehicle trips performed in a certain observation period. Private and commercial driving profiles that are publicly available or were collected for this thesis were presented and their differences were discussed. The following important findings can be summed up:

1. A long observation period is decisive for the analysis of individual driving profiles. Plug-in electric vehicles face the problem that they have to drive a significant amount of kilometers electrically to be able to economize while they are technically restricted by their electric range. An analysis of individual driving profiles allows to identify potential early adopters with respect to their driving. However, driving profiles with short observation periods tend to overestimate electric driving and market potentials subsequently.

2. In Germany there are two large private data sets with one week of observation that will be used in the further analyses: the German Mobility Panel (MOP) and a data set similar to the Mobility Panel for the region Stuttgart (MOPS). When compared to other large German data sets (MiD2002 and MiD2008) daily and annual vehicle kilometers traveled as well as garage availability are only slightly different between the data sets (slightly lower driving in MOPS).

3. As there is no data set with more than one day of observation, a data collection of more than 500 vehicle driving profiles for commercial vehicles has been performed for this thesis, the so-called REM2030 driving profiles. Driving in this data set is slightly higher than in large data sets that serve for comparison (KiD2002 and KiD2010) whose influence will be discussed in the further analyses. Yet, the data set can be considered as representative for commercial vehicle registrations.

Chapter 4

Model development and techno-economical parameters[44]

Introduction

The aim of this chapter is to introduce a new model for the co-diffusion of plug-in electric vehicles and their charging infrastructure. In the following Section 4.1, an overview of the model, its main assumptions and an argumentation for the approach are presented. Section 4.2 comprises a mathematical description of the model. The parameters needed to model the market diffusion of PEVs and charging infrastructure for Germany until 2030 are described in Section 4.3 followed by a discussion of the model in Section 4.4.

4.1 Model overview

In Chapter 2, the literature on models for the co-diffusion of alternative fuel vehicles and their infrastructure was presented to retrieve aspects that could be learned from earlier modeling approaches. The main findings of that chapter were that: (1) There is a tipping point for the co-diffusion of AFVs and their refueling infrastructure beyond which the system becomes self-sustaining. (2) Existing models on NGVs and FCEVs can reproduce historical market evolutions, for which simulation models were the most promising approaches. And, (3) PEV specialties compared to other vehicles like the different charging duration, frequency and charging infrastructure ownership cannot be integrated in the existing approaches without major adaptations. Hence, in this chapter a new approach for the simulation of the co-diffusion of plug-in electric vehicles and their charging infrastructure is proposed.

Based on the literature analysis in Chapter 2, an agent-based simulation model is developed since simulation models best fulfill the requirements for the co-diffusion of PEVs and their charging infrastructure extracted in Section 2.2.1.[45] In agent-based models (ABM) a number of agents interact based on a set of rules over a certain time [Bonabeau, 2002] while the complexity rises with the number of agents, rules and the complexity of rules that are integrated. According to [Bonabeau, 2002] an ABM is useful "when

[44]Parts of this chapter are based on Plötz, Gnann and Wietschel (2014) [Plötz et al., 2014a] and [Gnann et al., 2015b].
[45]For a classification of models refer to Section 2.2.2.

the interactions between the agents are complex, nonlinear, discontinuous, or discrete. [...] When the population is heterogeneous, when each individual is (potentially) different" [Bonabeau, 2002]. However, the topology of interactions or the behavior (e.g. learning) can be complex [Bonabeau, 2002]. An ABM incorporates several issues that have to be taken into account: Since the interaction of human behavior is modeled, several soft factors have to be integrated, yet "soft factors [in decision making processes are often] difficult to quantify, calibrate, and sometimes justify" [Bonabeau, 2002]. Also, like every bottom-up model, ABM is data intensive [Sensfuss, 2008] and can become computation intensive as well because of the individual agent behavior [Bonabeau, 2002]. The main challenge is to simplify user behavior and reduce data within the right level of detail to still gain valuable outcomes. It is common practice to distinguish between agent-based simulation (ABS) and multi-agent simulations (MAS) [Hare and Deadman, 2004]. The first type of ABMs is used for the simulation of individuals with different characteristics and those individuals interacting with each other (also called individual-based simulation [Huston et al., 1988]). The latter group of models additionally assumes that agents learn from each other and from their surroundings while interacting [Wooldridge and Jennings, 1995, Steinbach, 2015].

This is exactly the case for vehicle usage profiles as described in the previous Chapter 3. Individual vehicles differ from each other in their driving behavior and their socio-demographic characteristics (see Chapter 3) as well as their willingness to pay more for PEVs [Peters et al., 2011a]. An interaction at public charging stations is thus not predictable without the diffusion of PEVs *and* their individual driving behavior. They interact when several users arrive at the same time and only one vehicle is able to recharge. To model the market diffusion of PEVs and their charging infrastructure, the agent-based simulation model ALADIN (Alternative Automobiles Diffusion and Infrastructure) is developed in this thesis.

The model is structured as depicted in Figure 4.1. There are four main model steps, (1) the individual PEV simulation, (2) the individual utility calculation, (3) the aggregation in the stock model and joint PEV simulation and (4) the optimal charging infrastructure setup by the charging point operator. Within these steps there are certain parts where actual user behavior is integrated. The PEV simulation is based on driving profiles in an infrastructure scenario. Furthermore, the cost for infrastructure, the willingness to pay more and a brand loyalty of each individual user are incorporated into the utility calculation. While the first two model steps are performed individually for every vehicle driving profile, the stock model aggregates the preceding results to a market diffusion. A joint simulation of the vehicle stock allows the charging point operator to determine the public charging price and the infrastructure setup for the subsequent individual simulation.

This model includes social interaction, but the agents are not able to learn from each other. Individual agents are used since buying decisions for passenger cars are complex [Klöckner, 2014] and many factors play a role, both in private [Mueller and de Haan, 2009, de Haan et al., 2009] and commercial vehicle purchase decisions [Globisch and Dütschke, 2013, Sierzchula, 2014]. Based on a survey of private passenger car buyers [Peters and de Haan, 2006], Figure 4.2 gives an overview of factors ranked first in private users' decision making processes. Size, price and safety can be identified as the most important factors in the purchase decision.

The importance of the different vehicle attributes motivates to model the PEV pur-

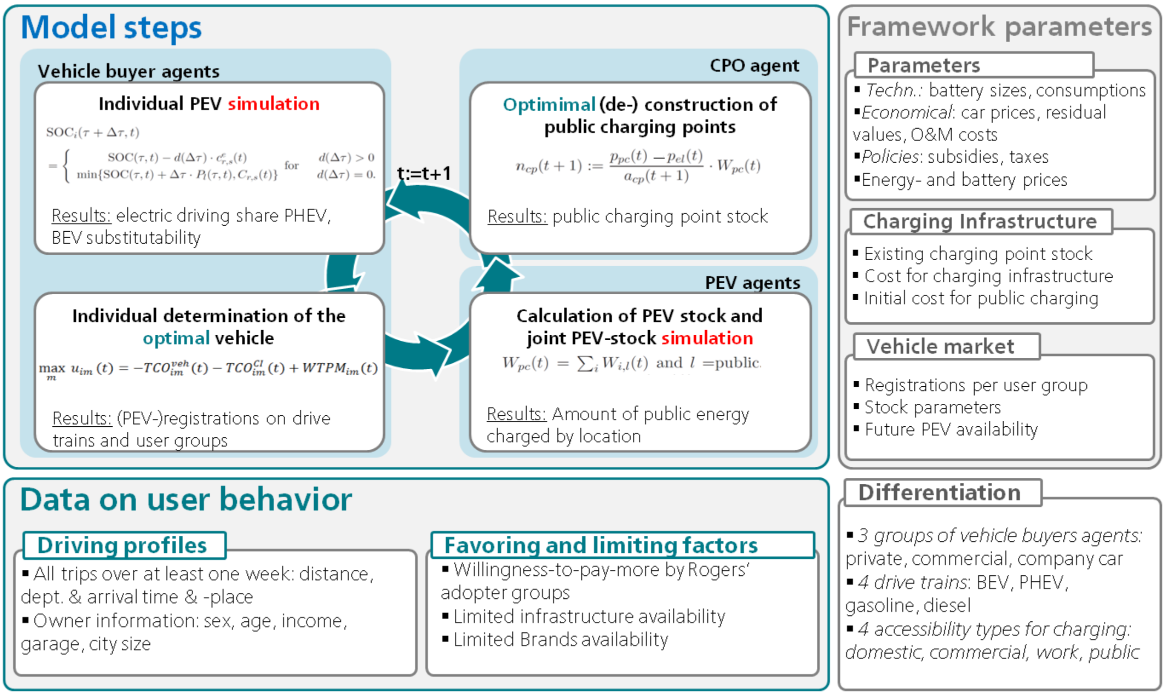

Figure 4.1: Overview of the model ALADIN - **Al**ternative **A**utomobiles **Di**ffusion and **In**frastructure. Based on individual driving data from private, commercial and company cars (left panel) and using techno-economical parameters (bottom), the market shares of different propulsion technologies are determined in four steps (central panel): (1) each driving profile is simulated as PEV and conventional vehicle; (2) based on the vehicle TCO, the cost for individual charging, the limited choice of PEV makes and models and the individual willingness to pay more, the utility maximizing vehicle option is chosen; (3) the vehicle choices are aggregated to a PEV stock and jointly simulated at public charging points; (4) the charging point operator decides about the public charging price and construction based on the amount of public charging from the previous model step.

chase decision as maximization of utility among several vehicle alternatives. For the future market diffusion of PEVs the model determines the users' utility obtained from vehicle size, price, brand, fuel consumption and fuel type, and to a certain extend engine power, emissions and acceleration. Since the focus is on the vehicles' propulsion technology, safety, gear shift and four-wheel drive are disregarded. The potential utility of each technology is calculated for each user (or agent) individually with these factors. Furthermore, three user groups are distinguished that differ in their purchase decisions: (1) private car buyers, (2) commercial vehicles used in commercial vehicle fleets only, and (3) company cars used by employees for both commercial and private purposes. For Germany each group amounts to about one third of the annual passenger car registrations [Pfahl, 2013]. Furthermore, four vehicle sizes are distinguished: small, medium, large and LCVs. To take the importance of vehicle size in the vehicles' utility into account, PEVs are only considered for the same vehicle size as the conventional ones in the profiles, i.e. there is no switch between vehicle sizes in the buying decision. That is, every user is assumed to buy a vehicle of the same size as his current vehicle. Purchase price and fuel consumption of a vehicle are aggregated to the vehicle's TCO. The consumption costs strongly depend on the annual VKT and the individual driving pattern, in particular the regularity of

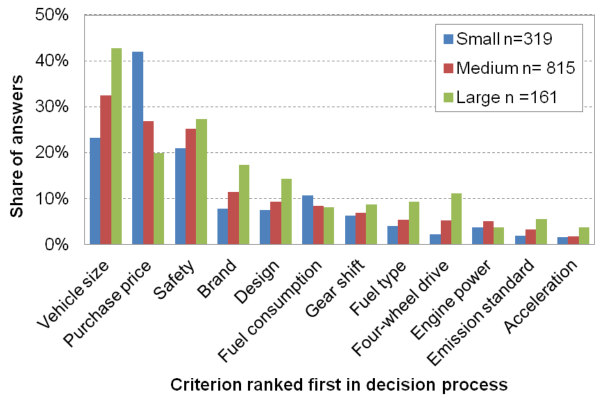

Figure 4.2: Criteria ranked first in the decision making process for passenger car purchase differentiated by vehicle size. Figure is based on data from [Peters and de Haan, 2006].

driving. For a reliable estimate, each user's driving profile is simulated as a vehicle with each of the propulsion systems (BEV, PHEV, diesel and gasoline) and the resulting fuel costs are calculated.

Fuel type, emission standards and acceleration are different for conventional internal combustion engine vehicles or plug-in electric vehicles. Furthermore, many consumers are willing to pay a price premium for a new technology [Rogers, 1962] in general and for PEVs in particular [Wietschel et al., 2012]. The positive factors of PEVs such as reduced noise, dynamic driving experience, their novelty and innovativeness are integrated in the model proposed here as willingness to pay more of some users [Peters et al., 2011b, Dataforce, 2011]. Other factors are difficult to model and are assumed to be comparable between conventional and plug-in electric vehicles, such as design, safety and engine power. Factors like design and safety can be quantified in relation to other attributes with conjoint analyses (see e.g. [Kreyenberg et al., 2013]), however, this is not the focus of this thesis and quantified data on these matters is not available to the author.

Apart from the positive image of plug-in electric vehicles as a new technology, there are some obstacles to overcome. One important factor is the need for frequent recharging caused by the limited electric range of PEVs [Tate et al., 2008, Kalhammer et al., 2007]. To address this issue, the cost for individual charging options is integrated into the buying decision while the cost for shared charging points are allocated to their users through a public charging price that includes the cost for public charging stations. In addition, the choice of PEVs in terms of brands and models as offered by manufacturers is still limited and likely to remain so for the next years. This will certainly restrain some users from buying a PEV despite their potential benefits. This effect of a limited choice of brands is integrated into the model by a two-step process: First, users are assumed to stick to their current vehicle brand if possible. Second, if a PEV would maximize the user's individual utility but is not available from his current manufacturer, then a share of users (equal to the share of brands offering PEVs in that year) is assumed to choose a PEV from another manufacturer and the rest of the users are assumed to choose their second best vehicle option.

One of the most important aspects of ALADIN is the usage of real-world driving profiles. This is a major improvement over existing models and has to the author's knowledge not been used comprehensively in a co-diffusion model for PEVs and their charging infrastructure so far. As explained in the previous chapter, the distribution and regularity of trip lengths varies strongly between different users and influences the TCO and potential use of PEVs significantly. Consequently, driving profiles of at least one week are analyzed (cf. Section 3.1). Based on the individual driving profile, each vehicle profile is simulated as BEV and PHEV based on the existing charging infrastructure. The resulting electric driving share and annual VKT are used to calculate the individual TCO of each driving profile and vehicle option. Based on the individual TCO and the additional positive and negative factors integrated in the model as user specific utility, the utility maximizing propulsion technology for each driving profile is chosen. Thus, in each user group, a share of driving profiles will correspond to PEVs. This share is then extrapolated to the annual registrations of vehicles in this user group. The first model outputs are the individual utility of each vehicle technology and the individual purchase decision in a given year. The technological and economical parameters vary over time and the decision process is repeated for each year. The annual registrations are built up to a stock of PEVs via a stock model.

To determine the need for public charging spots, the PEV agents in stock are simulated to calculate the amount of energy charged at public charging points. This is different to the first simulation where vehicle buyer agents are simulated individually for registrations in comparison to the PEV stock simulation for the usage of charging points. Based on the public charging cost, their batteries' state of charge and the availability of a free charging spot, PEV agents decide to charge in a joint simulation. Thereafter, the charging point operator (agent) decides about a new public charging price that covers price for electricity and charging points and the optimal (de-) construction of public charging points. The market diffusion of charging points on the other hand is based on economical assumptions and the return on invest since charging stations have to become profitable soon after they are built (see argument C in Section 2.2.1). In the following simulation run, these charging points can be used in the individual simulation of vehicle driving profiles to obtain higher electric driving shares and thus a a higher PEV utility. Since model steps 2, 3 and 4 are based on earlier steps that can be performed independently the results section is divided into three sections that address the model steps individually. The mathematical details of the model will be described in the following section.

4.2 Mathematical description of the model

The four model steps of ALADIN are explained in the following subsections: the individual PEV simulation (4.2.1), the determination of the individual utility (4.2.2), the stock model and joint simulation of PEVs (4.2.3) and setup of charging points by the charging point operator (4.2.4).[46]

In the following, let i be a vehicle driving profile of user group u (private, fleet, company vehicle) and vehicle size r (small, medium, large, LCV), s the propulsion technology regarded (Gasoline, Diesel, PHEV, BEV) and t the year of observation to name the main indices. All costs are VAT exempted for commercially licensed vehicles and include VAT for privately owned cars. All units of variables are shown in the abbreviations at the beginning of this thesis.

[46]The description of the first three subsections is based on [Plötz et al., 2014a, Gnann et al., 2015b].

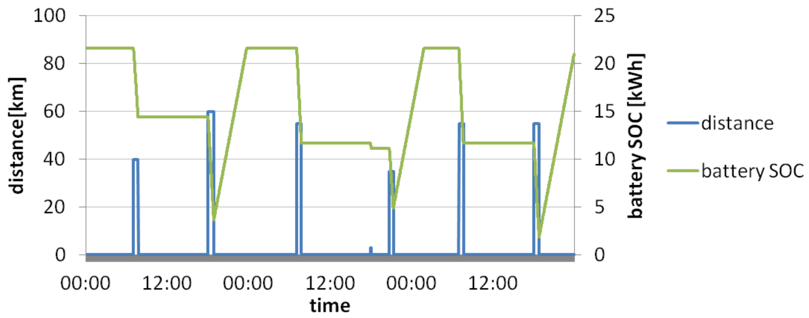

Figure 4.3: Example for battery simulation. Assumed is an electric consumption of 0.18 kWh/km and overnight charging with 3.7 kW. Distances in blue on left abscissa, battery SOC in green on right abscissa.

4.2.1 Individual plug-in electric vehicle simulation

In the PEV simulation, the battery's state of charge (SOC) of BEVs and PHEVs is simulated for each driving profile to determine whether it could be performed by a BEV or which electric driving share would result for a PHEV of the same vehicle size. More specifically, the SOC is calculated for each point in time τ as

$$\mathrm{SOC}_i(\tau+\Delta\tau,t) = \begin{cases} \mathrm{SOC}(\tau,t) - d(\Delta\tau)\cdot c^e_{r,s}(t) & \text{for } d(\Delta\tau) > 0 \\ \min\{\mathrm{SOC}(\tau,t) + \Delta\tau \cdot P_l(\tau,t), C_{r,s}(t)\} & \text{for } d(\Delta\tau) = 0. \end{cases} \tag{4.1}$$

where the initial value for each year t is given by $\mathrm{SOC}_i(\tau_i^0,t) = C_{r,s}(t)$. $C_{r,s}(t)$ is the net capacity of the battery analyzed, calculated as the gross capacity multiplied by its maximum depth of discharge (DoD), and τ_i^0 is the starting time of the driving profile. $\mathrm{SOC}_i(\tau,t)$ denotes the state of charge at time τ in year t. The distance driven between τ and $\tau+\Delta\tau$ is given by $d(\Delta\tau)$. $c^e_{r,s}(t)$ is the consumption of electric power in kWh/km, depending on car size r and propulsion technology s. $P_l(\tau,t)$ in kW describes the power for charging at the location where car i was parked at τ and year t. If no charging infrastructure is available, $P_l(\tau,t)=0$. The locations l of $P_l(\tau,t)$ are private, work or public grounds for charging facilities, while for public charging $P_p(\tau,t) = (P_{p,z_{min}}(t),...,P_{p,z_{max}}(t))^T$ and $P_{p,z}(t)$ signifies the power for public charging in zone z at time t. Figure 4.2.1 holds an example of the PEV simulation.

For public charging there are additional conditions integrated: Since public charging is always considered less convenient and more expensive than charging at home or work, a BEV is only recharged when (1) its battery capacity is below 50% (to return home) and (2) there is a predefined minimum number of charging points available within the area where the vehicle is parking. The minimum number of charging points will be determined in Section 5.3.1. Furthermore, (3) for PHEV also the cost for electric driving has to be lower than for conventional driving since the vehicle could drive with conventional fuel otherwise.

With this simulation, it is possible to determine the VKT with positive SOC divided by the distance of all VKT for each profile, i. e. the electric driving share

$$s_{i,s}(t) = \frac{d^{el}_{i,s}(t)}{d_i} \tag{4.2}$$

Here, $d^{el}_{i,s}(t)$ is the VKT in the driving profile that is driven in electric mode by vehicle i with propulsion technology s and $d_{i,s}$ is the total VKT in the profile. Note, that not the number of trips with positive SOC, but the distances are considered for the electric driving share. When analyzing a BEV, the electric driving share $s_i(t)$ must be 100% to fulfill the whole profile and to be considered in the utility analysis. For a PHEV, the electric driving share is an important measure to determine its variable cost, since cost for electric and conventional driving is significantly different. For both PEVs, regular driving favors a high electric driving share $s_{i,s}(t)$ while a significant amount of (electric) kilometers has to be performed because of the PEV's economics (see also Chapter 3).

4.2.2 Determination of utility

Based on this first model step, the most beneficial vehicle type from the four propulsion technologies s (Gasoline, Diesel, PHEV and BEV) for every user i is determined by:

$$u^a_{i,s}(t) = -\mathrm{TCO}^{a,\mathrm{veh}}_{i,s}(t) - \mathrm{TCO}^{a,\mathrm{CI}}_{i,s}(t) + \mathrm{WTPM}^a_{i,s}(t) \tag{4.3}$$

That is, the utility function consists of the TCO of the vehicle $\mathrm{TCO}^{a,\mathrm{veh}}_{i,s}(t)$, the TCO of the individual charging infrastructure $\mathrm{TCO}^{a,\mathrm{CI}}_{i,s}(t)$, and the willingness to pay more (WTPM) $\mathrm{WTPM}^a_{i,s}(t)$; the latter being added to the first two terms that are subtracted and all terms are discounted to an annual value. In this function monetary and non-monetary factors are combined in a utility function measured in EUR/yr. The inclusion of the vehicle's TCO assumes that users weigh the purchasing costs as important as the operating costs, which is a common approach for PEV market diffusion models (see [Plötz et al., 2014a, sec.4]). Utility is calculated for each vehicle type. Note that, some terms can also be zero, e.g. the charging infrastructure cost or the WTPM if conventional vehicles are considered.

The vehicle's annual TCO are calculated as

$$\mathrm{TCO}^{a,\mathrm{veh}}_{i,s}(t) = \underbrace{a^{\mathrm{veh,capex}}_{i,s}(t) + a^{\mathrm{veh,opex}}_{i,s}(t) - dep^{\mathrm{veh,capex}}_{i,s}(t) - dep^{\mathrm{veh,opex}}_{i,s}(t)}_{(1)} + \underbrace{g^{\mathrm{veh}}_{i,s}(t)}_{(2)} \tag{4.4}$$

They consist of (annual) capital expenditures $a^{\mathrm{veh,capex}}_{i,s}(t)$ and operating expenditures $a^{\mathrm{veh,opex}}_{i,s}(t)$ that may be reduced for commercial vehicles by depreciation allowances for capital $dep^{\mathrm{veh,capex}}_{i,s}(t)$ and operating expenditures $dep^{\mathrm{veh,opex}}_{i,s}(t)$. For company cars the tax that has to be paid by the driver for using a company car (a so-called fringe benefit) is added $g^{\mathrm{veh}}_{i,s}(t)$. These additional costs are added to consider the company's (1) as well as the user's vehicle buying decision (2) which is in line with other approaches [Pfahl, 2013].

The discounted cash-flow method with resale values[47] is used to calculate the investment annuity for user i and propulsion technology s as

$$a^{\mathrm{veh,capex}}_{i,s}(t) = \Big(\mathrm{LP}_{r,s}(t) \cdot (1 + z_u(t))^{T^{\mathrm{veh}}_u(t)} - \mathrm{SP}_{i,s}(t)\Big) \cdot \frac{z_u(t)}{(1 + z_u(t))^{T^{\mathrm{veh}}_u(t)} - 1} \tag{4.5}$$

Here, the list price $\mathrm{LP}_{r,s}(t)$ (for vehicle and battery)[48] is multiplied by the annuity factor consisting of the interest rate $z_u(t)$ and the investment horizon $T^{\mathrm{veh}}_u(t)$. $\mathrm{SP}_{i,s}(t)$ denotes

[47] For an introduction to accounting, see [Wöhe and Döring, 2002].

[48] $\mathrm{LP}^{PEV}_{r,s}(t) = p^{car}_{r,s}(t) + \kappa_{r,s}(t) \cdot p^{batt}_s(t))$.

the sale price of vehicle i for resale after $T_u^{\mathrm{veh}}(t)$ years and depends on the vehicle's annual VKT, its age and its list price. The resale value is calculated for each vehicle i with the individual annual VKT_i. To determine $\mathrm{SP}_{i,s}(t)$, results of [Dexheimer, 2003, Linz et al., 2003] are used with $\mathrm{SP}_{i,s}(t) = \exp\left[\alpha_1 + 12 \cdot \beta_1 T_u^{\mathrm{veh}}(t) + \beta_2 \mathrm{VKT}_i/12\right] \cdot \mathrm{LP}_{r,s}(t)^{\beta_3}$ where the parameters $\alpha_1 = 0.97948$, $\beta_1 = -1.437 \cdot 10^{-2}$, $\beta_2 = -1.17 \cdot 10^{-4}$ and $\beta_3 = 0.91569$ have been obtained by regression (see [Dexheimer, 2003, Linz et al., 2003] for details).[49] $T_u^{\mathrm{veh}}(t)$ depends on the user group u to reflect the different average holding times for private and commercial users.

The operating expenditure of vehicle i for one of the propulsion technologies (s) is calculated as

$$a_{i,s}^{\mathrm{veh,opex}}(t) = \mathrm{VKT}_i \cdot \Big(C_i^e(t) + (1 - s_i(t)) \cdot c_{r,s}^c(t) \cdot k_{r,s}^c(t) + k_{r,s}^{\mathrm{OM}}(t)\Big) + k_{r,s}^{\mathrm{tax}}(t) \tag{4.6}$$

The individual annual VKT_i are multiplied by the costs for driving in electric mode $C_i^e(t)$ plus the costs for driving in conventional mode and the costs for operations and maintenance $k_{r,s}^{\mathrm{OM}}(t)$. The costs for conventional driving consists of the share of conventional driving $(1 - s_i)$, the conventional consumption $c_{r,s}^c(t)$ and the costs for conventional fuel $k_{r,s}^c(t)$. The annual vehicle taxes $k_{r,s}^{\mathrm{tax}}(t)$ are independent of VKT_i.

The cost for electric driving is the sum of cost for energy charged at different charging locations:

$$C_i^e(t) = \sum_{l \in L} p_{i,l}(t) \cdot W_{i,l}(t) = \sum_{l \in L} p_{i,l}(t) \cdot \sum_{\tau=\tau_i^0}^{\tau_i^{max}-1} W_{i,l}(\tau, \tau+1, t) \tag{4.7}$$

Since four types of accessibility $L = \{\text{domestic, commercial, work, public}\}$ are considered, the costs for electric driving consist of the energy charged $W_{i,l}(t)$ at home multiplied by the domestic electricity price $p_{i,l}(t)$, the energy charged at work times the price for charging at work and the public charging price multiplied by the energy charged publicly for private and company vehicles. For fleet vehicles only the commercially and publicly charged energy is multiplied with their respective prices.

For commercially licensed vehicles, there are depreciation allowances which reduce the vehicle costs [BMF, 2001]. The value of capital assets in companies may be reduced by

$$dep_{i,s}^{\mathrm{veh,capex}}(t) = \mathrm{LP}_{r,s}(t) \cdot \frac{(1 + z_u(t))^{T^{dlim}} \cdot z_u(t)}{(1 + z_u(t))^{T^{dlim}} - 1} \cdot DR \tag{4.8}$$

Thus, the vehicle's list price $\mathrm{LP}_{r,s}(t)$ can be depreciated linearly over a certain time horizon T^{dlim}, which is currently six years for vehicles in Germany [BMF, 2001]. Since this reduces the taxes for profits a company has to pay, the depreciation rate DR is similar to a company tax rate. Also for the operating expenditures, a company can reduce its profits and reinvest the resulting lower tax payments: $dep_{i,s}^{\mathrm{veh,opex}}(t) = a_{i,s}^{\mathrm{veh,opex}}(t) \cdot DR$.

[49] Please note that the regression results for the PEV resale values imply a higher absolute resale price SP but lower relative or percentage resale value $\mathrm{RV} \equiv \mathrm{SP}/\mathrm{LP}$. If the vehicle's age and annual VKT are assumed as fixed at average values, the sales price is given as $\mathrm{SP} = c \cdot \mathrm{LP}^{\beta_3}$. Thus the relative resale value will be given as $\mathrm{RV} \equiv \mathrm{SP}/\mathrm{LP} = c \cdot \mathrm{LP}^{\beta_3 - 1}$ and accordingly $\mathrm{RV}^{\mathrm{PEV}}/\mathrm{RV}^{\mathrm{ICE}} = \left(\mathrm{LP}^{\mathrm{ICE}}/\mathrm{LP}^{\mathrm{PEV}}\right)^{1-\beta_3} < 1$ since $\mathrm{LP}^{\mathrm{ICE}} < \mathrm{LP}^{\mathrm{PEV}}$ and $0 < \beta_3 < 1$.

The last term in equation 4.4 is the tax for company cars that users have to pay [BMF, 2015]:

$$g_{i,s}^{\mathrm{veh}}(t) = (LP_{r,s}^{G}(t) - TE_{r,s}^{PEV}(t)) \cdot (0.01 + 0.0003 \cdot ACD_i(t)) \cdot ITR_i(t) \cdot 12 \tag{4.9}$$

Starting point for this tax is the gross list price of the vehicle $LP_{r,s}^{G}(t)$ which is not VAT-exempted like all other costs for commercial vehicles. This price is multiplied by 1% (so-called 1%-rule) plus 0.03% times the average commuting distance $ACD_i(t)$ to receive the monthly taxable value for the vehicle. By multiplying the income tax rate of the owner of vehicle i, $ITR_i(t)$, and multiplying it by twelve, the annual costs for the user of a company car can be calculated. Company PEVs profit from a correction factor of the gross list price $TE_{r,s}^{PEV}(t)$ of up to 10,000 EUR, since company car drivers do not profit from the lower operating cost when they own a fuel card [BMF, 2015]. The term for company cars is added to the annual vehicle TCO in equation 4.4.

The second term in equation 4.3 is the cost for individual charging points and is zero for conventional vehicles since the cost for refueling stations of conventional vehicles is included in the fuel prices. This cost is integrated as plug-in electric vehicles will be charged at individual domestic, commercial or work charging spots - there is a one to one allocation of charging spot per vehicle. The cost for the individual charging points is calculated as their annual capital expenditures and their operating cost $a_{i,s}^{\mathrm{CI,opex}}(t)$.

$$\mathrm{TCO}_{i,s}^{a,\mathrm{CI}}(t) = I^{CI}(t) \cdot \frac{(1+z_u(t))^{T_u^{CI}(t)} \cdot z_u(t)}{(1+z_u(t))^{T_u^{CI}(t)} - 1} + a_{i,s}^{\mathrm{CI,opex}}(t) \tag{4.10}$$

By adding the infrastructure cost to the TCO calculation, the fact that users must have at least one charging point to charge their vehicle regularly is addressed. Private users and company car owners that own a garage are assumed to install a simple charging spot without large financial effort while users without garages need a more expensive solution [Gnann et al., 2013]. The garage availability is part of the socio-demographic information in the driving profiles.

The third term of the utility function (4.3) is the WTPM for a PEV discounted to one year which is simply calculated as

$$\mathrm{WTPM}_{i,s}^{a} = \mathrm{wtpm}_{i,s}(t) \cdot LP_{r,s}(t) \cdot \frac{(1+z_u(t))^{T_u^{\mathrm{veh}}(t)} \cdot z_u(t)}{(1+z_u(t))^{T_u^{\mathrm{veh}}(t)} - 1} \tag{4.11}$$

The WTPM is based on a percentage $\mathrm{wtpm}_{i,s}(t)$ that users are willing to pay more for a plug-in electric vehicle compared to a conventional one and will further be described in Section 4.3.4. This percentage is multiplied by the investment of a comparable conventional vehicle ($LP_{r,s}(t)$, powered with gasoline for small and medium, diesel for large vehicles and LCV). There is no WTPM for conventional cars.

In summary, the best vehicle option for each vehicle buyer agent is determined based on the individual utility which is determined by vehicle cost as well as infrastructure cost for individual charging points and WTPM for PEVs. Costs for commercial vehicles contain some specialties concerning taxes and they are VAT exempted in all calculations. Results for individual analyses of driving profiles are shown for the commercial passenger car sector in Section 5.1. The individual best vehicle choices are aggregated in the stock model. Figure 4.7 shows an example of different vehicle utilities.

4.2.3 Stock model and joint simulation

Stock model

The PEV simulation and utility calculation above are performed for every driving profile. Three different user groups (private, commercial fleet, company car) and four vehicle sizes (small, medium, large and LCV) are distinguished, where LCV are almost exclusively purchased by commercial fleets and accordingly neglected for the other user groups. Thus $m = 3 \cdot 3 + 1 = 10$ vehicle groups are considered in the stock model. To derive the share of driving profiles of individuals $f_{m,s}(t)$ that are assumed to buy a PEV according to their individual utility $f_{m,s} = \frac{\sum_i \{f_{i,m,s} | s \in \{PHEV, BEV\}\}}{\sum_i f_{i,m,s}}$ is multiplied by the number of vehicles in the corresponding user group and vehicle size $n_m(t)$. The annual PEV registrations are calculated as:

$$N_{m,s}(t) = f_{m,s}(t) \cdot n_m(t). \tag{4.12}$$

However, the vehicles that were purchased in a given year do not remain in stock forever. Instead vehicles will be scrapped with an age-dependent probability $P^{\text{scrap}}(a)$ and commercial vehicles diffuse into the private vehicle stock after the first registration period ($T_u^{\text{veh}}(t)$; second-hand car market). The survival probability $L(a) = 1 - \int_0^a P^{\text{scrap}}(a')\mathrm{d}a'$ for a vehicle to survive until age a. With this distribution at hand, the stock $S_{m,s}(t)$ of PEVs ($s \in \{PHEV, BEV\}$) of vehicle group m in year t can be written as the sum of PEVs purchased in earlier years $N_{m,s}(t')$ that survived until year t:

$$S_{m,s}(t) = \sum_{t'=t_0}^{t} N_{m,s}(t')L(t-t'). \tag{4.13}$$

The survival probability has been obtained from the official German vehicle statistics (see [Plötz et al., 2012] for details). A lifetime distribution for the vehicles to remain in stock is needed for the stock model introduced above. Data for the complete German vehicle fleet is used and the age dependent scrapping probability over ten years. These probabilities are calculated from the age structure of the German vehicle stock since 2001 by computing the change between adjacent ages in subsequent years for all years available. The Weibull distribution for the survivor function is given by $L(t) = \mathrm{e}^{-(t/\theta)^\beta}$, where the parameters $\theta = 14.7$ for scale and $\beta = 3.5$ for shape have been obtained from a least square fit (see [Bain and Englehardt, 1991, Lawless, 1982] for the justification of the Weibull distribution as a survivor function). These parameters imply an average age for scrapping of 13.8 years and an average age of the vehicles in stock of 7.3 years, both in good agreement with other studies of the German passenger car stock [Plötz et al., 2013]. This distribution will be used for the stock model of the German vehicle fleet.

Since PEVs are in an early market phase, the choice of models and brands is and will remain limited for the next years. This fact slows down the market diffusion of PEVs since brand and design are vehicle purchase criteria (cf. Figure 4.2). The limited choice of brands and models is included in the PEV market diffusion model in two steps: In a first step, the present and near-future choice of PEVs is collected (from press announcements), with announcements for up to two years in the future being available. Based on this data and a number of relevant brands (the 20 most sold brands in the German vehicle market) within each vehicle segment for normalization, a logistic regression of the upcoming brands

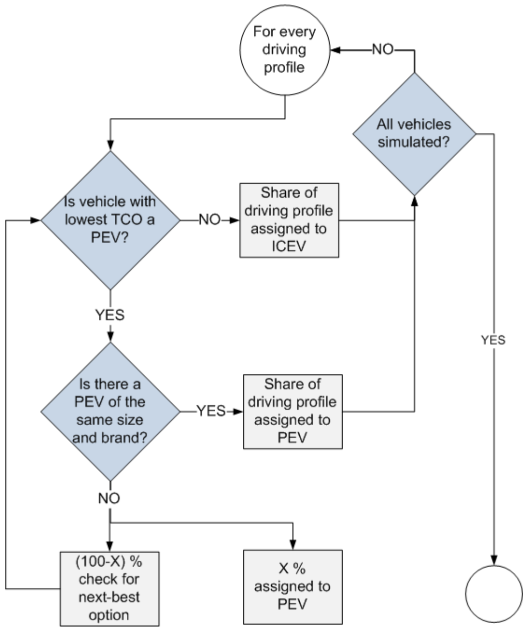

Figure 4.4: Algorithm for the inclusion of the limited availability.

is performed. The resulting logistic availability function is then extrapolated into the future (see Section 4.3.5 for details). The availability is integrated into the purchase decision as follows: If a PEV is utility optimal for a vehicle profile of brand b_i and this brand has announced a vehicle for the year under consideration (or earlier) the PEV will be bought by that user. If the user's brand b_i does not offer a PEV, then some of the users choose a PEV of a different brand ($lim_{m,s}(t)$ according to the logistic availability function) and the rest chooses the second best TCO option (see Figure 4.4 for graphical explanation of the algorithm). With the inclusion of the limited availability, one driving profile may be split into shares for each propulsion technology $f_{i,m,s}(t)$ with $f_{i,m,s}(t) \in [0,1]$ and $\sum_s f_{i,m,s}(t) = 1$, whereas before $f_{i,m,s}(t) \in \{0,1\}$. The inclusion of a limited availability (incl. brand loyalty) is only possible if the vehicle brand is available, which is only the case for MOP. Since REM2030 does not contain information about the vehicle's brand, the test for vehicle brand is skipped for REM2030.

To this point, the first three model steps form a market diffusion model for PEVs in which charging is only possible at domestic, commercial and work charging spots or at public charging points without public charging costs. Results based on these assumptions will be presented in Section 5.2. The inclusion of a public charging infrastructure diffusion is described in the following section.

Joint simulation

For an economic operation of public charging infrastructure, a sufficient occupancy rate by PEVs in the vehicle stock is decisive. Hence, for the simulation of the vehicle stock, not only the number but also the driving profiles of PEVs within stock are needed. Further, the occupancy of public charging spots is analyzed in a joint simulation of PEVs that interact when arriving at a charging point. Thus, the arrival of two or more vehicles at a charging point is to be simulated with an analysis of spatial driving behavior as well. This analysis is possible with the geographical information within the driving profiles MOPS

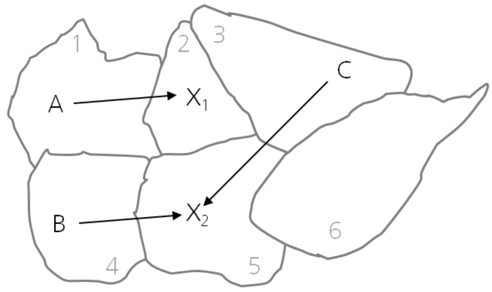

Figure 4.5: Example for PEV stock simulation when multiple users arrive at a charging point. Three users (A...C) arrive at two charging points (X_1, X_2) in zones 2 and 5.

and REM2030S.

The charging behavior of the PEV stock determines the total electricity consumed at public charging points. Here, the same charging rules as in the individual simulation (equation 4.1) apply except for the charging point density at public charging points, which is replaced by a real availability of charging points: a user may charge his PEV only if a charging point is not in use at his arrival. While in the individual simulation, every user performs a simple forecast of his driving behavior and estimates his charging shares based on his usual routes and his impression of charging stations available to him, in the simulation of the PEV stock the usage of individual charging points is simulated. Figure 4.5 shows an example where user A can recharge his battery at charging station X_1, but users B and C both arrive at charging point X_2 and only the user arriving first may recharge. Whenever a BEV arrives at a charging point which is not in use and the BEV's SOC is below 50%, the vehicle is recharged. The same holds for PHEVs, where in addition electric driving with the current public charging price has to be cheaper than conventional driving. The outputs of this model step are the amount of vehicles and their energy consumption distinguished by accessibility types for each year. The total amount of public charging $W_{pc}(t) = \sum_i W_{i,l}(t)$ and l =public is the main input for the consecutive model step.

4.2.4 Charging point operator

Based on the energy consumption at all public charging spots $W_{pc}(t)$, the number of public charging points and the price for public charging in the next period is determined in the fourth model step. Equation 4.14 shows the relationship between prices, charging points and public energy consumed:

$$p_{pc}(t) := p_{el}(t) + p_{cp}(t) = p_{el}(t) + \frac{n_{cp}(t) \cdot a_{cp}(t)}{W_{pc}(t-1)}. \tag{4.14}$$

The public charging price $p_{pc}(t)$ consists of a price for electricity $p_{el}(t)$ and a price for charging points $p_{cp}(t)$. The number of charging points $n_{cp}(t)$ multiplied by their annual cost $a_{cp}(t)$[50] and divided by the total energy consumed at public charging points $W_{cp}(t)$. While the energy consumed is derived within the PEV stock simulation, the price for electricity and the annual cost for charging infrastructure are exogenously defined.

[50] As in equation 4.10 the annual cost for public charging points is defined by its discounted investment and operating expenditure $a_{cp} = I^{CP}(t) \cdot \Big((1+z_u(t))^{T_u^{CI}(t)} \cdot z_u(t)\Big) / \Big((1+z_u(t))^{T_u^{CI}(t)} - 1\Big) + a_{i,s}^{\text{CP,opex}}(t)$.

Since the consumption of energy charged at public charging points changes with an increasing number of PEVs, the charging point operator will build new charging points based on the current public charging price $p_{pc}(t)$ and electricity price $p_{el}(t)$, but based on the new cost for public charging points $a_{cp}(t+1)$:

$$n_{cp}(t+1) := \frac{p_{pc}(t) - p_{el}(t)}{a_{cp}(t+1)} \cdot W_{pc}(t). \tag{4.15}$$

Note that increasing prices for electricity p_{el} or charging points p_{cp} may also lead to a decreasing number of public charging points, i.e. a shut down of several public charging points.

With the number of charging points, the electricity price and the charging point costs in the next period as well as the energy consumed at public charging stations, the public charging price for the next period $p_{pc}(t)$ is calculated with formula 4.14 and the simulation can start at the first step again.[51]

The mechanism to determine the zones in which charging points should be built, is shown in Figure 4.6. First, the number of charging points in the next and the current period determine the construction of charging points $\Delta n_{cp} = n_{cp}(t+1) - n_{cp}(t)$. If this delta is negative (there are fewer charging points in the following period), the charging stations with the lowest usage are put out of service. That is, the zone z^* with the minimal use per charging point (CP) is determined with

$$min_z use'_z(t+1) = use_z(t)/n_{CP,z}(t+1) \tag{4.16}$$

and one charging point is taken out of service in zone z^*.[52] This procedure is repeated until Δn_{cp} iterations are completed and Δn_{cp} charging points are taken out of service (see lower bound of Figure 4.6).

The construction of charging points in case of a positive delta is performed in two phases: At first, charging infrastructure is built in areas with a high *vehicle* occupancy until the minimum number of public charging points per zone is reached. Here, the zone z^{**} for a construction is determined by $max_z occ'_z = occ_z \cdot (1-(n_{CP,z}(t+1)/CPN_z)$. Thereafter, the charging infrastructure is built in places z^{***} with a high PEV occupancy to cover a higher need for public charging points $(max_z occ'_{z,PEV}(t+1) = occ_{z,PEV}(t)/n_{CP,z}(t+1))$. This two-step approach assures a minimum coverage at the beginning moving to a user-oriented approach after a minimal coverage is given [Funke et al., 2015].

To sum up, in the last part of the model the charging point operator decides on the public charging price as well as the (de-)construction of public charging points. Based on this simulation potential PEV users may buy a PEV based on the increased utility through new charging points. Thus, the new vehicle registrations are dependent on the charging point stock which completes the joint simulation of PEV and charging infrastructure simulation. Results for all four model steps will be shown in Section 5.3.

[51]Note again, that in formulas 4.14 and 4.15, the price for electricity $p_{el}(t)$ and the cost for public charging points $a_{cp}(t)$ are externally defined, while the amount of public charging $W_{pc}(t)$ is a simulation result. Both the price for electricity and the annuity of public charging points may include a contribution margin.

[52]The number of charging points per zone are initialized by $\forall z : n_{CP,z}(t+1) := n_{CP,z}(t)$.

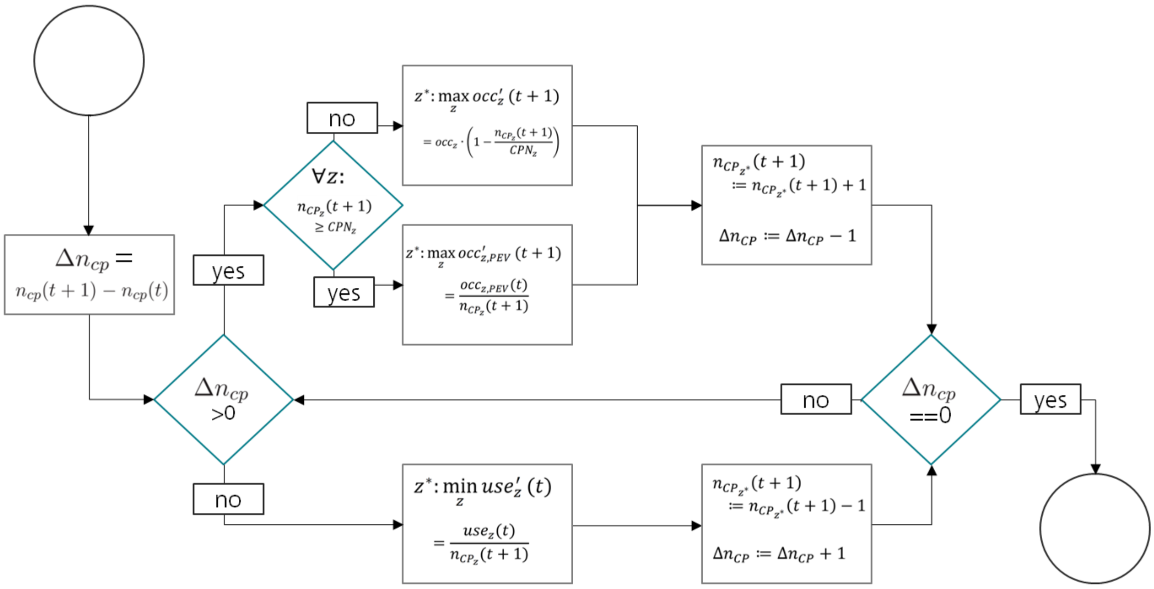

Figure 4.6: Algorithm for the construction and deconstruction of public charging points.

4.3 Techno-economical parameters

The calculations require a variety of parameters for modeling the interaction of PEVs and their charging infrastructure. The most important framework parameters are varied and combined in scenarios in the following Section 4.3.1. Thereafter, technical and economical parameters for vehicles and the vehicle market (4.3.3), the assumptions for the WTPM (4.3.4) and the limited availability (4.3.5) as well as several adaptations for the data sets with geographical information, MOPS and REM2030S (4.3.6) are presented. All costs are given in EUR_{2014} and real values for the future.

4.3.1 Scenario definition

In this subsection scenarios for the future development of several important framework conditions as well as for charging infrastructure are defined for Germany until 2030. Scenarios are used for the most important parameters since their future development is uncertain and their influence is large. Scenarios allow to evaluate outcomes based on these developments, yet they are no prognoses and no probability for their realization is given. However, the determination of consistent scenarios permits to show the range of potential results [Dieckhoff et al., 2014].

The market diffusion of plug-in electric vehicles is influenced by both the framework conditions in general and the parameters depending on the vehicles in particular. The framework conditions include the number of new car purchases divided into segments and user groups forming the general potential for electric cars. Other parameters like the oil price and the electricity price are almost independent from an early PEV diffusion which has not reached a mass market level. Vehicle dependent parameters such as purchase price or fuel consumption form the basis for the utility calculation for each segment and user group.

For illustrative purposes, Figure 4.7 shows a potential utility composition of parame-

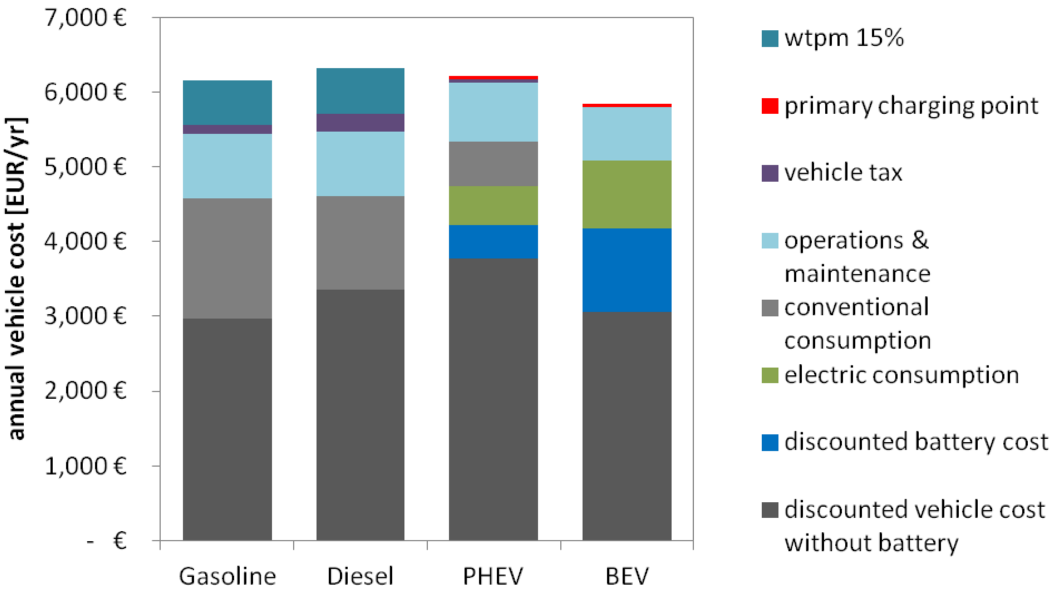

Figure 4.7: Composition of vehicle costs for different drive trains in 2020. Assumed are 15,000 kilometers traveled per year, 60% electric driving share for PHEV and garage ownership. Resale value exempted from vehicle and battery cost. All cost parameters for private user in medium scenario with VAT in EUR_{2014}.

ters for all four drive trains in 2020. The vehicle is assumed to travel 15,000 kilometers per year with an electric driving share of 60% for a PHEV and the vehicle owner is assumed to hold a garage. Further a gasoline price of 1.65 EUR/l, a diesel price of 1.58 EUR/l, an electricity price of 0.29 EUR/kWh and a battery price of 330 EUR/kWh are assumed.[53] A WTPM of 15% for PEVs is shown as price increase for conventional vehicles instead of decrease for plug-in electric vehicles for an easier reading.

The example in Figure 4.7 shows that some factors have a greater influence on vehicle utility than others. While vehicle taxes play a minor role, the cost for operations and maintenance for all drive trains are very close to each other. The largest differences between vehicle types can be found in capital costs (for vehicle and battery), costs for energy consumption and the WTPM which is in line with other studies [Hacker et al., 2011b, Mock, 2010, ESMT, 2011]. For this reason, battery and energy prices are varied in different scenarios. The influence of the WTPM is analyzed separately in Section 5.2.2.

For battery prices, as well as electricity and fuel prices, three scenarios are defined, which are summarized in Table 4.1. The first scenario makes rather optimistic assumptions with regard to the market success of plug-in electric vehicles (pro-EV scenario), the second more pessimistic assumptions (contra-EV scenario), and the assumptions made in the third scenario for Germany up to 2030 lie in-between these two (medium scenario). The battery prices for all three scenarios decrease exponentially from values up to 550 EUR/kWh in 2015 (pro-EV, medium, contra-EV) to below one third in 2030 (all values without VAT) [Pfahl, 2013, Plötz et al., 2013]. The prices for batteries used for the simulations were discussed with several experts of the German automotive industry [Plötz et al., 2013]. Battery costs are not distinguished between PEV types, although several

[53] Energy prices are taken from the later described medium scenario and resale values for vehicles and batteries are exempted from vehicle cost. All other values are described in the following Section 4.3.

studies suggest this due to different battery use patterns (see e.g. [Nelson et al., 2009, Santini et al., 2010]). Instead, a differentiation via depths of discharge was used. Long-term price estimates are at the upper end of estimates (see e.g. [Rousseau et al., 2012, Nykvist and Nilsson, 2015]), yet they present prices to the consumer, not at cell or pack-level. Prices for diesel and gasoline are equal for all scenarios in 2015 based on [IEA, 2013]. The development of fuel prices until 2030 is based on the New Policy Scenario in [IEA, 2013] for the medium scenario with an additional increase up to 2.00 EUR/l (including VAT) for gasoline in the pro-EV scenario and a decrease to 1.50 EUR/l in the contra-EV scenario in 2030. This corresponds to an oil price of 183 $/bbl in 2030 in the pro-EV scenario, 149 $/bbl in the medium scenario and 115 $/bbl in the contra-EV scenario for a constant mineral oil tax. These bandwidths are chosen since the future development of fuel prices is unclear. A relatively constant oil price until 2030 in the contra-EV scenario, an increasing price based on international experts in the medium scenario and a further increasing oil price based on the developments in the last years in the pro-EV scenario demonstrate the bandwidth of options.

Table 4.1: Scenario-specific parameters used in ALADIN. All prices with VAT in EUR_{2014}.

Parameter	year	Pro-EV	medium	Contra-EV
Diesel price[a]	2015		1.45	
[EUR/kWh]	2030	1.90	1.65	1.42
Gasoline price[a]	2015		1.52	
[EUR/kWh]	2030	2.00	1.75	1.50
Oil price[a]	2015		118	
[EUR/bbl]	2030	183	149	115
Electricity price private[b]	2015		0.29	
[EUR/kWh]	2030	0.27	0.32	0.35
Electricity price commercial[b]	2015		0.21	
[EUR/kWh]	2030	0.20	0.22	0.25
Battery price[c]	2015	450	500	550
[EUR/kWh]	2030	235	266	295

a: [IEA, 2013] and own assumptions; b: own assumptions based on [McKinsey, 2012, BCG, 2013]; c: [Pfahl, 2013]

In Germany, several studies predict a further increase of electricity prices in the future [Schlesinger et al., 2011, McKinsey, 2012, BCG, 2013]. For this thesis the following is assumed: The average wholesale price for electricity rises only slightly until 2020 and remains stable until 2030 due to the increase of renewable energies (in line with [BDEW, 2014, Capros et al., 2013]). Further, the investments for grid expansion slightly raise the electricity price (0.005 EUR/kWh in 2030). The revision of the renewable energy law of 2014 performs well and leads to price decreases of 0.04 EUR/kWh in 2030 in the pro-EV scenario, to 0.02 EUR/kWh in the medium scenario and to no change in the contra-EV scenario. Vehicle-to-grid operation allows to reduce prices by about 0.005 EUR/kWh between 2020 and 2030 in the pro-EV scenario [Dallinger and Wietschel, 2012]. This results in electricity prices as shown in Table 4.1.

These scenarios combine favorable and unfavorable conditions for plug-in electric vehicles which are consistent with other studies. These parameters are chosen to be integrated into scenarios as they contribute strongly to the individual vehicle utility (see Figure 4.7).

4.3.2 Cost for charging infrastructure

As mentioned in Chapter 3, three user groups from two data sets are distinguished. In the PEV simulation, it is assumed that private and company cars can charge with 3.7 kW whenever they are at home. The trip purpose "home trip" is used to decide about the parking spot of the vehicle [MOP, 2010]. For fleet vehicles, the trip purposes are unknown but the GPS-location allow to determine the distance from the company location [Fraunhofer ISI, 2014]. Thus fleet vehicles charge with 3.7 kW during the day when they are not further than 500 m away from their main company location.[54] In addition, they can charge overnight, assuming that the vehicle can be plugged in, no matter if it is parked at a private household or at the company site. In the socio-demographic information of [MOP, 2010], the common overnight parking spot of private and company cars is available, so vehicles with and without garage can be differentiated. Users of vehicles that are parked in a garage are assumed to buy a wallbox for charging, while non-garage-owners have to pay for a simple on-street charging facility (similar to [Plötz et al., 2013]). For the latter, the cheapest charging facility available is chosen – a charging point integrated into a lantern – and the investment and running cost are split up between two users, assuming they could share one charging point [Plötz et al., 2013]. With these assumptions for private car holders without a garage an upper limit for their PEV ownership is obtained. Investment and running cost for both solutions as well as investment horizons are given in Table 4.2.

Table 4.2: Cost for charging infrastructure options. All prices without VAT in EUR_{2014}.

Parameter	unit	2015	2020	2025	2030
invest wallbox[a]	EUR	404	370	343	323
operating cost wallbox[a]	EUR/yr	0	0	0	0
invest domestic on-street charging point[b]	EUR	657	537	444	372
operating cost domestic on-street charging point[b]	EUR/yr	287	246	211	182
invest public charging point (3.7 kW)[c]	EUR	1,314	1,074	888	744
operating cost public charging point (3.7 kW)[c]	EUR/yr	574	292	422	364
invest public charging point (22 kW)[c]	EUR	5,281	4,694	4,107	3,521
operating cost public charging point (22 kW)[c]	EUR/yr	795	712	628	544

a: 3.7 kW, domestic users with garage, commercial and work charging facilities;b: 3.7 kW, domestic users without garage; c: in public places. All cost assumptions based on [Kley, 2011, Plötz et al., 2013].

The one-to-one allocation of charging points is also assumed for private and company car users at work: in scenarios where charging at work is allowed, every vehicle owner pays for his individual work charging point. As the installation is assumed to be simple, the cost for wallboxes in Table 4.2 is considered. For public charging points, two slow-charging solutions are considered by the charging point operator: a 3.7 kW lantern charging option with one charging point and a 22 kW charging station with two charging points. While the first solution is a low-cost option, the second is an average charging point that is currently most common in Germany [Lemnet, 2014]. For all charging options an investment horizon of 15 years is assumed [Kley, 2011].

[54] A distinction of different distances with respect to company size shows no influences on scenario results.

4.3.3 Vehicle market and vehicle cost parameters

New vehicle registrations in Germany have been almost constant with 3.1 million vehicles over the past seven years [KBA, 2012a,KBA, 2012b]. Segment shares within the new registrations that did not change significantly [KBA, 2012a,KBA, 2012b]. Approximately 30% of all new purchased cars in Germany are company cars [NPE, 2011b, NPE, 2011a, Pfahl, 2013]. Combined with [NPE, 2012], the number of new purchased cars per car size and user group can be obtained (see Table 4.3). For the simulations, the number and segmentation of vehicle sales are assumed constant until 2030. Here and in the following, the simplified segmentation (see Chapter 3), compared to statistics of the German Federal Motor Authority (KBA) [KBA, 2012a, KBA, 2012b], predefined by the driving profiles is used. Table 4.3 also shows general cost parameters like the interest rate of 5%, which is considered for private and commercial users for vehicles and charging infrastructure. The investment horizons are based on [Pfahl, 2013] and equal to the first vehicle registration period.

Table 4.3: Vehicle registrations and general cost parameters.

Vehicle registrations	unit	value 2015 – 2030
vehicle registrations private small[a]	-	475,309
vehicle registrations private medium[a]	-	694,275
vehicle registrations private large[a]	-	143,309
vehicle registrations fleet small[a]	-	233,240
vehicle registrations fleet medium[a]	-	454,998
vehicle registrations fleet large[a]	-	46,339
vehicle registrations fleet LCV[b]	-	204,000
vehicle registrations company small[a]	-	106,996
vehicle registrations company medium[a]	-	497,681
vehicle registrations company large[a]	-	244,563
General cost parameters	**unit**	**value 2015 – 2030**
interest rate private[c]	-	0.05
interest rate commercial[c]	-	0.05
investment horizon private vehicles (T_1)[c]	years	6.2
investment horizon commercial vehicles (T_1)[c]	years	3.8

a: [KBA, 2012a], b: [KBA, 2012b], c: [Pfahl, 2013]

The cost differences between electric and conventional vehicles are significantly driven by the differences in purchase prices of the varying technologies. The purchase price of plug-in electric vehicles consists of two parts: a relatively constant price for the chassis and drive train and a price for the battery system. All other electric components, like the electric motor or power electronics are highly developed vehicle parts which are not assumed to profit from further economies of scale. The battery system which accounts for the majority of investments in a PEV is assumed to further reduce in price [Nykvist and Nilsson, 2015]. The net purchase prices (without battery) are taken from [NPE, 2011a] and extrapolated until 2030. For conventional vehicles, prices are increased until 2030 based on [Mock et al., 2013] to reflect the additional cost for the required efficiency gains to achieve EU fleet targets for CO_2 emissions [EC, 2009]. The combinations of drive trains and segments missing in [NPE, 2011b, NPE, 2011a] are calculated with the existing ratios of gasoline/diesel technology to alternative technology [NPE, 2011a]. This leads, for instance, to slightly higher chassis prices (medium size) of BEVs with 18,000 EUR compared to 17,500 EUR of gasoline vehicles in 2020 (all values in Tables B.1-B.4).

The total purchase price of PEVs is determined by the battery size and price of the battery. In combination with the maximum depth of discharge, limits the electric range of the PEV. Battery sizes result from of a combination of several studies (cf. [Hacker et al., 2011b, Gnann et al., 2012a, Linssen et al., 2012, Pfahl, 2013]), yet values are slightly different compared to [Plötz et al., 2014a, Gnann et al., 2015b, Plötz et al., 2013]: (1) The maximum depths of discharge (=percentage of usable battery capacity) is assumed to be 90% for BEVs and 80% for PHEVs. (2) Battery sizes for medium sized BEVs increase from 24 kWh in 2015 to 40 kWh in 2020, because of economies of scale paired with the desire for more electric range, and remain stable thereafter. (3) Batteries for large BEVs start at 55 kWh in 2015 and increase up to 80 kWh in 2020 and afterwards (see Tables B.1-B.4).

All values on fuel consumption are based on [Helms et al., 2011]. The main assumption for future development of fuel consumptions is an efficiency gain (diesel, gasoline) of at least 1.5% per year to meet the EU emission targets [EC, 2009].[55] Compared to past efficiency developments [Mock et al., 2013], these assumptions seem moderate. Consumption values were adjusted in case of higher weight due to larger batteries. Values are average annual fuel consumptions and do not reflect extreme values in winter or summer.[56] Note that the values represent real consumptions and not driving cycle values. As the model calculates the TCO depending on individual driving behavior with different shares of electric driving for PHEVs, the illustrated conventional values in Tables B.1-B.4 represent a purely conventional operation after having fully depleted the battery, i. e. PHEVs are simulated in charge-depleting mode.

Maintenance costs also differ among technologies and are currently unknown for PEVs. The simulation of failure probabilities for each drive train components, performed in [Propfe et al., 2012b], leads to specific maintenance costs for large vehicles. Small deviations in battery size of BEV and PHEV between the model and [Propfe et al., 2012b] lead to minor adaptations. These maintenance costs also incorporate battery degradation due to cycling [Linden and Reddy, 2002]. Values for other size classes (gasoline and diesel) rely on [Frühauf, 2012, ADAC, 2013] and are transferred to the other technologies based on [Propfe et al., 2012b].

Vehicle taxes are calculated based on the current German tax legislation with a tax exemption for BEV owners [BMF, 2014]. PEVs are tax exempted for ten years if they are registered prior to the 1st of January 2016 and for five if they are registered thereafter although this is not legally fixed at the moment. A further exemption from tax after 2021 is considered. All technical and economical parameters for vehicles are shown in Tables B.1-B.4. For company car taxes only the gross list price ($LP^G_{r,s}(t)$) is changing over time according to Tables B.1-B.4 and the tax exemption ($TE^{PEV}_{r,s}(t)$) according to [BMF, 2015]. The modeling considers a reduction of the gross list price of 500 EUR multiplied by its battery capacity, but not more than 10,000 EUR in 2013. Thus, the gross list price for

[55] This implies a slight hybridization of conventional drive trains.

[56] For an analysis on deviations of consumption due to auxiliaries for heating and cooling see [Gnann, 2010], due to variations in driving in winter or summer see [Michaelis et al., 2013a], and due to variations due to driving aggression see [Funke and Plötz, 2014, Gnann et al., 2015a].

a BEV with 18 kWh battery capacity was reduced by $18 \cdot 500$ EUR $= 9,000$ EUR in 2013 for the calculation. The deduction per kWh and the maximum deduction are reduced by 50 EUR/kWh and 1000 EUR per year, so that a PEV bought in 2020 with 18 kWh can reduce its gross list price by $18 \cdot 150$EUR $= 2,700$ EUR which is still lower than the maximum of 3,000 EUR. For the other term in formula 4.2.2, fixed values are used: The average commuting distance ($ACD_f(t)$) is assumed to be 15 km and the income tax rate ($ITR_f(t)$) is equal to the maximum income tax rate in Germany (42%) since company cars are most often available to persons with high income.

4.3.4 Willingness to pay more for plug-in electric vehicles

An important aspect of a PEV's utility are its positive non-monetary characteristics. PEVs are perceived as new and innovative, as silent and environmentally friendly [Dütschke et al., 2011b, Peters et al., 2011b]. These positive aspects of PEVs are modeled with a willingness to pay more of some users, the magnitude of which depends on the users position in the adoption process [Rogers, 1962, Laroche et al., 2001]. Of course, a stated willingness to pay is not equal to the actual willingness to pay in a buying decision [Huang et al., 1997, Bradley and Daly, 1991]. However, the stated WTPM gives an indication for the appreciation of a new technology and an approximation of the actual WTPM. Using a WTPM is a common approach in market diffusion models for plug-in electric vehicles [Mock, 2010, Eppstein et al., 2011].

To assess a private user's position in the adoption process of PEVs and their individual WTPM, two empirical data sets are combined (see [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011a], cf. [GFK, 2012, Heupel et al., 2010, Knie, 1999]). The purpose of the original survey was to identify and characterize the different adopter groups in the adoption of PEVs according to Rogers' "Diffusion of Innovations" and they are ideal to assess the adopter groups' WTPM. In these studies the WTPM has been determined independently for four adopter groups with a different attraction to plug-in electric vehicles: (1) users of PEVs, identified as likely innovators, (2) attracted individuals with purchase intention in the near future, identified as likely early adopters, (3) attracted individuals without purchase intention, identified as likely early and late majority, (4) uninterested individuals, identified as likely laggards (cf. Table 4.4). The four adopter groups were formed by the participants' answers concerning their current vehicle usage, the interest in PEVs, and their intention to buy a PEV in the near future (see [Peters et al., 2011b, Dütschke et al., 2011a, Plötz et al., 2014b] for details). For an individual analysis of vehicles and users, these survey results have to be combined with the driving profiles. Each driving profile is thereby assigned to one of the four adopter groups with their WTPM.

Members of the four adopter groups differ significantly in socio-economic variables like household income, employment status, household size, city size and the willingness to accept a higher price for a PEV [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011b, Dütschke et al., 2011a]). As the data set also contains information about age, sex and education of the user groups, it is possible to assign each driving profile to one of the four groups according to their resemblance with the other group members (see [Plötz et al., 2014a, sec. 3.2] for a validation of this assignment). The participants stated an individual WTPM for PEVs. Here, the adopter group average WTPM is used to include the positive aspects of PEVs mentioned earlier. The percentage WTPM is

Table 4.4: Definition of private adopter groups according to [Peters et al., 2011b] and their willingness to pay more. Participants in survey answered the indicated questions and were considered members of the four indicated adopter groups. A small number of respondents answered the questions as no, no, yes and have been excluded from further analysis. The numerical values for the WTPM are median values of the group members' answers.

Group definition				Attributes	
group label	PEV user?	PEV interest?	purchase intention?	share of users^a	willingness-to-pay-more^b
innovators	yes	-	-	0.5%	30%
early adopters	no	yes	yes	1.5%	15%
majority	no	yes	no	48%	10%
laggards	no	no	no	50%	1%

a: [Wesche, 2013, Dütschke et al., 2013]; b: [Peters and Dütschke, 2014], [Wietschel et al., 2012, Peters et al., 2011a]

converted to absolute monetary values by using the conventional reference vehicle for the vehicle size (Gasoline for small and medium sized vehicle, Diesel for large and LCVs). For the individual user, the positive aspects are finally included in the utility calculation by subtracting the absolute WTPM from the vehicle list price (eq. (4.3)). The specific values are summarized in Table 4.4.[57]

Although the described data set contains about 1,000 respondents, it is not representative for the group sizes in Germany [Peters and Dütschke, 2014, Wietschel et al., 2012], users of PEVs and other PEV friendly groups are clearly overrepresented. It is still useful for the validity of the average WTPM in the groups. To correct the non-representative group sizes, a second survey representative for private German car buyers is used [Wesche, 2013, Dütschke et al., 2013]. The groups are defined in the same way, i.e. according to PEV ownership, interest in PEVs and purchase intention. Since the latter survey is representative, it is used to determine the relative size of the adopter groups. The resulting share of each adopter group is summarized in Table 4.4.

To assign each driving profile of MOP to one of the adopter groups with their WTPM, the following algorithm was used. For each driving profile, first the agreement in socio-demographic characteristics with each survey respondent was calculated. Matches were collected from seven variables: sex, age, employment status, education, household size, household income and city size (all variables were categorical). That is, a driving profile could achieve up to seven matches with each of the survey respondents from a known adopter group. The number of matches $m_{ijk} \leq 7$ of user i with adopter group member $j = 1, \dots, L_k$ (out of the $k = 1, \dots, 4$ groups) were collected and normalized $M_{ik} = \sum_j m_{ijk}/(7L_k)$. The driving profile i should then be assigned to group k where the overlap was the largest $M_{ik} > M_{il} \; \forall l \neq k$. However, since the relative group size should be limited

[57]The data on WTPM used here contains only positive values for WTPM. However, studies on willingness to pay for PEV range show that the limited range of PEVs a major drawback for potential users [Dimitropoulos et al., 2011]. Apart from methodological problems of many PEV range willingness to pay studies (the survey participants have not experienced PEVs) that are met in the WTPM data used here (a noteworthy share of respondents in [Peters and Dütschke, 2014] has used PEVs), the usage of only positive WTPM is valid for the suggested model since range limitations are explicitly included via the PEV simulation and the cost for individual charging points. That is, whatever a user's potential WTPM is, he is excluded from BEV purchase in the model if his driving exceeds the BEV range.

(the number of innovators is rather small), only the top 0.5% (cf. Table 4.4), i.e. those 0.5% with the largest overlap with the survey innovators, were considered as innovators. The other potential innovators were then assigned to their second best matching adopter group. The same procedure was applied to the following groups in descending order in the innovation process: innovators, early adopters, majority and laggards (see [Plötz et al., 2013, p. 182] for computational details). As a result of this algorithm, each driving profile has a position in the adoption process according to its socio-demographic variables with an associated WTPM. The validity of this assignment is analyzed in [Plötz et al., 2014a, sec. 3.2].

To assess the WTPM of commercial vehicle fleets, results from a survey of approximately 500 German fleet managers is used [Dataforce, 2011]. About half the fleet managers stated a WTPM with an average of 10%. Again, this WTPM needs to be assigned to individual commercial vehicle driving profiles [Fraunhofer ISI, 2014]. The company size (measured as number of employees) was used as a proxy for the position in the adoption process. Since larger companies seem more likely to engage early in innovative technologies [Dataforce, 2011], commercial vehicles from companies with more than 250 employees were assigned a WTPM of 10%. About 50% of the driving profiles are from such a company in agreement with the results from [Dataforce, 2011]. However, a sensitivity analysis showed that the assignment of WTPM to other groups of commercial car owners had no strong effect on the model results. No reliable data was available for WTPM of company car buyers, thus company car buyers are assumed to have zero WTPM in the model.

Further, the WTPM was determined in 2011 and the newness of a technology diminishes over time. As there are, to the best of the author's knowledge, no publicly available studies about the decline of a WTPM over time, it is assumed that the WTPM declines linearly to 60% of its value until 2020 based on [Plötz et al., 2013] and to zero until 2030.

4.3.5 Limited plug-in electric vehicle availability

The diffusion of innovations and new technologies typically follows an S-shaped curve, well described by a logistic function [Rogers, 1962, Geroski, 2000, van der Vooren and Alkemade, 2010, Massiani, 2010, Meade and Islam, 2006]. It is assumed that the availability of PEVs from different brands can be described by a logistic function, too. That is, the share of brands per segment that offer a PEV grows logistically over time $A(t) = [1 + \mathrm{e}^{-(t-t_0)/\eta}]^{-1}$. t_0 denotes the point in time when 50% of the brands in a given segment offer a PEV and η is the time scale of change of PEV availability. Technically, PEV announcements were collected from different brands and the cumulative number of brands per year that already offer or have announced to offer a PEV in the given year were calculated (see [Plötz et al., 2013, Ch. 7.4]). This cumulative number of brands has been divided by the number of brands active in that segment for normalization. For the case of Germany, all brands with non-zero new registrations in 2011 were defined as active (26 brands in the small segment, 32 in medium and 29 in large). The parameters of the logistic function to estimate future availability of PEVs were obtained by least-squares regression and assumed to be partly equal between the groups (see [Plötz et al., 2013] for details). The results for future availability of PEVs from different brands in Germany are summarized in Figure 4.3.5 and Table B.5.

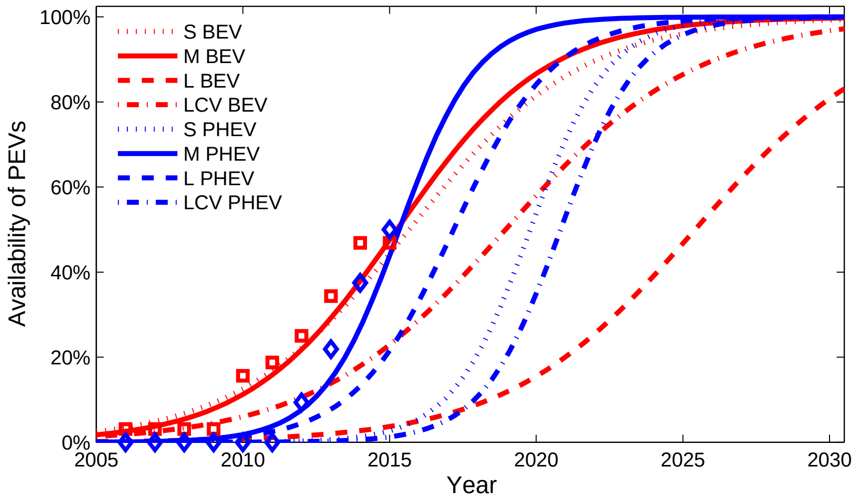

Figure 4.8: Limited availability of PEVs based on press announcements for different brands (see [Plötz et al., 2013, Ch. 7.4]).

4.3.6 Adaptations for the geographical simulation

For the simulation of charging stations and the PEV stock, geographical information about the driving behavior is needed for a simultaneous simulation of PEVs at charging facilities. For this reason, the data sets MOPS and REM2030S, a subset of driving profiles of REM2030, are used. However, these profiles lack of several information that is required for the previous model steps: (1) there is no information about the car holder, i. e. a distinction of private users and company cars is not possible, (2) the socio-demographic variables are not sufficient to assign the WTPM as for MOP and (3) information about garage ownership is not provided. Since this information is important for the simulation, several steps are performed to assign this information to the MOPS driving profiles. Since this might influence results, the following chapter contains two sections without public charging where MOP and REM2030 are used for simulation (Section 5.1 and 5.2). The inclusion of public charging points in Section 5.3 necessitates driving profiles with geographic information - MOPS and REM2030S. Differences will be discussed in Section 5.3.5.

The distribution of registrations to user groups in this region is different to that of Germany in total. The federal state Baden-Wuerttemberg, of which Stuttgart is the capital city, has a slightly higher share of commercially licensed vehicles [KBA, 2014a], while total registrations per area and capita are even higher in the region of Stuttgart than in Baden-Wuerttemberg and Germany [KBA, 2014c]. Since a data set with both attributes (user groups and rural districts) is not available, the share of commercial vehicles for the region of Stuttgart is assumed to be equal to the share of commercial vehicles for Baden-Wuerttemberg [KBA, 2014a] and the share of company cars and fleet vehicles in commercial passenger car registrations is assumed to be equal based on [Pfahl, 2013]. These numbers are shown in Table 4.5.

Table 4.5 shows that the number of profiles in company cars is equal to the registrations, which is an assumption of the author with the following argumentation. The purpose of the MOPS data is to provide a data set that is representative for the vehicle stock [Hautzinger et al., 2013]. While the German vehicle stock is distributed 90% to private vehicles and 10% to commercial vehicles, it is unclear how the commercial vehicle

Table 4.5: Vehicle registrations in region of Stuttgart and corresponding driving profiles.

attribute	private vehicles	company cars	fleet vehicles
registrations in observation area[a]	63,772	39,391	39,391
vehicle driving profiles in MOPS	1,273,426	39,391	164
driving profiles used for simulation	15,943	9,848	164
driving profiles multiplier registrations	4	4	240

a: [KBA, 2014c, KBA, 2014a, Pfahl, 2013]

stock is distributed to company cars and fleet vehicles. It is thus assumed that company cars have a shorter holding time than fleet vehicles and their share in the commercial vehicle stock is about one quarter. Hence, the share of company cars in the MOPS-profiles should be 2.5%/(90%+2.5%)=2.8% of all vehicle profiles which is almost equal to its registrations.[58] Whenever the vehicle stock is needed, all profiles of MOPS are considered.

For the determination of company cars the following procedure is performed: The company car owners of MOP are significantly different to private car owners in variables sex, occupation, household size, cars in household and driving behavior - expressed as μ and σ of an assumed individual log-normal distribution of driving days (see Section 5.1.1 and [Plötz, 2014]). Hence, these variables are used to describe the company car owners. Now, all driving profiles of MOPS are compared to these company cars of MOP and the ones with the equally weighed lowest squared differences were considered assigned company cars in MOPS. Table 4.6 shows the mean, median and quartiles of company cars in MOP (n=162) and MOPS (n=39,391).

A good agreement of mean and median values for company cars in the two data sets is found for variables household size, cars in household as well as μ and σ. Company cars seem to slightly differ in medians and means for the variables occupation and sex, although this might also result from equal weights for all variables. The smaller variation in MOPS (e.g. quartiles are equal to median in household size and cars in household) arises from the comparison to average values of MOP. These differences will be discussed in Chapter 5.

The WTPM was assigned to users from MOP using the attributes household income, sex, age, education, employment status, household size, and city size, which describe user groups in [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011a] reasonably well. However, only the employment status, sex and age are available in MOPS, thus an assignment with the above described algorithm (Section 4.3.4) is not possible. For this reason, the WTPM is randomly assigned to driving profiles and the influence of a random assignment to results is tested with MOP in Section 5.2.2.

Lastly, information about the vehicles is not available for MOPS. Yet, the geographic information is a sufficient condition for the analysis of public charging infrastructure, which is the focus of this study. Since the availability of garages depends on the city sizes or settlement structures (see [Gnann et al., 2013] for a display of garage availability and city sizes of [infas and DLR, 2002]), the settlement structures of the profiles are considered

[58] Since only a share of vehicles is used for simulation due to limited computing capacities, this assumption is not decisive.

Table 4.6: Comparison of assignment of company cars in MOPS and MOP.

attribute	data set	25% quartile	median	75% quartile	mean
sex[a]	MOP	1	1	2	1.303
	MOPS	1	2	2	1.526
occupation[b]	MOP	1	1	2	1.975
	MOPS	1	2	2	1.634
household size[c]	MOP	2	3	4	3.082
	MOPS	3	3	3	3.057
cars in household[d]	MOP	1	2	2	1.639
	MOPS	2	2	2	1.809
individual log-normal μ	MOP	3.437	3.909	4.300	3.856
	MOPS	3.465	3.726	3.980	3.895
individual log-normal σ	MOP	0.572	0.922	1.284	0.964
	MOPS	0.550	0.757	0.993	0.779

a: non-metric scale with 1=male, 2=female; b: ordinal scale with 1=fully occupied, 2= partially occupied, 3=not occupied, 4=student, 5=trainee, 6=housewife/househusband; c: number of household members; d: number of vehicles in household

for an assignment of garage availability based on [infas and DLR, 2002]: The rural district of Stuttgart has the highest settlement structure based on [infas and DLR, 2002], 45.1% of all profiles of this area get assigned to own a garage. All other rural districts in the observation area are in the second highest category of settlement structures and 56.8% of profiles from these areas are appropriated with garages. As vehicle sizes are not available in MOPS, all vehicles are considered medium sized.

The inclusion of the limited availability is slightly adjusted since both data sets do not contain vehicle brand information and because of the necessary information about the vehicle usage of PEVs in the vehicle stock: Vehicles are only registered up to the limited availability $N_{m,s} = s_{m,s}(t) \cdot n_m(t) \cdot lim_{m,s}(t)$. The driving profiles that are part of the PEV stock simulation are randomly chosen from the registrations of each group $N_{m,s}$.

Since model results should be available for Germany, results have to be scaled up from the region of Stuttgart. Many factors should be considered like the population density, income or car ownership. All these factors are reflected when the vehicle registrations are used for up-scaling as they include the earlier mentioned factors. Hence, results from the region of Stuttgart are multiplied by 20.54 to retrieve results for Germany [KBA, 2014c]. The initial number of charging stations for the region of Stuttgart is extracted from [Lemnet, 2014]. 374 charging points with 3.7 kW and 289 charging points with 22 kW can be found. For the calculations, these charging points are assumed to be of equal power levels. With these adaptions of the input data and all previous assumptions, a simulation with ALADIN is possible.

4.4 Discussion

The introduction of a new model is based on a variety of assumptions, since models are always a simplification of reality for a special purpose [Hartmann and Frigg, 2006]. While the need for a new model approach was discussed in Section 2.2.3 and the data in Chapter 3, this section holds a discussion of the modeling approach. It is divided into three parts: a validation of the model (4.4.1), a general discussion of the approach (4.4.2) and the coverage of the stylized facts of Section 2.2.1 (4.4.3).

4.4.1 Validation

Since the sales for PEVs are still limited, it is not possible to compare model results to actual PEV registrations. A model that is able to reproduce market shares of different historical propulsion technologies seems better suited to predict future market shares than a model that does not reproduce these historical market shares. However, there is data publicly available for some early PHEV-users [Voltstat, 2014]. Their electric driving shares serve for comparison as a first validation. Further, an assessment of historical diesel market shares is included as a validation for the inclusion of a TCO calculation proposed here. Also, the validity of the WTPM assignment was analyzed in [Plötz et al., 2014a, sec. 3.2]. Since a comparison of model results for market diffusion with real-world sales data is not possible, the important influence factors will be discussed in sensitivity analyses in Chapter 5.

Comparison of electric driving shares

The first validation comprises a comparison of calculated electric driving shares with real electric driving shares. For this analysis, data from MOP and REM2030 is used for simulation and data from [Voltstat, 2014][59] for real-world electric driving shares of PHEVs. The simulation is performed for medium sized vehicles in the medium scenario in 2020 (as then sample sizes are reasonably large for simulated PHEVs) and results are shown in Figure 4.9.[60]

Figure 4.9 shows the electric driving shares over the annual vehicle mileage as a scatter plot. Results are shown for users for which PHEV receive the highest utility in REM2030 (red) and MOP (blue). Further, the real-world data from [Voltstat, 2014] is displayed with green crosses. On the one hand, it can be observed that simulation results reach from very small to very large values for similar annual VKT which may result from driving that does not allow to regularly recharge the vehicle and respectively perform a high amount of VKT electrically. On the other hand, simulated and actual users obtain high electric driving shares and perform a relevant amount of annual VKT, although not more than technically possible. A window for plug-in electric vehicles can be identified, the boundaries of which are determined by cost (for the lower boundary) and technical limitations of battery and recharging facilities (for the upper boundary). The 10%, 25%,

[59] Data for this section was retrieved by the authors of [Plötz et al., 2015] who kindly permitted to use it in this thesis.

[60] A comparison of data from US and Germany seems reasonable since their driving behavior does not vary much [Gnann et al., 2012a].

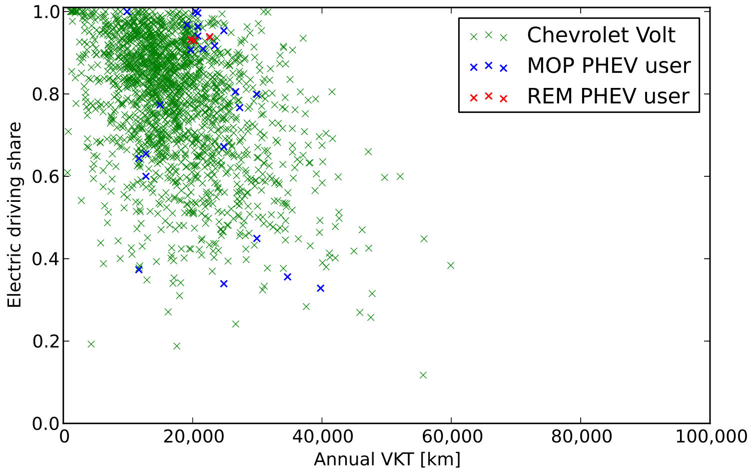

Figure 4.9: Electric driving shares over annual VKT for medium sized vehicles of three different samples: PHEV-users in 2020 of MOP with blue crosses (n=131), PHEV-users in 2020 of REM2030 with red crosses (n=17) and real users of Chevrolet Volts from [Voltstat, 2014] with green crosses (n=1,831).

75% and 90%-quantiles of these samples as well as their median, mean and standard deviations are shown in Tables 4.7.

Firstly, it should be mentioned, that a lot of users of both samples obtain high electric driving shares (median and mean above 65% for MOP and above 75% for REM2030). Secondly, the electric driving shares for simulated vehicles with PHEV as utility maximizing option are significantly higher than in the full sample[61] (above 80% for both samples), which is not surprising since a high electric driving share favors the adoption of PEVs. Thirdly, the observed electric driving shares of [Voltstat, 2014] are also high and very similar to the values obtained from the simulation for MOP and REM2030. Thus, the simulation results can reproduce the buying behavior of PHEVs in terms of electric driving share.

Table 4.7: Comparison of electric driving shares and annual VKT[62].

electric driving share	q-10%	q-25%	median	mean	q-75%	q-90%	stdev
MOP	0.29	0.44	0.67	0.66	0.91	1.00	0.27
MOP PHEV	0.67	0.74	0.82	0.81	0.90	0.98	0.13
REM2030	0.39	0.57	0.84	0.76	1.00	1.00	0.25
REM2030 PHEV	0.70	0.74	0.85	0.83	0.93	0.96	0.10
Chevrolet Volt	0.56	0.69	0.82	0.79	0.90	0.96	0.15
Annual VKT	q-10%	q-25%	median	mean	q-75%	q-90%	stdev
MOP	5,683	8,760	12,775	16,201	19,710	29,930	13,288
MOP PHEV	16,615	18,980	20,805	21,673	24,820	28,229	4,974
REM2030	6,256	8,103	13,976	18,076	22,878	37,583	13,197
REM2030 PHEV	17,115	19,569	22,159	22,814	25,811	27,997	4,694
Chevrolet Volt	8,359	12,079	16,313	17,418	21,582	27,579	8,265

[61] A two-sided t-test with unequal sample sizes and unequal variances rejects the null hypothesis at p =2.5% for REM2030 and p <1% for MOP.

Results are similar for PHEV and their annual VKT. Also here, a good agreement of medians, means and upper sample limits is found. However, in [Voltstat, 2014] there are also vehicles with lower annual VKT than in the simulated samples. An explanation might be, that these vehicles were bought even though they are not economical for the user or the WTPM is of these users might be higher than for others. However, also vehicle taxes and fuel prices are different in the US which is the origin of this data. Still, this analysis shows that real electric driving shares of PHEV users can be reproduced by the model.

Reproduction of Diesel market shares

The reproduction of diesel market shares may serve for validation of the TCO-based part of the model approach. For this comparison, neither costs for individual charging points nor a limited PEV availability applies. To rule out an eventual willingness to pay more, the commercial fleet vehicle market is considered whose buying decisions largely base on cost [Golob et al., 1997, Globisch and Dütschke, 2013, Laroche et al., 2001]. This supports the general proposal of including TCO as one important factor in the purchase decision for passenger cars. The fact that commercial fleets are only one of the three user groups under consideration here is acknowledged. However, it is responsible for about one third of the annual registrations of passenger cars in Germany and thus an important market.

For this analysis a large sample of German commercial passenger cars is studied which was collected in 2002 [IVS et al., 2002] and has already been described in Section 3.3. This data set is used as REM2030 does not contain information about the actual fuel type of the vehicles which is available in this data set. For each vehicle in the database that has been used on the day of the survey, the lengths of all daily trips are summed up and multiplied by the average number of working days in Germany (which is 220 days per year) to obtain an estimate for the vehicles annual VKT. In this case, the latter was not part of the survey and thus had to be calculated. For each vehicle, the TCO as gasoline and diesel car is calculated and the vehicle is assigned the fuel type with lower TCO. For the validation purpose, only medium sized vehicles are studied and a purchase price of 19,560 Euro for gasoline and 21,560 Euro for the diesel vehicle is assumed. The average fuel prices in 2002 have been taken from [Plötz et al., 2012] and were 1.34 Euro/liter for gasoline and 1.26 Euro/liter for Diesel fuel. The assumptions for the fuel consumption for passenger cars in German commercial fleets of 2002 are 7.6 liters/100km for gasoline and 6 liters/100km for Diesel fuel. Furthermore, average operation and maintenance costs amounted to 0.025 Euro/km for Gasoline and 0.023 Euro/km for Diesel fuel whereas vehicle taxes were 114 Euro/a for Gasoline and 242 Euro/a for Diesel vehicles. The share of diesel vehicles in the different commercial branches estimated by the TCO model proposed here are shown in Figure 4.10 together with the actual market share as stated in the corresponding survey.[63]

[63] In the display of Figure 4.10 the estimates of diesel market shares in German commercial sectors are shown with confidence bands based on [Plötz et al., 2014a]. Shown are the $\alpha = 0.1, 1, 5, 10, 30$ % confidence bands (from light to dark blue), i.e. the "true" value should lie within the confidence band in 99.9, 99, 95, 90, 70 % of the cases where confidence bands are estimated. The width of the confidence bands increases with decreasing sample size (shown in parentheses in the abscissa). In most cases the observed market share is within or close to the range of the confidence bands. Thus, the TCO calculation seems to capture important aspects of the purchase decision. Also, the calculated confidence bands help to distinguish purely statistical uncertainty from possible systematic inaccuracies.

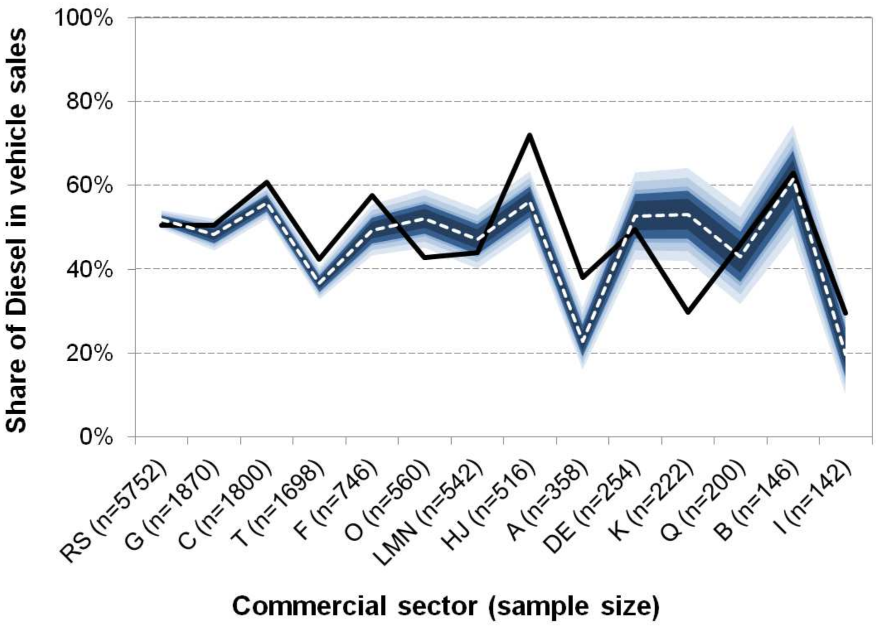

Figure 4.10: Diesel market shares within different commercial branches in Germany. Shown are the actual values from a large-scale survey (solid line) and the estimate from a simple TCO calculation (dashed line) together with confidence bands (in blue) from the finite sample sizes (given in parentheses). See text for details of the calculation.

Figure 4.10 shows that the estimated and actual market shares of commercial diesel passenger cars in Germany are 40–60% in the major commercial branches and 20–70% over all branches. In Figure 4.10 the commercial sectors are sorted by sample size which roughly follows the registrations of passenger cars in these segments.[64] In most cases, the estimated market shares are very close to the actual market shares with significant deviations in the sectors HJ (Transport and Telecommunications), A (Agriculture and Forestry), and K (Finance). Even if the share of diesel in a sector is well reproduced, one could still question whether the individual vehicle assignments are correct. In total, 54.2% of the individual assignments are found to be correct with a lowest success rate of 38% in branch of industry K (Finance) and the highest rate of 66% in branch B (Mining). Thus, it is concluded that the proposed model is in principle able to reproduce the market shares of diesel passenger cars of German commercial fleet vehicles. TCO is thus one important aspect of the purchase decision and accordingly part of many market diffusion models for PEVs.

4.4.2 Discussion of modeling approach

Generally the modeling approach, scenarios and techno-economical parameters as well as the adaptations for Stuttgart have to be discussed.

For the co-diffusion of PEVs and their charging infrastructure a simulation model is proposed. This is not only the most common approach for the interaction of AFVs and their refueling infrastructure, but also permits to identify niches when individual

[64]The commercial branches were introduced in Section 3.3.2. In 2002, the classification was slightly different, thus several commercial branches were combined to be similar to [Eurostat, 2008].

user behavior is analyzed (see Chapter 2). The variations in driving behavior between users and days within individual profiles favors an agent-based simulation approach with individual agents and their vehicle purchase decisions that depend on their vehicle usage (see Section 5.1.1). Driving profiles for a large number of vehicles for private users are publicly available and commercial vehicle driving profiles were collected for this thesis, both with an observation period of at least one week. Yet, the vehicle purchase behavior does not only depend on cost, but also on several non-monetary factors (see Figure 4.2) which were partly monetized in an individual utility function (eq. 4.3). This is the favoring WTPM for a new technology that was explicitly collected for PEVs [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011a] and integrated into the model as well as the obstructing factors charging infrastructure which is integrated as cost for individual charging points. The interaction between individual agents is needed when the PEV stock and their public charging point usage is simulated and a charging point operator decides about the public charging price and infrastructure stock of the following period.

ABMs incorporate several issues that have to be taken into account. Firstly, they are very data intensive [Bonabeau, 2002] like many bottom-up models (see Section 2.2.2). With the publicly available private and for this purpose collected commercial driving profiles as well as the comprehensive collection of data for the WTPM [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011a], data sets are available in sufficient amount and were discussed in detail in the previous chapter and Section 4.3.4. Secondly, the simulation of ABMs is computation intensive [Bonabeau, 2002]. Also this issue could be resolved with a parallel simulation of some 15,000 agents in the individual simulation that has to be run for 16 times between 2015 and 2030 and up to 200,000 agents in the joint simulation that could not be parallelized. A simulation of 16 years takes about 16 hours on a 32 kernel server with 384 GB RAM. Thirdly, soft factors like the WTPM often are difficult to quantify [Bonabeau, 2002]. The large and comprehensive data collections of [Peters and Dütschke, 2014, Wietschel et al., 2012, Peters et al., 2011a] allow to retrieve quantifiable and statistically reliable data for user behavior on the WTPM. For driving behavior the earlier mentioned data collections permit a detailed and statistically sound analysis of vehicle usage data with a large amount of additional information about vehicle and vehicle owners (see Chapter 3). Quite often, such data is unavailable and the collection of data and the connection of the different data sources requires real effort. However, driving data with limited observation time is available for many industrialized countries and the interest in PEVs has triggered driving data collections over long time spans [Karlsson and Kullingsjö, 2013, Smith et al., 2011]. Thus, more driving data is becoming available and can be used for modeling in the future. Fourthly, "another issue has to do with the very nature of the systems one is modeling with ABM in the social sciences: they most often involve human agents, with potentially irrational behavior, subjective choices, and complex psychology - in other words, soft factors, difficult to quantify, calibrate, and sometimes justify. Although this may constitute a major source of problems in interpreting the outcomes of simulations, it is fair to say that in most cases ABM is simply the only game in town to deal with such situations." [Bonabeau, 2002] For this reason, a new approach to model the co-diffusion of PEVs and their charging infrastructure is proposed in a detailed, user specific and empirical way. The model decision for different propulsion system is based on an individual utility calculation resulting from a PEV simulation descending in the vehicle's TCO extended by a willingness to pay more for new and environmental friendly vehicles of some vehicle buyers and the cost for individual charging infrastructure reflecting the current lack of public charging infrastructure and the corresponding range anxiety. A joint simulation of the PEV stock where vehicle agents interact permits a charging point operator to decide about public charging cost and (de-)construction based on the public charging point usage. Note, that the model is an agent-based simulation and no multi-agent system, since, e.g. neighboring effects, could not be incorporated as there is no data publicly available in the desired quality.

The distinctive features of the present model are the individual utility maximization based on a detailed analysis of many individual driving profiles as well as in the inclusion of commercial vehicles and company cars. The user specific analysis allows to cover a wide range of usage scenarios and to study specific user groups such as commercial drivers or potential early adopters [Plötz and Gnann, 2013, Plötz et al., 2014b]. Furthermore, the large number of driving profiles allows the modeler to use statistical methods to assess the statistical quality of the model results. Additionally, PEV specific purchase decision factors such as the limited electric range and the need for frequent recharging are addressed by the model proposed here.

The individual model steps also depend on assumptions that can be discussed. The driving data of private users in the model extends over one week which might not contain rare long-distance trips that seem important for PEV adoption. The robustness of the model can be tested by calculating the number of days per year with more daily VKT than the BEV range and including the cost for a substitute vehicle following the methodology of [Plötz, 2014]. This will be analyzed in Section 5.2.3.

The individual PEV simulation is probably more abstract or mathematical than the actual purchase decision of private users. Yet it covers the important aspect of the regularity of an individual users' driving behavior. Users are aware of PEVs' limited electric range and understand the general economics of low operating costs for electric driving [Dütschke et al., 2011b]. Similarly, the TCO calculation of Eq. (4.4) is rather complex but the purchase and operation costs of a vehicle are an important aspect in the purchase decision both for private [Peters and de Haan, 2006] and commercial buyers [Dataforce, 2011]. This is indicated by the average annual VKT for diesel vehicles (22,300 km) and gasoline vehicles (11,800 km) in Germany [Follmer et al., 2010] – reflecting the average fuel economy under the German conditions of both propulsion technologies. Accordingly, TCO calculations are a part of many PEV market diffusion models [ESMT, 2011, NPE, 2011b, Plötz et al., 2012, Peters et al., 2012, Mock, 2010, McKinsey, 2011]. Along the same direction, recent studies pointed out that the costs of PEVs are a major influence in the purchase decision [Götz et al., 2011, Peters and Dütschke, 2014, Wietschel et al., 2012, Knie, 1999, Gnann et al., 2015b].

Although the TCO are an important factor in the vehicle buying decision, they alone cannot explain purchase decisions of car users, neither for private nor commercial car purchases [Peters and de Haan, 2006]. Furthermore, private buyers of hybrid and conventional vehicles seem to lack knowledge necessary for a TCO-based decision [Turrentine and Kurani, 2007]. An analysis of the potential early adopters of PEVs in Germany shows that more criteria than only the vehicle's TCO are important [Peters and Dütschke, 2014, Wietschel et al., 2012, Plötz et al., 2014b]. Accordingly, the proposed model covers further important aspects of the purchase decision: The need of frequent recharging is addressed in the model by adding the cost for individual charging options to the vehicle's TCO and the WTPM of some user groups has been derived from surveys and is added to the driving profiles based on the vehicle owner's socio-demographic characteristics. Overall, it is attempted to make the most important factors in the PEV buying decision explicit and measurable. They have been included in the model in an empirical way that allows updates or corrections when more data on WTPM or choice of models become available in the future, especially the evolution of the WTPM could be of interest. In this approach for the utility calculation, neither a potential downsizing effect is reflected since vehicles are always purchased in the same vehicle size as the driving profile, nor is car-sharing which might reduce the number of vehicles in total. A change of user behavior in the future is not considered in this approach. However, there is no reliable data for these effects that could be incorporated into the model. Also the modeling approach for company cars is slightly different to private and fleet vehicles: the purchase of the company as vehicle owner is reflected with the first four terms of equation 4.3 while the decision process of the vehicle owner is presented by the fifth factor. With this approach, the preselection of the company that provides a limited offer to the vehicle driver is reflected as well as the vehicle driver's decision when also reflecting the cost he has to pay monthly for this car. Since a company car is often also a status symbol and the purchase decision may not only depend on cost, this might be the minority of cases, since also other studies rely on the same approach [Pfahl, 2013].

The limited choice of brands and models is included according to the current share of brands offering PEVs. It is retrieved from press announcements of PEVs, yet it could have been externally defined based on historical evolutions of other technologies. However, the derivation from future vehicle announcements puts these curves on a data-based foundation that permits to determine location and scale of the assumed logistic curves based on the technology itself.

The charging point operator is designed to behave like a company that is cost-oriented and wants profits from its investments. The total energy charged at public charging stations retrieved from the PEV stock simulations is a key performance indicator that will be technically available for every company working with charging points. Basing the construction and public charging price on this figure would be a common approach for an economical decision making process (Section 2.2.3). An annual change might be discussible, yet the variations in the public charging price mainly depend on the change in charging point cost (see formula 4.10) which changes only slightly and the availability of charging stations is the main focus of this research. An inclusion of potential subsidies through a charging point operator or state will be discussed in Section 5.3. Further, the rules for charging point placements are questionable as well, yet they base on reasonable assumptions: As long as only a few PEVs are on the roads, charging points are erected in areas where a lot of vehicles are parked - also to gain attention. When a minimal geographical coverage is fulfilled, highly PEV-frequented charging stations will be extended. These two rules could also be applied at the same time in reality, yet the amounts of conventional vehicles and PEVs differ too much to compare setup needs to each other. Lastly, the deconstruction of public charging points could be scrutinized, yet the operating cost of public charging points is considerably high. For this reason, charging points are taken out of service until they are needed to reduce sunk costs.

4.4.3 Coverage of stylized facts

In Section 2.2.1 a number of stylized facts were retrieved that models treating the co-diffusion of PEVs and their charging infrastructure should consider. These are are listed and discussed for the presented model approach in the following.

(A) ✓ *An initial amount of AFV refueling or recharging infrastructure:* The initial amount of (public) charging infrastructure is incorporated into the model. For private households the availability of garages is considered and for public charging points the currently available ones in the region of Stuttgart.

(B) ✓ *AFV and AFV refueling infrastructure market shares:* Market shares of PEVs are explicitly considered in the PEV stock simulation. Market shares for public slow charging points can be extracted, yet they are hardly comparable to current refueling stations.

(C) ✓ *Profitability of refueling or charging stations:* The profitability of public charging stations is a precondition of the charging point operator.

(D) ✓ *Fuel prices for conventional and alternative fuels:* Both fuel prices and prices for electricity are integrated in the utility function of each individual user. Also their ratio is considered in the decision to recharge for PHEVs when arriving at a public charging point.

(E) ✓ *Different user groups:* Different user groups are reflected with driving profiles that are individually analyzed. Also different configurations of the utility function are incorporated for private, commercial fleet and company car users. Further, different adopter groups are regarded.

(F) *(✓) Decreasing user concerns with AFV use:* Currently PEVs are only publicly recharged when their battery SOC is below 50%. Decreasing concerns for users could be modeled with a descending minimal SOC that users are willing to accept, yet this had to be externally defined, since networking effects are not incorporated into the model. The increasing range through efficiency gains in electric consumption could be argued as implicit consideration of this factor. Further, different minimal SOCs will be tested in a sensitivity analysis.

(G) ✓ *Potential policy measures:* Monetary policy options such as subsidies for vehicles and charging infrastructure can be incorporated into the model. These will be discussed in Section 5.3.

(H) ✓ *Refueling duration and frequencies can differ between PEV and conventional vehicles:* The duration and frequency of refueling for PEVs are explicitly considered in the individual and joint PEV simulation.

(I) ✓ *Multiple types of infrastructure have to be differentiated by accessibility:* This distinction is a prerequisite of the model as well.

With eight out of nine factors, the model is considered well-fitted to simulate the co-diffusion of PEVs and their charging infrastructure.

Summary

The aim of this section was to introduce a model for the joint simulation of PEVs and their charging infrastructure. Also scenarios and further parameters were discussed. The following should be maintained:

1. The agent-based diffusion model ALADIN allows to determine the co-diffusion of PEVs and their charging infrastructure based on real-world vehicle usage data. An initial PEV simulation with BEV feasibility and PHEV electric driving share as outcomes followed by the utility maximizing propulsion technology based on vehicle and infrastructure TCO and WTPM permits to determine every user's best vehicle option. In a stock model that also incorporates a limitation of diffusion due to limited PEV availability, the PEV stock is determined and simulated thereafter to provide the public charging point usage. With this usage a charging point operator decides on the (de-)construction of the PEV stock and thus the electric driving cost for the consecutive individual simulations.

2. A validation of the model shows that electric driving shares of PHEVs when compared to real-world electric driving shares and the historic market share of diesel vehicles can be reproduced. A further validation of the model is not possible, since market shares for PEVs are still low.

3. Three scenarios for framework conditions (fuel, battery and electricity prices) were defined with positive conditions for PEVs (pro-EV), negative conditions (contra-EV) and conditions in between (medium). These are no extreme scenarios, but show the range of results. The availability of charging infrastructure increases in the calculations in the next chapter: While in Section 5.1 only home charging (domestic and commercial) is considered, additional charging at work is reflected in Section 5.2. In Section 5.3 also public charging is analyzed.

4. Several adaptations are necessary for the driving profiles with geographic information (MOPS and REM2030S): Company cars are assigned based on the similarity to the average company car owners in MOP, the WTPM is randomly assigned and garage ownership is randomly assigned after a distinction of settlement structures. For this reason, MOP and REM2030 will be used for analysis in Section 5.1 and 5.2, MOPS and REM2030S in 5.3. The influence of these random allocations will be tested in the following chapter.

Chapter 5

Model results

Introduction

The market diffusion of plug-in electric vehicles is a current and important field of research [Al-Alawi and Bradley, 2013] and a relevant topic to decrease the dependency from fossil fuels and reduce GHG emissions [Kahn Ribeiro et al., 2007, IEA, 2010]. A large number of models study driver behavior to predict a future market evolution of PEVs[65], yet they suffer from several insufficiencies: (1) In studies for Germany, the commercial vehicle sector is often neglected[66], although it accounts for more than half of the vehicle registrations. (2) Several studies analyze driving behavior of only one day[67], which could lead to inaccuracies, since driving behavior varies between users and days [Smith et al., 2011, Amjad et al., 2011, Neubauer et al., 2012]. (3) The vehicle buying decision is often modeled with vehicles' TCOs[68], although it comprises a variety of factors to integrate. (4) Charging infrastructure is often discussed as a key barrier to market diffusion of PEVs[69] and a co-diffusion of PEVs and charging infrastructure is demanded[70]. However, this co-diffusion is not modeled up to now.

The model ALADIN which was introduced in the previous Chapter 4 addresses these issues explicitly: More than 500 driving profiles with an observation period of 21 days for the commercial vehicle sector have been collected for this thesis. They are analyzed individually in a PEV simulation and consecutive utility comparison of different drive trains. The vehicle buying decision is based on the TCO for a vehicle and is extended by the WTPM for PEVs as a favoring aspect and the cost for charging infrastructure as well as the limited availability of PEVs as obstructing factors. For the simulation, driving profiles with an observation period of at least seven days are considered. And, the charging behavior of PEVs at various charging points is analyzed in a joint simulation of PEVs in stock.

In the following, the model will be applied to determine the market diffusion of PEVs

[65]See e.g. [Dagsvik et al., 2002, Santini and Vyas, 2005, Keles et al., 2008, Lamberson, 2008, Mock et al., 2009, Nemry and Brons, 2010, Wansart and Schnieder, 2010, Shepherd et al., 2012].

[66]See e.g. [Hacker et al., 2011b, Redelbach et al., 2013, Schühle, 2014].

[67]See e.g. [Dagsvik et al., 2002, Santini and Vyas, 2005, Lamberson, 2008, Mock et al., 2009, Wansart and Schnieder, 2010, Shepherd et al., 2012].

[68]See e.g. [Thiel et al., 2010, McKinsey, 2011, Pfahl et al., 2013, Wu et al., 2015]

[69]See e.g. [Dütschke et al., 2011b, Egbue and Long, 2012, Steinhilber et al., 2013].

[70]See e.g. [Lin and Greene, 2011, Dong et al., 2014, NPE, 2012, Kalhammer et al., 2007, BCG, 2009, Ma et al., 2014, Chen et al., 2013]

and their charging infrastructure for Germany until 2030. The chapter is divided into three parts (see Table 5.1): First, the driving behavior of commercial and private passenger car owners and their market potentials in 2020 are analyzed (5.1). In this analysis, the first two model steps of ALADIN are used and only private or commercial charging in the medium scenario is considered to focus on the differences between private and commercial driving behavior and resulting PEV market potentials. Second, the market evolution of PEVs until 2030 is analyzed by including the stock model in Section 5.2. Here, all three scenarios for framework conditions are considered while domestic, commercial and work charging is allowed. The diffusion of PEVs without public charging infrastructure and their main influence factors shall be tested in this section to be able to put the influence of public charging infrastructure into context. Third, the interaction of PEVs and charging infrastructure diffusion is considered in Section (5.3). Here, all infrastructure options are considered in the medium scenario in Section 5.3 focusing on the influence of different charging options on PEV market diffusion. While in Section 5.1 and Section 5.2, the data sets MOP and REM2030 are used for simulation, public charging analyses necessitates geographic information available in the data sets for the region of Stuttgart - MOPS and REM2030S.[71] The differences of results due to data sets, based on the adaptations made in Section 4.3.6, will be discussed in Section 5.3.5.

Table 5.1: Consideration of scenarios in results.

Options	Section 5.1	Section 5.2	Section 5.3
ALADIN modeling steps			
Individual PEV simulation	✓	✓	✓
Individual utility maximization	✓	✓	✓
Stock model		✓	✓
Charging point operator			✓
Scenarios			
contra-EV		✓	
medium	✓	✓	✓
pro-EV		✓	
Availability of charging infrastructure			
domestic & commercial	✓	✓	✓
work		✓	✓
public			✓

Table 5.1 gives an overview of modeling steps, framework scenarios and charging infrastructure consideration in the following sections. Each part contains an individual discussion and summary of results while a synopsis at the end of this chapter (Section 5.4) merges results of all three section.

[71]See Chapter 3 for a description of the vehicle usage data sets.

5.1 Market potentials of private and commercial plug-in electric vehicles[72]

The commercial vehicle market is important for PEVs since it comprises more than 60% of annual vehicle registrations in Germany (cf. Section 3.1 and [Gnann et al., 2015a]). When market potentials are calculated, the commercial vehicle market is often neglected (see e.g. [Redelbach et al., 2013, Schühle, 2014]). Only some studies for Germany include commercial vehicles explicitly[73] or as a part of their analysis[74]. The driving profiles of MOP and REM2030 introduced in Chapter 3 permit to analyze the regularity of driving behavior in different user groups as well as an individual analysis of BEV feasibility and electric driving shares of PHEVs. Because of the observation period of more than one day, it is possible to compare private and commercial driving behavior on a statistically sound data basis (see Section 3.1).

In the next subsection, the private and commercial driving profiles introduced in Chapter 3 are compared to each other regarding their individual daily distance and regularity of their driving which is important for PEVs (Section 5.1.1. Thereafter, the focus is on the market potential of PEVs in the different user groups (Section 5.1.2). Market potentials are calculated by using the first two model steps (cf. Section 4.2.1 and 4.2.2). A discussion (Section 5.1.3) and summary (Section 5.1.4) complete the first part of model results. Calculations in this section are performed with techno-economical parameters for 2020 as subsamples then are large enough for statistically sound conclusions.

5.1.1 Comparison of private and commercial vehicle usage

The economics of PEVs suggest they should drive many kilometers in order to economize but at the same time not too many because of the limited range of PEVs. This issue can be resolved by driving behavior that is very regular with higher than average daily VKT. In the present section, the regularity of driving and daily VKT of German commercial passenger cars is analyzed and compared to private passenger car driving. The regularity of daily driving is measured by the standard deviation of the logarithm of daily VKT. For each vehicle, the daily VKT r_{ij} by vehicle i on day j are analyzed. The logarithm of these daily VKT $\ln(r_{ij})$ is studied since daily VKT are right-skewed and their logarithms are approximately Gaussian distributed [Plötz, 2014, Lin et al., 2012]. For each vehicle i, the typical scale of daily driving $\mu_i = \frac{1}{n}\sum_{j=1}^{n}\ln(r_{ij})$ and the variation, i. e. standard deviation, in daily driving $\sigma_i = [\frac{1}{n-1}\sum_{j=1}^{n}(r_{ij}-\mu_i)^2]^{1/2}$ are calculated. The latter measures the individual regularity of daily driving. The former measures the typical scale of driving since the vehicle's median daily VKT is given by $r_{\text{med},i} = \exp(\mu_i)$ and the mean daily VKT by $\bar{r}_i = \exp(\mu_i + \sigma_i^2/2)$.

As explained in the previous chapters, there are three user groups under observation: private vehicles, company cars and commercial fleet vehicles. For the first two groups, the data of MOP is used, while fleet vehicles are based on REM2030. The scales and variances

[72]This section is based on [Gnann et al., 2015a].

[73]See [Berg, 1985, Golob et al., 1997, Gnann et al., 2012c, Ketelaer et al., 2014, Hacker et al., 2015, Gnann et al., 2015a]

[74]See [Hacker et al., 2011a, Kihm and Trommer, 2014, Wietschel et al., 2014b] and [Al-Alawi and Bradley, 2013] for a recent review on market diffusion models for hybrid electric vehicles and PEVs.

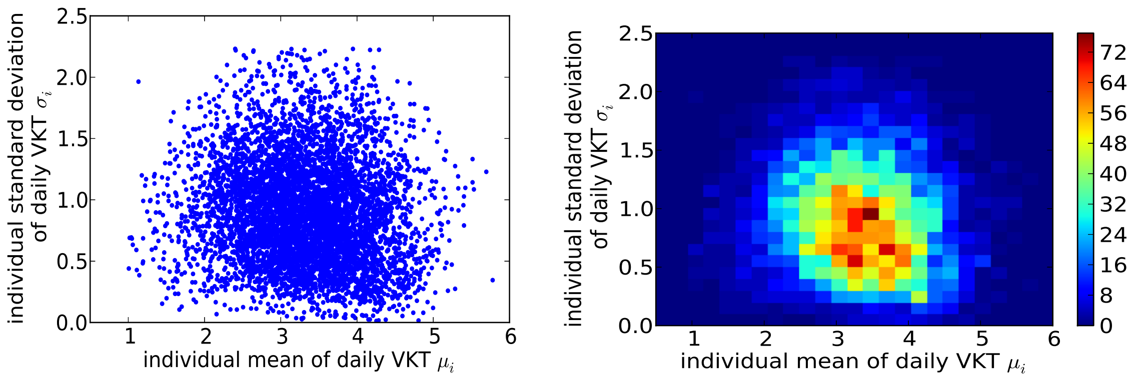

Figure 5.1: Mean and variation of log-normal distribution for private driving profiles. Data from [MOP, 2010]. The color indicates the number of profiles in specific bin.

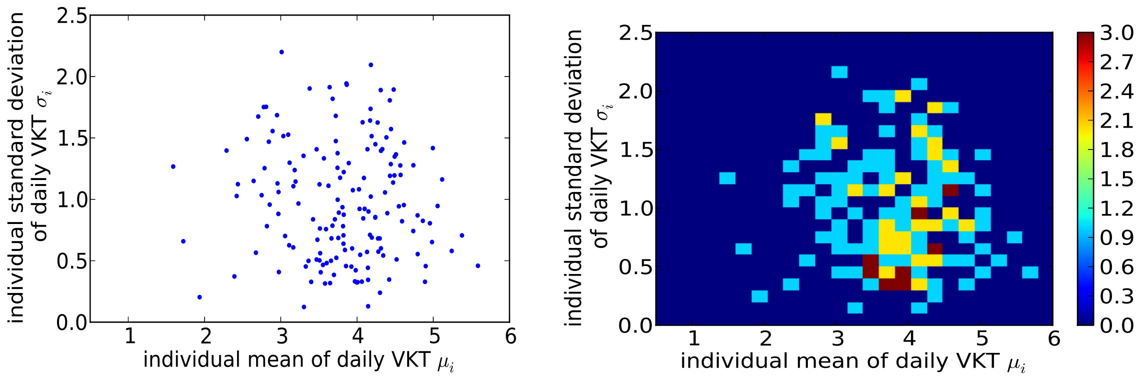

Figure 5.2: Mean and variation of log-normal distribution for company car driving profiles. Data from [MOP, 2010]. The color indicates the number of profiles in specific bin.

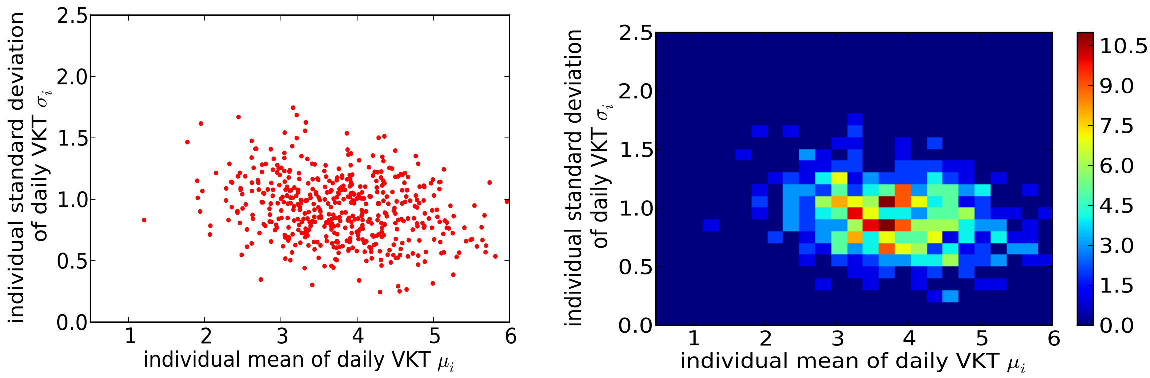

Figure 5.3: Mean and variation of log-normal distribution for commercial fleet driving profiles. Data from [Fraunhofer ISI, 2014]. The color indicates the number of profiles in specific bin.

of individual daily driving have been calculated for these vehicles. Figure 5.1, Figure 5.2 and Figure 5.3 show scatter plots and two-dimensional histograms of the individual scales μ_i and standard deviations σ_i for the three aforementioned data sets with more than one day of observation. The histograms indicate that commercial fleet and company vehicles show higher average daily VKT than private ones. Furthermore, both private and commercial driving behavior show a large variation of daily VKT between vehicles (the μ_i range from 1 to 6) and between the days of one individual vehicle (the σ_i range from 0 to 2.5). Note that several days of observation for each vehicle are required for the calculation of the individual variance of daily VKT.

It is now possible to compare the distances and regularity of daily driving distances between private, commercial fleet and company vehicles. The μ_i and σ_i are calculated for each vehicle from the three data sets. Table 5.2 shows the median, mean and standard deviation of the daily VKT for their vehicle usage. Commercial vehicles (fleet vehicles and company cars) show higher average daily distances since the median and mean of typical daily VKT are larger for commercial vehicles. However, commercial fleet vehicles show smaller variation in daily driving between different days compared to private vehicles and company cars. The median and mean of standard deviation of daily VKT are smaller for commercial fleet vehicles indicating a larger regularity of driving.

Table 5.2: Summary statistics for daily VKT of private and commercial vehicles. Data from [MOP, 2010, Hautzinger et al., 2013, Fraunhofer ISI, 2014]

	mean of daily VKT μ_i			SD of daily VKT σ_i		
vehicle group	fleet[a]	private[b]	company[c]	fleet[a]	private[b]	company[c]
data set	REM2030	MOP	MOP	REM2030	MOP	MOP
median	3.77	3.33	3.83	0.83	0.87	0.93
mean	3.79	3.32	3.81	0.91	0.90	1.00
standard deviation	0.81	0.73	0.72	0.50	0.43	0.49

a: n=498, b: n=6177, c: n=162

Statistical tests are performed to measure the significance of these differences and are presented in Table 5.3. Here, the means and medians of the average μ's and σ's of the three data sets are compared to each other. To compare the means, a t-test for unequal variances and unequal sample sizes for the means with the null hypothesis of equal means is performed. The medians are tested with a Wilcoxon rank-sum test for unequal variances and unequal sample sizes for the means with the null hypothesis of equal medians. The resulting p-values of these tests are shown in Table 5.3 while small values (p <0.05) indicate significant differences.

Table 5.3: Statistical comparison of driving behavior in different user groups. Shown are the p-values for different statistical tests.

parameter	mean of daily VKT μ_i			SD of daily VKT σ_i		
	private vs. fleet	private vs. company	fleet vs. company	private vs. fleet	private vs. company	fleet vs. company
mean[a]	0.000	0.000	0.811	0.829	0.021	0.055
median[b]	0.000	0.000	0.567	0.010	0.040	0.399

a: t-test for unequal means and unequal sample sizes
b: Wilcoxon rank-sum test for unequal medians and unequal sample sizes

Starting with the daily distances (μ_i), one finds highly significant results for the comparison of private and commercial fleet vehicles as well as for private vehicles and company cars, both for the means and medians (p <0.01). Thus, commercial vehicles drive significantly more than private ones. No significant differences can be found for commercial fleet vehicles and company cars. Turning to the right part of the table, the standard deviations (σ_i) between different days are analyzed. Here, significant differences are found between private vehicles and company cars, i.e. private vehicles drive more regularly than company cars. While the medians of private and fleet vehicles are also significantly different, their means are not (fifth column). Lastly, the regularity of driving between fleet vehicles and company cars is marginally significant with $p = 0.055$ while their means do not show a significant difference.

To summarize, the statistical tests confirm a significantly higher driving for fleet vehicles and company cars compared to private vehicles. Further, commercial fleet vehicles have the most regular driving, directly followed by private cars. Company cars have the most irregular driving of the three user groups. For the potential of PEVs in these user groups, fleet vehicles seem to best fit requirements - long distances and high regularity - followed by private vehicles and company cars.

5.1.2 PEV market potentials in different user groups

Having tested the regularity of driving in the different user groups, the profiles are now simulated as PEVs with the first model step (see Section 4.2.1). The simulations are performed for 2020 for the commercial fleet vehicle profiles of REM2030 and for private and company car profiles of MOP. Each profile is simulated individually as BEV and as PHEV while the feasibility as a BEV and the electric driving share as PHEV is found in Table 5.4. Further, the table shows the market share of utility maximizing BEVs and PHEVs with and without limited availability based on the second model step (Section 4.2.2). Market shares of profiles are shown with confidence bands.[75]

Table 5.4: PEV market potential of different user groups.

user group	fleet	private	company
number of profiles	498	6,177	162
share of technically feasible BEVs[a]	48.8%±4.4%	57.2%±1.2%	28.4%±6.9%
average share of feasible trips with BEV	90.9%	96.9%	93.8%
average electric driving share PHEV	64.0%	67.7%	47.0%
BEV utility optimizing[a]	6.5%±2.2%	1.1%±0.3%	0.0%±0.0%
PHEV utility optimizing[a]	13.1%±2.9%	8.2%±0.7%	0.6%±1.2%[b]
BEV utility optimizing & lim. availability[a]	5.4%±2.0%	1.1%±0.3%	0.0%±0.0%
PHEV utility optimizing & lim. availability[a]	11.7%±2.8%	7.9%±0.7%	0.5%±1.1%[b]

a: electric vehicle shares with 95% confidence intervals.
b: lower bound for market potential at 0%.

Starting with the technical replaceability of BEVs, the largest values can be found for private vehicles, followed by fleet vehicles and company cars. The shorter daily distances of private vehicles compared to the other user groups favor BEVs from a technical point of view. However, the higher regularity in driving of fleet vehicles returns a higher amount

[75] The relative frequency of PEVs is the number of PEVs k divided by the number of all vehicles n as: $p = k/n$. The 95% confidence interval is calculated by the standard normal approximation (see e.g. [Fahrmeir et al., 2011]): $\Delta p \approx 1.96 \cdot [p \cdot (1-p)/n]^{1/2}$.

of driving profiles feasible with a BEV compared to company cars. This is also visible in the average share of feasible trips with a BEV, which indicates that some company car profiles may contain some exceptionally long trips that are not feasible for BEVs while the average share of feasible trips is higher than for fleet vehicles. That confirms the necessity to use driving profiles with long observation periods. Results slightly change for average electric driving shares of PHEVs. Here fleet and private vehicles obtain similar average electric driving shares of about 65% while those of company cars are distinctly lower. The reason for this circumstance are again the regularity and distances of the driving profiles. It is important to mention again that the profiles of REM2030 contain three weeks of observation and MOP one week, which make results of the fleet vehicles more reliable than those of the other two groups. The influence of the observation period on technical results was analyzed in [Plötz et al., 2014a].

Inferences change when turning to the results for the utility calculation. First of all, PHEVs tend to receive higher market shares than BEVs in all user groups. This derives from the large batteries used in BEVs which are not affordable for a large number of users, while several PHEVs profit from high electric driving shares (see also Figure 4.9). Further, the effect of the limited availability is already low in 2020, since results do not change largely when it is considered.[76] Moreover, PEVs have the largest market potential within fleet vehicles, followed by private vehicles and company cars.[77] This derives from two reasons: First, the driving distances of most private vehicles are too low to profit from the lower operating costs of PEVs compared to their investment. With the higher mileage of fleet vehicles the share of vehicles with PEVs as utility maximizing solution rises. They also profit from their large technical potentials due to a more regular driving compared to company cars. Second, differences in the TCO calculation within the utility values are a reason for the different market potentials which is discussed in the following.

Utility differences of plug-in electric and conventional vehicles[78]

The utilities of each propulsion technology for the individual user with his driving behavior forms an important part of his buying decision. To demonstrate the wide range of utilities for different users and the importance of the individual user behavior, the utility gaps (differences between PEVs and CVs with highest utility) between the different drive trains are analyzed using results of the second model step (see Section 4.2.2). In Figure 5.4, the utility-gaps are plotted against their share of users with this or a smaller utility gap. While the left panel shows the utility gaps for medium sized vehicles differentiated by user groups, the right panel contains private users and distinguishes vehicle sizes.

To understand this display, it should be noted that there are many individual utility gaps (differences in the utility between the drive systems) due to the large number of driving profiles, some of which have very different driving patterns. With approximately 7,000 driving profiles and four drive trains, there would be about 42,000 individual utility differences to compare. However, most important for the decision in favor of or against a PEV is the utility difference between the utility maximizing conventional vehicle and

[76]See Section 5.2.2 for a further analysis of the influence of the limited availability.

[77]Note that these market shares are calculated for new vehicle registrations and are, because of the secondhand car market, different to shares in the vehicle stock which is often shown in studies on PEV market diffusion. The difference will be discussed in Section 5.2.1.

[78]This section is based on [Gnann et al., 2015b]

the utility maximizing PEV. In the following, utility gap or utility difference will denote the difference in utility between the utility maximizing PEV and the utility maximizing conventional vehicle (i.e. $\Delta \mathrm{u} \equiv \min_{p \in \mathrm{PEV}} \mathrm{u}_p - \min_{p \in \mathrm{CV}} \mathrm{u}_p$ where PEV = {BEV, PHEV} and CV = $\{\text{gasoline}, \text{diesel}\}$).[79] Figure 5.4 shows these utility gaps in ascending order on the abscissa with the share of users (respectively driving profiles) on the ordinate which have this or a smaller utility gap. The graph corresponds statistically to a relative cumulative frequency distribution or empirical cumulative distribution function [Fahrmeir et al., 2011]. The cumulative distribution function of utility gaps in Figure 5.4 shows the broad range of individual utility gaps in a statistically robust representation. Furthermore, utility-based market shares - and thus the potential impact of subsidies - can be read off directly: The market share is the share of users with utility gap smaller than zero.

Figure 5.4 demonstrates that PEVs are utility optimal for some users already in 2020 ($\Delta u < 0$) and display a rising tendency to be so in the future (increasing share of vehicles with $\Delta u < 0$ between 2020 and 2030). In this case, the annual mileage is decisive. At low mileages, gasoline cars continue to dominate because PEVs are not able to compensate for their higher purchasing costs via their lower variable costs per kilometer. At very high annual mileages, in contrast, diesel engines are the utility maximizing option, because PHEV have to use their combustion engines too often and battery electric vehicles are unfavorable because of their limited range. The electric driving share together with the annual mileage is decisive for the difference in utility of each user. Sufficient annual mileage alone is not enough.

When comparing the graphs of the three user groups (left panel of Figure 5.4), it is noticeable that the curve of private users has the steepest slope and that of commercial fleet vehicles has the flattest slope. There are several reasons for this: First, the effect of VAT and depreciation has to be mentioned. Because VAT has to be paid on fuels by private users, the consumption savings between PEVs and CVs per kilometer driven are higher for private than for commercial users. In addition, the depreciation options for commercial drivers have the effect that utility gaps shrink further. Second, commercial users tend to have more uniform driving profiles and undertake longer trips more rarely (cf. Section 5.1.1). As a result, the electric driving shares within this group tend to be more similar compared to private users, and especially when compared to company car drivers (see also [Plötz et al., 2014a, sec. 3.1]). Yet, the tax for company cars raises their utility difference curve when compared to fleet vehicles. Although there is a special allowance in Germany for PEVs to reduce this company car tax because of high battery costs, it still increases the cost for PEVs compared to conventional vehicles significantly. Also, a WTPM is not incorporated for company cars as there is no publicly available data for it. A comparison of the utility gaps in 2020 with those in 2030 reveals that a low potential for PEVs exists under the assumptions made in 2020, but it increases over time.

Turning to the right panel of Figure 5.4, it is apparent that large passenger cars have the highest possibility to increase the share of private users with PEVs as utility-maximizing option.[80] There are significant market shares for large vehicles and LCVs (about 40%), while small and medium vehicles' market shares are around 5%. Large vehicles are able to economize faster because of the large advantages in operating cost of PEVs. Decreasing the utility for the utility maximizing PEVs by 1,000 EUR, market

[79] See Section 4.2.2 for the calculation of utility values.

[80] Results for commercial fleet vehicles and company cars are not shown with the same display, as their qualitative results are similar to those of private vehicles.

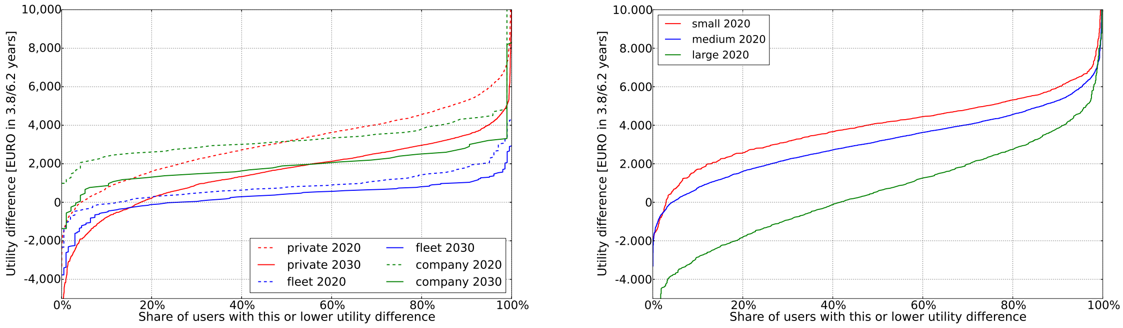

Figure 5.4: Differences between individual utilities of best plug-in electric and conventional vehicle including the cost for vehicle and charging infrastructure as well as the WTPM in the medium scenario. The difference is shown on the abscissa in EUR_{2014} while the share of driving profiles is given on the ordinate. *Left panel:* Results for medium sized cars. Graphs are shown as cumulative distribution functions with dashed lines for values of 2020 and and solid lines for 2030. Private vehicles in red, fleet vehicles in blue and company cars green. *Right panel:* Results for different sized private vehicles. Graphs are shown as cumulative distribution functions for values 2020. Small cars in red, medium sized cars in blue and large cars in green.

shares of small, medium and large vehicles would increase by 5%, 10% and 20%. Such a change might, e.g., result from an increase of the gasoline price by 15% if the gasoline vehicle was the cheapest conventional car.[81]

The analyses of the driving profiles and utility gaps show that several drivers could achieve comparatively high electrical driving shares and have higher utilities for a PEV than compared to the respective cheapest conventional vehicle. Many of these users can be expected to buy a PEV.

5.1.3 Discussion

The presented results are subject to several assumptions that have to be discussed: The approach to determine the PEV replacement potential might be questioned as well as assumptions for driving data and technical and economical parameters that are used in the analysis. Furthermore, results are discussed in light of other studies on this topic.

In this analysis, a comparison of different drive trains is performed for every single driving profile to determine the utility-optimizing vehicle option for each profile. The potential market share of PEVs is calculated by the share of PEVs within their user group. Calculating market shares with total cost of ownership is a common approach [Thiel et al., 2010, McKinsey, 2011, Pfahl et al., 2013], although the buying decision for a single vehicle is often not solely based on cost [Globisch and Dütschke, 2013, Dataforce, 2011, Sierzchula, 2014].[82] Some studies indicate a willingness to pay more for alternative fuel vehicles which would increase PEV market shares [Eppstein et al., 2011, Laroche et al., 2001, Mock, 2010] and is not easy to quantify. Other factors that influence the commercial buying

[81] If the gasoline consumption for an average sized conventional car is 0.06 l/km, its annual mileage is 20,000 km and the initial gasoline price is 1.34 EUR/l, an increase of 15% would be calculated as: $0.15 \cdot 1.34$ EUR/l $\cdot$ 0.06 l/km $\cdot$ 20,000 km $\cdot$ 3.8 a $\approx$ 1000 EUR.

[82] This type of analysis also reflects the growing amount of leasing vehicles with leasing rates reflecting the vehicle TCO.

decision [Berg, 1985] or specific use cases (like overnight inner city logistics with reduced noise or car-sharing) were not considered here. Since in company car fleets, trips could be rescheduled, PEVs could reach higher market shares when trips within the electric range were allocated to PEVs and long-distance trips to conventional vehicles (see [Haendel et al., 2015]).

The analysis of commercial fleet vehicles is based on driving profiles collected with GPS-trackers for three weeks [Fraunhofer ISI, 2014]. Although the sample is limited, it especially covers the large commercial branches in terms of registrations in Germany (see Section 3.3). The observation period of three weeks is longer than in previous studies [IVS et al., 2002, WVI et al., 2010] and decisive for realistic estimates of the technical feasibility of BEVs [Gnann et al., 2012a], the electric driving shares of PHEVs [Plötz et al., 2014a] and the market potential [Gnann et al., 2012c] since driving varies largely between drivers and days (see [Neubauer et al., 2012] and Chapter 3). Since the REM2030 data was collected with GPS-trackers, the availability of a charging point after each trip is unknown. In this analysis, vehicles are assumed to park at the company site (where charging is possible) when their bee distance is not more than 500 meters from the main company site. A distinction of different distances depending on the company size (larger distances for companies with more employees) showed no considerable changes in results. For private and and company car profiles, a data set with seven days of observation allows a more detailed analysis of market potentials than with one day. Limited observation periods may not include some rare long-distance trips, e.g. for long travels, that may not be possible for BEVs. The necessity for such trips may occur less often for fleet vehicles than for private or company cars, yet the transferability of the BEV feasibility in one or three weeks to one year is limited. A variation of the calculation for BEVs with an estimated number of long-distance trips will be discussed in the following Section 5.2. Also, the data sets with a limited number of observations influence results. For this reason, the market diffusion of PEVs in the following Section 5.2 is shown with confidence bands due to the limited sample size.

Furthermore, the results are based on assumptions for technical and economical parameters. The main assumptions for parameters were discussed in Section 4.3 and parameters are based on a large study that discussed several further parameter options [Plötz et al., 2013]. A further analysis of electric consumptions in [Gnann et al., 2015a, sec. 5.3] allowed to determine the impact of changes to these parameters. This analysis of electric consumptions showed that the average values chosen for the market potential analysis reflect the peaks of electric consumption distributions and are thus justifiable. The battery degradation resulting from an intense use is reflected in an auxiliary analysis which shows that all trips performed by PEVs are covered [Plötz et al., 2013, sec. 7.8]. Also, the choice of battery sizes has an impact on results. The technical feasibility of BEVs as well as the electric driving share for PHEVs rises with the battery capacity (see e.g. [Kley, 2011, Gnann et al., 2012a]). Yet, market potentials might decrease when raising battery sizes above an affordable limit (see [Kley, 2011]). Also the battery sizes for PHEVs and BEVs influence each others market potentials [Zischler, 2011]. An analysis of commercial fleet vehicles with similar assumptions for technical and economical parameters, yet smaller batteries, showed lower PEV market shares [Gnann et al., 2015a].

5.1.4 Summary

In this section, results for the vehicle usage in different user groups and the market potential of PEVs within these groups were presented for Germany in 2020. A PEV simulation of individual vehicle profile was performed to determine the technical potential for PEVs followed by an individual calculation of the utilities of different drive trains. From the evidence presented in this section the following can be summed up:

- Vehicle driving profiles with long observation periods permit statistical analyses of driving distances and regularity. A comparison of the means and variations of individually calculated log-normal distributions show that, on average, commercial fleet vehicles and company cars drive significantly more than private vehicles. Further, fleet vehicles tend to drive more regularly than private vehicles, while both groups drive significantly more regularly than company cars. This confirms the necessity to distinguish between private and commercial driving profiles.

- The driving of private vehicles is technically favorable for PEVs, followed by fleet vehicles and company cars which tend to drive too irregular. However, PEV market shares based on the utility maximizing drive trains are highest for commercial fleet vehicles, followed by private and company cars. The higher amount of VKT of commercial fleet vehicles makes them more favorable for PEVs compared to private vehicles, since they are able to profit from the lower operating costs of PEVs. Company cars suffer from the high mileage paired with a more irregular driving.

- Apart from driving, the differences in market shares stem from the exemption of VAT and depreciation allowances for commercial vehicles (fleet vehicles and company cars) which decrease the differences in utilities. Company cars, however, cannot profit of these fiscal instruments since the company car tax that has to be paid by the vehicle user. The reduction of the gross list price by a certain amount connected with the battery price is not sufficient to make them affordable to users. The missing WTPM for PEVs as company cars further decreases their market potentials.

5.2 Market diffusion of plug-in electric vehicles[83]

The first three parts of the model ALADIN form a market diffusion model of PEVs without the co-diffusion of public charging points. After analyzing the market potential for PEVs as commercial passenger cars, understanding their diffusion and timely evolution is the goal of the following section. A special focus is put on factors that influence the PEV diffusion apart from charging infrastructure to set their influence into context. The model is extended by the stock model for PEVs (see Table 5.1) and the obstructing and favoring factors are included: the cost for individual charging points, the limited availability as obstructing as well as the WTPM for PEVs as favoring factor. In this section the influence of charging at home and at work (for private users) and at commercial sites (for fleet users) on the market diffusion of PEVs are analyzed.

This section is structured as follows: Results for PEV market diffusion are presented in Section 5.2.1. The sensitivity of results on changes in monetary and non-monetary influence factors is presented in Section 5.2.2 followed by a comparison of ways to increase the range of PEVs (Section 5.2.3). A discussion (5.2.4) and summary (5.2.5) round up this section.

Plug-in electric vehicle market diffusion models

The diffusion of new technologies and PEVs in particular has received considerable attention in the literature (see [Al-Alawi and Bradley, 2013] for a recent review of PEV market diffusion models). Since the literature review in Chapter 2 did not comprise the PEV market diffusion models, they are introduced briefly in the following. Results will be compared to those of other market diffusion models of PEVs for Germany in the discussion section.

A general classification of market diffusion models was given by Geroski [Geroski, 2000]. He describes two groups of models for market diffusion of innovations: population and probit models. Since probit models are one classification of consumer choice models (see e.g. [Train, 2009]), it is referred to consumer choice models for the second group. The latter also includes the frequently used agent-based models. These two model classes are discussed briefly and some of the existing market diffusion models for PEVs are classified accordingly in order to categorize the first three parts of ALADIN.[84]

Population models describe users or adopters not as individuals, but as groups. Population models assume for example that the rate of adoption is proportional to the number of adopters and the remaining population that has not adopted a technology yet. This leads to the well-known logistic differential equation and can be interpreted via the spread of information about a technology [Geroski, 2000]. Population models offer a simple structure and interpretation. They are usually applied by calibrating the market diffusion curve to existing market data or by assuming hypothetical growth rates. This procedure is rather sensitive in early market phases when little data is available. Furthermore, the heterogeneity of the individual buying decisions and preferences of users, for example reflected in the willingness to pay more for new technologies of some users as well as the individual economics of the driving behavior, cannot be incorporated explicitly into these models.

[83] Several results in this section have been published in [Gnann et al., 2015b].

[84] The classification of Geroski is appropriate for the diffusion of technologies, while the one used in Section 2.2.2 fits better if (energy) systems are analyzed.

Population models for PEV market diffusion or market diffusion of other alternative fuel vehicles can be found in [Duleep et al., 2011, Richter and Lindenberger, 2010, Keles et al., 2008, Köhler et al., 2010, Lamberson, 2008, Meyer and Winebrake, 2009, Nemry and Brons, 2010, Shepherd et al., 2012, Wansart and Schnieder, 2010, McManus and Senter Jr., 2009], which range from simple mathematical equations to complex system dynamics models.

The second group of market diffusion models, consumer choice and agent-based models, studies adopters individually. These models are often applied when the purchase decision is more complex or the technologies to be adopted are rather expensive. For example, a simple probit model for PEV adoption would calculate the average ownership cost difference between conventional and plug-in electric vehicles and estimate a PEV market share based on this difference. As fuel and battery prices change over time, these cost differences change and with them the estimated PEV market share. Thus, consumer choice models develop market diffusion bottom-up and acknowledge that individual users can be very different. This is particularly important to identify niche markets in early phases of market development. However, these models face the problem that consumer statements about their preferences for PEVs are often inaccurate. Given the current market shares of PEVs, the vast majority of users has never experienced a PEV and can hardly judge its utility. Accordingly, the majority of studies uses stated preference data to study AFV diffusion (see e.g. [Bočkarjova et al., 2014, Brownstone et al., 2000, Batley et al., 2004, Potoglou and Kanaroglou, 2007, Glerum et al., 2013]).

Consumer choice and agent-based models were used to model PEV market diffusion in [Eppstein et al., 2011, Hacker et al., 2011b, Mock et al., 2009, Propfe et al., 2012a, Zhang et al., 2011, Shafiei et al., 2012, Yabe et al., 2012, Sullivan et al., 2009, Elgowainy et al., 2012, Brown, 2013, Higgins et al., 2012, Kihm and Trommer, 2014] where modeling approaches range from determining user shares by stated preference experiments to agent-based models. Some of these models are based on driving behavior of conventional vehicles [Hacker et al., 2011b, Mock et al., 2009, Brown, 2013, Kihm and Trommer, 2014]. This would in principle allow one to analyze user behavior in more detail. However, the latter models use driving profiles of only one day which can cause severe inaccuracies on the individual level, as a single day might not represent the individual's typical driving (see [Neubauer et al., 2012, Gnann et al., 2012a, Plötz et al., 2013] and Section 3.1).

In summary, agent-based models offer the possibility to include several aspects of great relevance for the market diffusion of PEVs in the current market development phase: individual purchase preferences, individual driving behavior (to account for the limited range of PEVs and the VKT related usage costs), the need for frequent recharging and infrastructure as well as the limited choice of PEV brands and models. In ALADIN, these these factors are explicitly taken into account in an agent-based model with different user groups and their individual decision making processes. It is possible to determine and quantify the influence of external conditions as well as (monetary) policy options. Especially the user-specific decision making is a particular strength of the model that permits to identify niche markets in early market phases. Results will be compared to other ABMs from Germany, i. e. [Mock et al., 2009, Hacker et al., 2011b, Propfe et al., 2012a, Kihm and Trommer, 2014], in Section 5.2.4.

5.2.1 Market diffusion of plug-in electric vehicles until 2030

Three scenarios for framework conditions for market diffusion were defined in Section 4.3. The results for PEV market diffusion in the three scenarios can be found in Figure 5.5. It shows the total number of PEVs in German stock on the ordinate over the years from 2015 until 2030 on the abscissa. Results are shown for the contra-EV scenario in red, the medium scenario in blue and the pro-EV scenario in green with 10% to 90%-confidence bands due to limited sample size (cf. [Plötz et al., 2014a] for details).[85] Within the 10%-confidence band 1.5 to 1.9 million PEVs for the contra-EV scenario (≈4% of the German passenger car stock in 2030), 4.5 to 5 million PEVs for the medium scenario (≈11%) and 9.5 to 10.5 million PEVs for the pro-EV scenario (≈23–24%) are found.[86] These broad ranges arise from limited data samples that are considered as well as error propagation over the years. The large differences between the three scenarios also show the influence of the input parameters. Even small changes within the main drivers may change results significantly. In the medium scenario, PEV penetration rates of more than 10% of car sales are found after 2022, which derives from the increased availability of PEVs from different brands as well as decreasing vehicle and energy prices. The compound annual growth rates of all three scenarios[87] are still within the range of other AFVs or new technologies [Wietschel et al., 2014a, p.13,14]. The increasing PEV sales can be observed in Figure 5.6.

Figure 5.6 shows the registrations in the medium scenario for all drive trains on the left panel and for PEVs differentiated by user groups on the right panel. Studying the registrations distinguished by drive train, a high share of gasoline vehicles (about 60% of registrations) can be observed which is slightly higher than the current German average (about 50%). This results from the assumed fuel price ratios and costs for conventional vehicles which require about 20,000 km for medium sized diesel vehicles to economize against gasoline cars in 2015. PEV registrations are dominated by PHEVs in the beginning, while BEVs gain almost equal market shares until 2030. The lower market shares

[85] The statistical uncertainty due to finite sample size is statistically expressed as confidence bands or confidence intervals [Fahrmeir et al., 2011]. More precisely, one estimates the sales share $p_{l\tau}$ of vehicle type l (e.g. propulsion technology or vehicle size or a combination of such distinctive characteristics) from the number of driving profiles $k_{l\tau}$ that fulfill the required condition (e.g. that should be PEVs) and the number of all driving profiles in that group K_l as $\hat{p}_{l\tau} = k_{l\tau}/K_l$. Here, the hat ˆ indicates an estimate for the "real" market share $p_{l\tau}$. Given a confidence level $0 < \alpha < 1$, the confidence band "contains the real value of $p_{l\tau}$ in $(1-\alpha)\cdot 100\%$ of all cases in which confidence intervals are estimated" [Fahrmeir et al., 2011]. For a given confidence level α an upper value $p^+_{l\tau}$ and a lower value $p^-_{l\tau}$ are calculated, such that $\hat{p}_{l\tau} \in [p^-_{l\tau}, p^+_{l\tau}]$ in $(1-\alpha)\cdot 100\%$ of the cases. Using a conservative approach, often referred to as "exact", the upper and lower confidence interval boundaries are given by [Brown et al., 2001] $p^-_{l\tau} = \mathrm{Beta}^{-1}(\alpha/2, k_{l\tau}, K_l - k_{l\tau} + 1)$ and $p^+_{l\tau} = \mathrm{Beta}^{-1}(1-\alpha/2, k_{l\tau}+1, K_l - k_{l\tau})$. Here, $\mathrm{Beta}^{-1}(x; a, b)$ denotes the inverse of the cumulative Beta distribution $\mathrm{Beta}(x; a, b) = (B(a,b))^{-1} \int_0^x t^{a-1}(1-t)^{b-1}\mathrm{d}t$ with the Beta function $B(x,y) = \int_0^1 t^{x-1}(1-t)^{y-1}\mathrm{d}t$ for normalization. Additionally, the statistical uncertainty can easily be propagated to derived quantities. See [Plötz et al., 2014a, sec. 2.3.3] for details.

[86] Again, it is important to mention that the scenario results do not represent exact forecasts of the future development, but allow a model-based assessment of the main influence factors which are combined in scenarios.

[87] The compound annual growth rate (CAGR) is calculated as $\mathrm{CAGR}(t_0, t_1) = (n_1/n_0)^{1/(t_1-t_0)} - 1$ with t_0 being the initial year and and t_1 the year of observation. n_0 and n_1 are the corresponding values to observe, here the vehicle registrations. For the contra-EV scenario a CAGR(2030,2015)=14% is found, 19% for the medium scenario and 20% in the pro-EV scenario. However, the CAGR depends on the initial year and the years of observation (see [Wietschel et al., 2014a]).

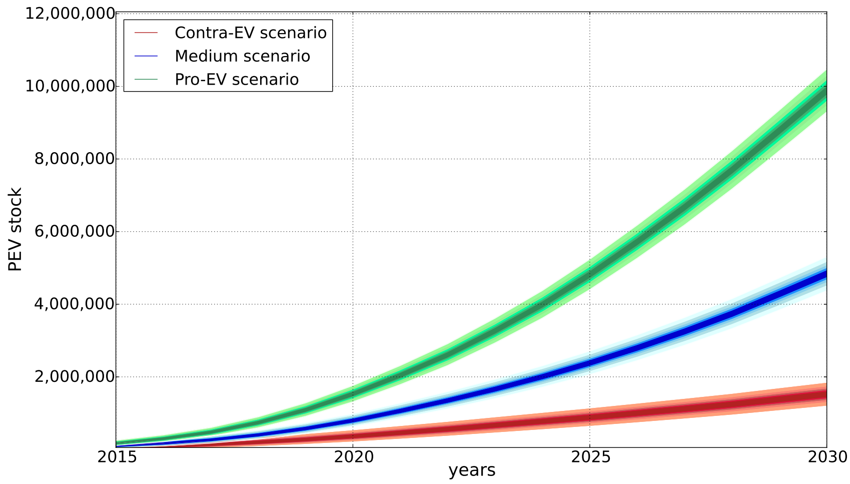

Figure 5.5: Results for the three PEV market diffusion scenarios for Germany. Shown are the years on the abscissa and the total PEV stock on the ordinate. Results are shown with 10%, 30%, 50%, 70% and 90% confidence bands (cf. [Plötz et al., 2014a]), contra-EV scenario in red, medium scenario in blue and pro-EV scenario in green.

of BEVs stem from the high investments for large batteries which cannot be economized for a large group of vehicles until the prices for batteries are low enough.

Turning to the right panel of Figure 5.6 a domination of fleet vehicles in PEV registrations can be observed until 2020 (about two thirds for fleet vehicles and one third for private cars). Thereafter, the share of private vehicles increases until 2030 (about 40%) and company cars start to enter the market in 2023 increasing up to 10 % in 2030. The dominating position of fleet vehicles in PEV registrations results from the favoring conditions for PEVs: a PEV favoring driving behavior (Section 5.1.1), reimbursement of VAT and depreciation allowances (see Section 5.1.2). In 2030 almost every fourth registered car is a PEV in the medium scenario. These results are similar for the other scenarios. Table 5.5 sums up the results of PEV stocks in 2030. Results are distinguished by scenario, user group, vehicle size and PEV type.

Table 5.5: PEV stock in 2030 differentiated by scenario, user group, vehicle size and PEV type.

PEV STOCK 2030	contra-EV	medium	pro-EV
private	1,080,000	3,388,000	7,193,000
fleet	387,000	1,177,000	2,151,000
company	52,000	273,000	540,000
small	175,000	921,000	2,110,000
medium	251,000	1,807,000	4,565,000
large	714,000	1,327,000	1,937,000
LCV	379,000	784,000	1,272,000
PHEV	976,000	2,946,000	5,824,000
BEV	543,000	1,893,000	4,060,000
TOTAL	1,519,000	4,839,000	9,884,000

When taking a look at Table 5.5, one may question the distribution of user groups in stock and those of registrations in Figure 5.6 which clearly differ. As mentioned in

Section 4.2.3, it is assumed that all PEVs diffuse into the second-hand car market after their first holding period. These holding periods are 3.8 years for commercial and 6.2 years for private vehicles after which they diffuse into private ownership until their scrapping. For this reason, the majority of PEVs in 2030, about 70%, are privately owned, a small share (3–5%) are company cars and about one quarter of the PEV stock are fleet vehicles, independent of the scenario. PEV potentials for company cars may be lower since no WTPM is considered for these vehicles and the additional hurdle of the company car tax has to be overcome. Yet, the regularity of driving of company cars is similar to private vehicles paired with higher distances travelled which does not favor the adoption of PEVs.

Concerning car size, the distribution in the three scenarios is different. Large PEVs are less affected by market conditions and double or triple their stock with more favoring conditions (from contra-EV to pro-EV scenario). All other vehicle sizes show large variations to parameter changes. The fastest growing group of private PEVs between contra-EV and pro-EV scenario are medium sized vehicles. At a first glance, these high numbers for large vehicles seem counter-intuitive, yet longer distances are driven by large cars. With comparable investment differences and varying differences in variable costs, higher mileages allow large vehicles to economize easier. For example, the investment for a large commercial PHEV in 2020 is $LP_{large,PHEV} = 38,017$ EUR[88] while a large diesel vehicle's investment is $LP_{large,diesel} = 33,387$ EUR and the difference 4,430 EUR. For small commercial vehicles the investment is $LP_{small,PHEV} = 16,822$ EUR[89] for PHEVs and $LP_{small,diesel} = 12,888$ EUR for diesel vehicles resulting in a difference of 3,934 EUR. Thus the differences of vehicle investments are very close and additional investments for PHEVs are slightly higher for large vehicles. Assuming an electric driving share of 60% for both size classes, fuel cost differences would amount to 0.013 EUR/km for small vehicles and to 0.022 EUR/km for large vehicles.[90] Thus, at about 200,000 km a large PHEV would amortize against a diesel vehicle in this example and a small PHEV at about 300,000 km. Not only that the needed mileage is lower for large vehicles, but also the average mileage performed by large vehicles is higher (cf. Table 3.5 and 3.7). Although this is only an example and in the model calculations more options have to be taken into account (e.g. BEVs and gasoline vehicles as other vehicle options, different resale prices, costs for operations and maintenance or vehicle taxes) the example shows that both conditions (necessary mileage to economize and driven mileage) allow larger PEVs to gain higher market shares than smaller ones.

As mentioned already for PEV registrations the more promising PEV group is PHEVs until 2020, while BEV shares increase until 2030. In the stock BEVs account for 33% (contra-EV) to 40% (pro-EV scenario). This stems from the large batteries for medium and large for BEVs which need very high mileages to economize. PHEVs instead can gain market shares if their electric driving shares are sufficient and their mileages are high enough which is the case for an increasing number of vehicles until 2030.

Lastly, one may take a look at the number of individual charging points which are

[88] $LP_{large,PHEV} = 34,351 \text{ EUR} + 13 \text{ kWh} \cdot 282 \text{ EUR/kWh} = 38,017 \text{ EUR}$

[89] $LP_{small,PHEV} = 14,566 \text{ EUR} + 8 \text{ kWh} \cdot 282 \text{ EUR/kWh} = 16,822 \text{ EUR}$

[90] The fuel cost for PHEVs would consist of a share for electric and one for non-electric driving, i. e. $cons_{small,PHEV} = 0.6 \cdot 0.144 \text{ kWh/km} \cdot 0.185 \text{ EUR/kWh} + 0.4 \cdot 0.051 \text{ l/km} \cdot 1.262 \text{ EUR/l} = 0.042 \text{ EUR/km}$ for small PHEVs and $cons_{large,PHEV} = 0.6 \cdot 0.193 \text{ kWh/km} \cdot 0.185 \text{ EUR/kWh} + 0.4 \cdot 0.078 \text{ l/km} \cdot 1.262 \text{ EUR/l} = 0.061 \text{ EUR/km}$ for large PHEVs in the medium scenario. The fuel costs for diesel vehicles would be $cons_{small,diesel} = 0.043 \text{ l/km} \cdot 1.262 \text{ EUR/l} = 0.053 \text{ EUR/km}$ for small and $cons_{large,diesel} = 0.066 \text{ l/km} \cdot 1.262 \text{ EUR/l} = 0.083 \text{ EUR/km}$ for large diesel vehicles.

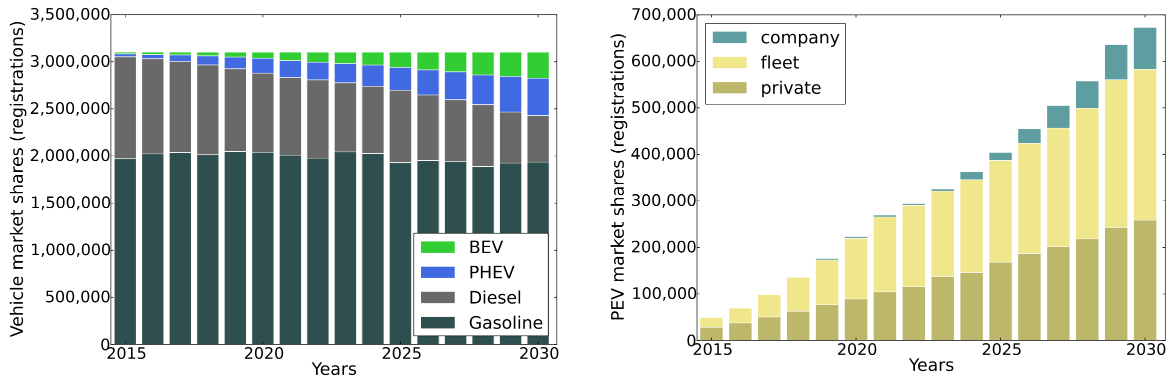

Figure 5.6: Simulation results for vehicle registrations in 2015–2030 in the medium scenario. *Left panel:* All vehicles distinguished by propulsion technologies. BEV in green, PHEV in blue, diesel vehicles in light grey and gasoline vehicles in dark grey. *Right panel:* PEVs distinguished by user groups. Company cars in turquoise, fleet vehicles in yellow and private vehicles in khaki.

necessary for these market penetrations. Although this seems simple, as every vehicle gets assigned one charging point, the second-hand car market and the decommissioning of vehicles complicate the approach. A charging point is sold to every vehicle that is bought in the first car market which in the beginning is dominated by fleet users. Yet, more vehicles of the vehicle stock are private cars after several years. Also, it remains unclear if the owner of a PEV, that is replaced, needs to buy another charging point. Hence, there are three different options to determine the charging point stock of individual charging points (see also Figure 5.7 for the medium scenario): (1) Every vehicle sold needs one charging point. This would not consider the charging points necessary for private users in the second car market. (2) New charging points are needed for every PEV at the first registration and in the second-hand car market. For the second-hand car market the ratio of simple wallboxes and expensive domestic charging points is assumed equal to the share of new private PEV registrations. (3) Every charging point that was installed once is re-used while calculation of the ratio of wallboxes and more expensive charging points is similar to option 2. While option 1 can be ruled out completely, since it does not consider the distribution of vehicles in stock, the real number of charging points must be between options 2 and 3. However, as framework conditions ameliorate for PEVs in all scenarios a profile for which a PEV has once been utility-maximizing will not switch back to a conventional vehicle in a later period. A user that once bought a PEV will always be replace his vehicle by a PEV, hence option 3 seems to be most appropriate for the charging point calculation. One large advantage of this approach is that total charging point numbers of private (incl. company cars) and fleet vehicles are equal to their vehicle stock (cf. right bar in Figure 5.7 and PEV stock in the medium scenario in Table 5.5). Thus, the charging point shares are equal to the number of PEVs in stock in the contra-EV and pro-EV scenario. The share of private users that are in the need of a more expensive charging point, as they do not own a garage, is 6% of all charging points in the contra-EV scenario, 8% in the medium scenario and 10% in the pro-EV scenario in 2030.

In summary, the main findings of the PEV market diffusion are: (1) PEV market diffusion is largely influenced by framework conditions. (2) A large number of private and fleet driving profiles for which PEVs are, according to the model, a utility maximizing

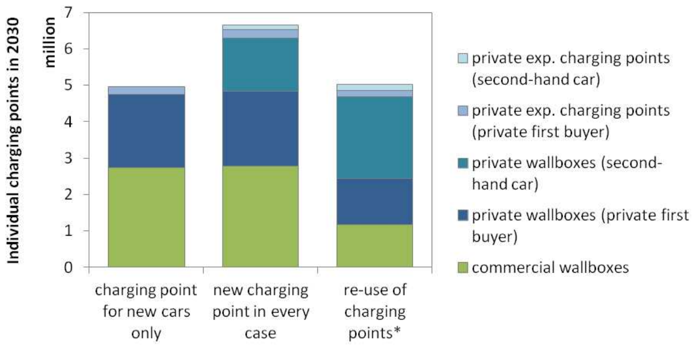

Figure 5.7: Different inventory calculations of individual charging point stock for the medium scenario in 2030. The first bar shows the stock if only charging points of first vehicle buyers are considered, the second if also the second-hand car buyers and their charging points are reflected. In the third bar a re-use of charging points is considered. *Approach considered in this thesis.

solution. This is resulting in high PEV market shares (5% of new vehicle registrations in the medium scenario in 2020, 20% in 2030). (3) PEV registrations are dominated by fleet vehicles until 2020 which remain important in registrations until 2030, while the PEV stock is dominated by private users. (4) Although the availability of models in the vehicle market is especially limited for large PEVs, the highest market potential lies within this vehicle class as it has the highest possibility to economize. (5) High shares of PHEVs compared to BEVs are found. This results from some exceptional long trips that users might not fulfill with BEVs or the lower investments of PHEVs which is easier to economize.

5.2.2 Sensitivity analyses

The influence of individual factors is important for a deeper understanding but obscured in scenarios in which several parameters change simultaneously. Thus, the individual influence of monetary factors (retrieved in 4.3) and non-monetary factors (described in sections 4.2 and 4.3) are analyzed. In this section, all analyses refer to the medium scenario for framework conditions and only home charging is considered.

Influence of monetary factors

In Section 4.3, the cost composition of utility values for different vehicles was shown for an example and the most important factors were aggregated to scenarios (cf. Figure 4.7). Since the capital costs for the vehicles vary largely between propulsion technologies, the influence of battery prices and interest rates are chosen for variation. Further, electricity and fuel prices are varied as variable cost is different between drive trains. The influence of non-monetary factors is analyzed thereafter.

Figure 5.8 shows the influence of single parameter changes in relation to the total PEV stock in 2020 (left panel) and 2030 (right panel). On the ordinate a parameter change from 75% of the original value up to 125% is shown, while the abscissa shows the resulting total PEV stock in 2020 (2030). Changes for electricity prices are shown in dashed green, fuel prices in solid red, battery prices in dash-dotted blue and interest rates in dotted light blue. In the sensitivity analysis, the value for 2015 was fixed and

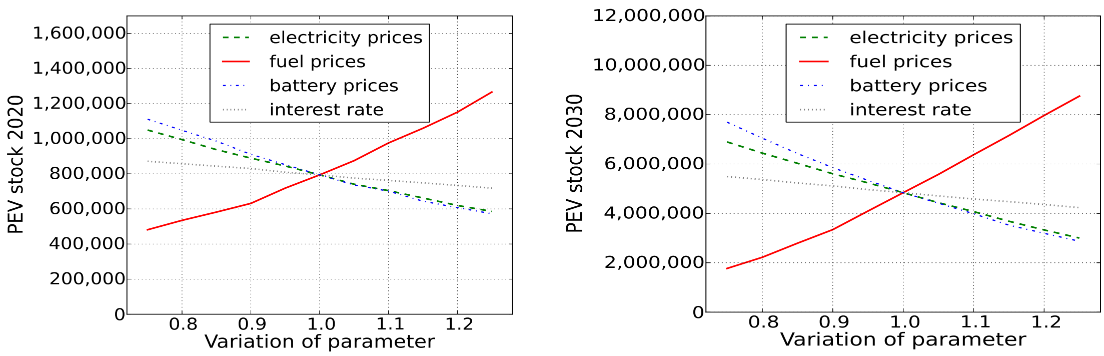

Figure 5.8: Sensitivities to parameter variation. Displayed is the influence of a variation of one single parameter on the total PEV stock. The variation of parameters is shown as factor of assumed value for every single parameter on the ordinate and the total PEV stock on the abscissa. Electricity prices in green dashes, fuel prices in solid red, battery prices with blue dash-dots and interest rates in light blue dots. *Left panel:* Variations until 2020. *Right panel:* Variations until 2030.

values for 2020 (2030) were changed by the percentage shown. Values between 2015 and the last year were adjusted accordingly. Further, in the sensitivity for electricity prices the private *and* commercial electricity prices were changed, the diesel *and* gasoline price in the fuel price sensitivity and the interest rates for private *and* commercial users in the interest rate sensitivity.

Some clear and expected results are observable in both panels of Figure 5.8. Higher numbers of PEVs can be found with increasing fuel prices and lower PEV numbers when fuel prices decrease. For all other parameter changes, lower values lead to higher market shares, e.g. there are more PEVs in stock when batteries are cheaper or the electricity price is lower. As investments for PEVs are higher than for conventional vehicles, clearly a decreasing interest rate is favorable. More interesting is the magnitude of changes caused by parameter variation: Fuel prices have the highest influence in positive and negative direction both in 2020 and 2030. The small knee in the red curves at a variation of 0.9 might derive from a switch of conventional fuel vehicles (from gasoline to diesel) or PEVs (from BEV to PHEV) as corresponding benchmarks. The second most important input factors are the battery price and electricity prices. The lowest influence is found for changes in the interest rates. These parameters are externally defined and can only slightly be influenced by PEV sales (only the battery price might decrease with economies of scale). Further, the effect of changes is naturally stronger in 2030 than in 2020. A 25% decrease of battery prices leads to a PEV stock increase of 40% in 2020 and 55% in 2030.

A monte-carlo-simulation was performed to test the robustness of results. A random change of fuel, electricity and battery prices in [Gnann et al., 2015b] was run 1,000 times. In this simulation slightly different parameters were used and simulations ran until 2020. The qualitative results, however, can be transferred to this work. A normal distribution $\mathcal{N}(\mu, \sigma^2)$ was used for the parameter variation with the value of the medium scenario as μ and the maximum of the differences between the pro-EV and medium or contra-EV and medium scenario as σ for the random variation of parameters. Model results ranged from 50,000 to 2.2 million PEVs in 2020, while the average was about 750,000 and the median 644,000 PEVs. The first quartile was at 443,000 PEVs, the third at 995,000, resulting in an interquartile range of 552,000 PEVs. Thus the medium range of most results was

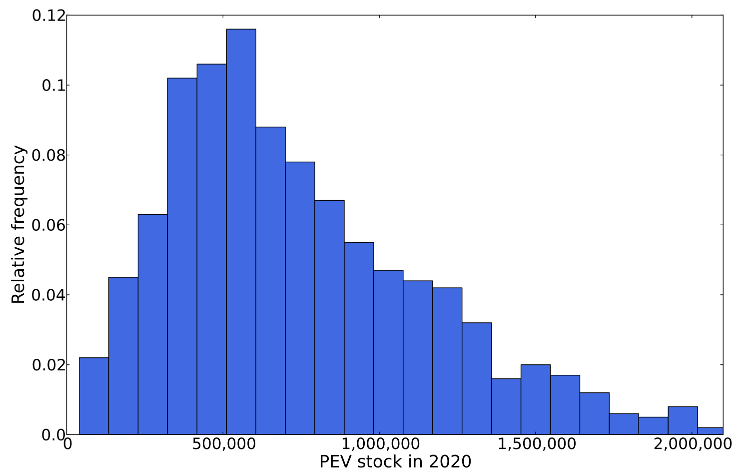

Figure 5.9: Monte-carlo-simulation for variation of scenario parameters. Shown is the plug-in electric vehicle stock on the ordinate and its absolute frequency on the abscissa resulting from a random variation of fuel, electricity and battery prices.

not as wide as suggested by the scenarios. Also the medium scenario (620,000 PEVs) was very close to the median of the simulations.

From the results in this subsection, one may conclude that (1) the market evolution of PEVs is susceptible to changes in fuel prices, followed by battery and electricity prices. (2) The sensitivity analysis shows that an increase or decrease of the main influence factors by 25% can result in doubling the PEV stock in 2030 or cutting it by about 60%. (3) The monte-carlo-simulation further showed that "good" conditions favor the PEV market evolution more than "unfavorable" conditions hamper it.

Influence of non-monetary factors

One major advantage of ALADIN compared to pure TCO-models is the inclusion of several "soft factors" into the individual buying decision. These are: the availability of individual charging points, the limited choice of PEVs as hampering factors and the WTPM for PEVs as favoring factors. The model construction allows to individually exclude these factors from the buying decision and thus to test their influence on results. Figure 4.7 underlines the influence of the WTPM, the distinction of private garage owners and curbside parkers as well as the limited availability on the market diffusion of PEVs. Hence, their influence is analyzed in the following. Figure 5.10 shows the differences to the medium scenario if the three non-monetary factors are switched off individually (individual charging points in dark blue, limited availability in green and WTPM in orange) and altogether (light blue). The absolute changes in the resulting PEV stock can be found in the left panel while the right panel shows the relative changes when compared to the case with all non-monetary factors included.

The highest absolute differences can be found for individual charging points and the WTPM in 2030 when factors are considered individually. The exclusion of the limited availability has a low absolute influence. This is slightly different for the relative influence of these factors. Here, the limited availability and the WTPM have a very high influence in the beginning which decreases until 2030. This is certainly an effect of the assumed

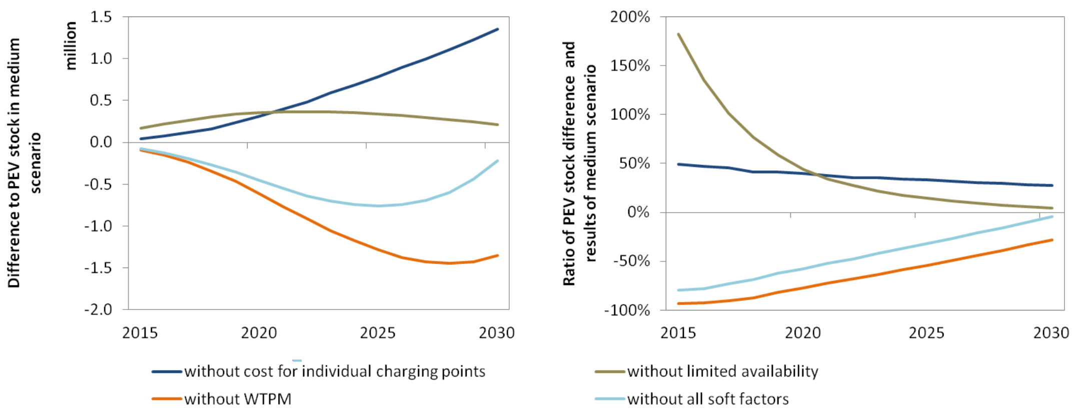

Figure 5.10: Influence of non-monetary factors on PEV market diffusion. Shown are the differences to the medium scenario when the cost for individual charging points is not considered (dark blue), without the limited PEV availability (green), without the WTPM (orange) and when all factors except for the vehicle TCO are not considered (light blue). *Left panel:* Absolute change of PEV stock. *Right panel:* Relative change of PEV stock.

phase out of the WTPM until 2030 (see Section 4.3.4) and the decreasing limitations of PEV availability (see Section 4.3.5). Yet, the stock model causes a postponement of a zero-difference between the base case and a model without the WTPM. The charging infrastructure gains relative importance over the years and in 2030, the effects almost cancel each other, i. e. PEV market diffusion results are almost equal when soft factors are considered or not.

While the influence of individual charging points is analyzed in the next subsection, a deeper look at the allocation of the WTPM was taken in [Plötz et al., 2014a, Gnann et al., 2015b]. In [Plötz et al., 2014a], the allocation method of the private WTPM data to the driving profiles was tested and concluded that it is slightly better than a random allocation. Since a random allocation may still influence results of PEV market diffusion, a monte-carlo simulation for a random allocation of the WTPM was performed in [Gnann et al., 2015b]. Slightly different parameters until 2020 were used for the random allocation of the WTPM and the simulation was conducted 1,000 times. A decrease of the PEV stock of about 10% in 2020 was found compared to the structured allocation. Users who have been assigned a high WTPM were generally better suited for PEVs. Thus, users that are willing to pay a price premium already have favorable conditions because of their driving behavior. Beside this interesting effect, that is still valid under changing parameter assumptions, the negative effect of a random allocation might be about 5% in 2030 when the phase-out of the WTPM on the left panel of Figure 5.10 is considered.[91]

To conclude, a noteworthy impact of the soft factors on market diffusion can be observed especially in the beginning of PEV market diffusion. This impact decreases over time. The limited PEV availability has the strongest effect in the beginning of the market diffusion, while the cost for individual charging points and the WTPM strongly influence the PEV market diffusion until 2030. The influence of a random allocation of the WTPM should be around 5% in 2030 which is important for the interpretation of results in Section 5.3.

[91]The influence of the WTPM of changes to market diffusion results is at 80% of the PEV stock of the medium scenario in 2020 and 40% in 2030, thus the influence of a random allocation should also halve.

5.2.3 Increasing range with non-public charging or rental cars

Additional infrastructure increases the effective range of BEVs. However, there are multiple other options that might serve to address the problem of a BEV's limited range and which several users might be willing to accept to fulfill their driving needs (see also [Kurani et al., 1994, Funke and Plötz, 2014]). These will briefly be discussed to put charging infrastructure options into context:

1. Switch to PHEV: A potential BEV user could simply switch from BEV to PHEV. This solution is incorporated in the model, since BEVs are excluded from the further analysis, if their range is not sufficient to fulfill the full driving profiles. The switch becomes visible when results of Section 5.1 are compared to those of [Gnann et al., 2015a] where BEV batteries are smaller and the share of PHEVs is higher since not all trips could be fulfilled by BEVs.

2. Use substitute vehicles for unfeasible trips: Another option is to switch to other vehicle options for trips that exceed the range of BEVs. For fleet vehicles, this would be possible if company vehicle fleets are scheduled according to their abilities: E.g. BEVs for frequent medium distances that occur regularly, diesel vehicles for very long-distance trips and PHEVs of gasoline vehicles for shorter irregular trips. This multi-dimensional optimization problem is analyzed in [Haendel et al., 2015][92] finding that several company fleets could be optimized by sparing vehicles completely and several companies could replace their vehicles by PEVs with even higher economic benefits than with an individual optimization. For private vehicles, it would also be possible to use different cars in the household or use rental cars for days on which the vehicle ranges might be exceeded. While for the first option the data set is not sufficient, the latter is analyzed in [Jakobsson et al., 2014][93] and briefly described in the following.

3. Raise charging options: The effective range of BEVs (and also PHEVs) could be increased by additional public or semi-public charging infrastructure. The influence of additional charging options at work will thus be analyzed in the following. The additional availability of public charging spots was analyzed e.g. in [Kley, 2011, Gnann et al., 2012a] and compared to battery size increases in [Gnann et al., 2012b]. However, these studies did neither permit to determine a number of charging points nor was any cost for public charging considered. This will be part of the following Section 5.3.

4. Increase BEV battery size: Larger batteries would logically raise BEVs' ranges, yet it is more difficult to economize because of currently high battery prices. The possibility to economize does not only depend on framework conditions, but also on technical parameters of concurrent technologies, such as PHEVs. A comparison of the dependence of market shares with differing battery sizes for BEVs and PHEVs was analyzed in [Zischler, 2011].

Since option 1 is a permanent part of the model, options 2 and 3 (work charging) will be analyzed in the following. Public charging as an option to increase range (3) and the variation of battery sizes (4) will be part of the next Section 5.3.

[92] Haendel, Gnann and Plötz (2015,i.p.)
[93] Jakobsson, Plötz, Gnann, Sprei, Karlsson (2014)

Rental or car-sharing vehicles for long-distance trips[94]

When ranges of BEVs are exceeded, the occasional use of rental or car-sharing vehicles might be considerable. To include this calculation in ALADIN, the number of days on which a substitute car is needed has to be determined. Therefore, a method proposed in [Plötz, 2014] is used that allows to calculate the number of days requiring adaptation.[95] The individual daily VKT r_l are assumed to be independent and identically distributed (iid) random variables. Let $f(r)$ denote the user-specific distribution of daily VKT. The probability of driving more than L km on a driving day is then given by $\int_L^\infty f(r)dr = 1 - F(L)$ where $F(r)$ is the cumulative distribution function of $f(r)$. Let n denote the number of driving days out of N days of observation such that $\alpha = n/N$ is the share of driving days. Thus, $D(L) = 365(n/N)[1 - F(L)]$ is the number of days per year with more than L km of daily VKT. Accordingly, $D(L)$ is the number of days requiring adaptation for a potential BEV user. Following [Plötz, 2014], the log-normal distribution $f(r) = \exp[-(\ln r - \mu)^2]/(r\sqrt{2\pi}\sigma)$ is used to model the random variation in daily VKT of the drivers. For each individual driver, the log-normal parameters for the typical scale of daily driving μ and the variation in daily VKT σ are obtained by maximum likelihood estimates. The number of days requiring adaptation is calculated as follows: For each driver, the share of driving days is estimated as n/N and the driver-specific log-normal parameters are estimated from likelihood maximization. These were already introduced in Section 5.1.1. Using the cumulative distribution function of the log-normal distribution $F(x) = 1/2[1 + \text{erf}((\ln x - \mu)/\sqrt{2}\sigma]$ the user-specific number of days requiring adaptation $D_i(L)$ is calculated ($\text{erf}(x)$ denotes the error function). This procedure is repeated for each driver in the data base. In very rare cases (37 out of 6339), there is no variation in daily driving distance between the days reported, i.e., σ_i=0. σ_i is set equal to the sample mean in this case. However, this has almost no effect on the results reported below.[96]

Figure 5.11 shows the results when BEVs are simulated with an additional cost for every day on which the range of BEVs is exceeded in relation to results of the medium scenario. Figure 5.11 uses the same display as Figure 5.12. Absolute changes in relation to the medium scenario are found on the left, their relative changes on the right panel. Four options are considered that differ in cost for rental cars: In options A0 and A1, the daily costs for a rental car, in B0 and B1, costs for a car-sharing vehicle are assumed.[97] Options A0 and B0 do not consider the costs per kilometer driven, while A1 and B1 also integrate the driving-dependent costs (with diesel) for the substitute vehicle. Until 2025, all options show a similar behavior: a raise of the PEV stock until 2020 and a decline until 2025, which is only differentiated by the height resulting from price differences for substitute vehicles. After 2025, BEVs with a rental-car option seem to be too costly compared to alternatives (PHEV, gasoline, diesel) and the difference in total BEV stock turns even negative. Car-sharing vehicles may be an option for later years since they show a positive trend even in 2030. However, the relative changes (right panel) indicate that results are positively affected in the beginning of a market evolution. But, the influence after 2025

[94]This section is based on Jakobsson, Plötz, Gnann, Sprei and Karlsson (2014) [Jakobsson et al., 2014]

[95]See [Weiss et al., 2014] for another approach to determine the days above a vehicle's range.

[96]Please note that this log-normal estimate is expected to be valid for different driving ranges L but seems to slightly overestimate the actual number of days requiring adaptation [Plötz, 2014].

[97]The cost for rental cars and car-sharing were retrieved with different time horizons before car rental, duration of car rental and in different German cities on www.billiger-mietwagen.de and www.flexauto.de/pages/carsharing-vergleich.php.

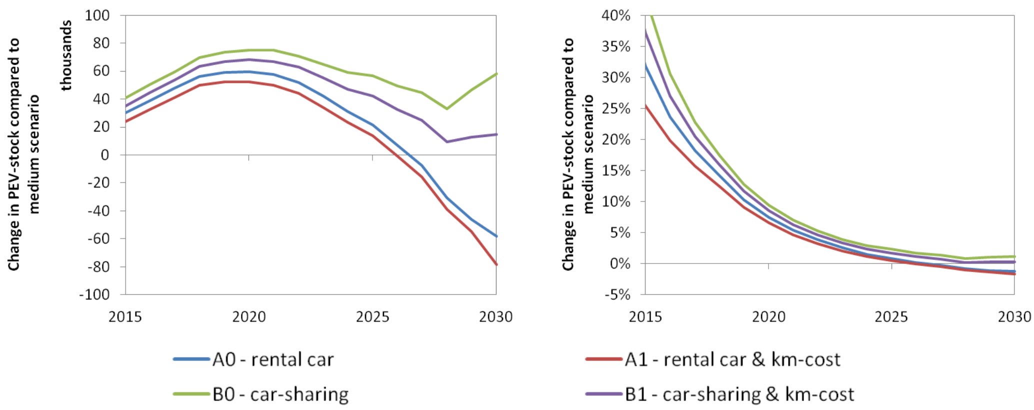

Figure 5.11: PEV stock development including substitute vehicles for long-distance trips. Shown are the differences between options in which private users may use a rental car when the range of BEVs is exceeded and medium scenario. Options differ in cost for rental cars. A0 (blue): rental car cost for small vehicles 50 EUR/day, medium sized vehicles with 65 EUR/day and large vehicles with 75 EUR/day. A1 (red) with same costs plus the cost for driving with a conventional diesel vehicle. B0 (green) and B1 (violet) with half the rental car prices of A0 and A1. *Left panel:* Absolute change of PEV stock. *Right panel:* Relative change of total PEV stocks (including commercial PEVs).

is only incremental. This is also visible when units of the abscissae of Figure 5.12 and Figure 5.11 are compared. Under the assumed parameters, the option to offer alternative vehicles for days when BEVs ranges might be exceeded, seems to be interesting until 2020 where they can raise PEV market shares. When such options are considered until 2030, results do not change noteworthy compared to the standard PEV simulation of ALADIN.

Influence of non-public charging infrastructure

In the previous subsections every vehicle has been assigned an individual charging point at home (for private and company car owners) or at the company site (for commercial vehicles). Yet, private vehicles might have the opportunity to recharge their vehicle at work as well, and for some users, the charging point at work might be even more useful than at home. For this reason, the following charging options for private users are studied in this section: (1) home only charging, (2) work only charging, (3) home and work charging. All simulations are performed in the medium scenario for framework conditions. Commercial vehicles remain unaffected and private users have to pay for either one (case 1 and 2) or two (case 3) individual charging points.

Figure 5.12 shows the differences between charging options work only vs. home only (dash-dotted blue) and home and work vs. home only (dashed red) and their timely evolution. On the left panel the absolute and on the right panel the relative changes are displayed. Results show that charging only at work would reduce the number of PEVs to half of the vehicle stock in 2030. Thus, one charging point at home is a prerequisite for PEVs given the facts that half of the registrations are commercial PEVs. Adding an additional charging point at work would instead increase the number of PEVs in stock by 20% by 2030. Thus, the additional charging point is affordable for a large number of vehicles since they are able to perform a higher share of trips electrically.

Summing up, the results of this section show (1) that rental car options (or mobility

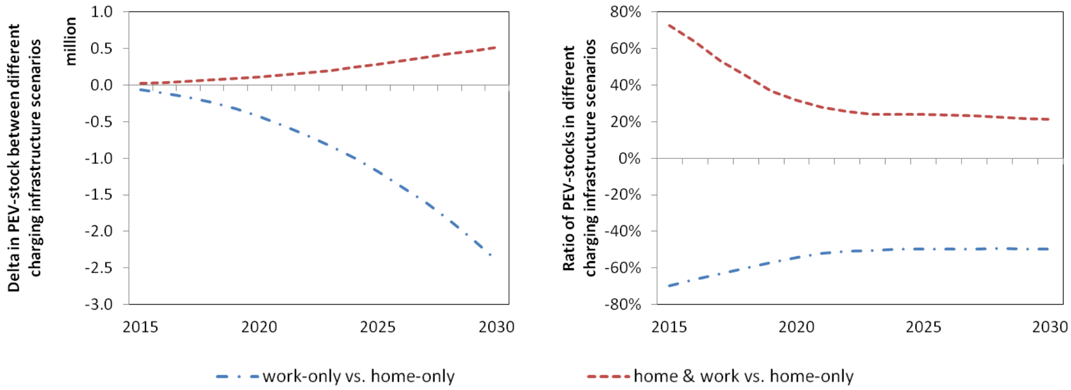

Figure 5.12: Influence of individual charging infrastructure on PEV market diffusion. Shown are the differences between charging options in which private users only charge at work compared to charging at home (dash-dotted blue) and between charging options in which private users may charge at home and at work vs. only at home (dashed red). Commercial users without changes. *Left panel:* Absolute change of PEV stock. *Right panel:* Relative change of total PEV stocks (including commercial PEVs).

guarantees) may increase PEV sales in the beginning, yet they are no long-term option from a techno-economical point of view, as results in 2030 are not significantly different to the base case. (2) Additional charging infrastructure at work may increase electric ranges at an affordable cost for a PEV-user. This option increases the PEV-stock. (3) Charging only at work is not sufficient for the majority of potential PEV users. The impact of public charging points as well as the variation of battery prices will be discussed in Section 5.3.

5.2.4 Discussion

The results of the model ALADIN are subject to a number of uncertainties: (a) an inherent model design uncertainty, (b) an uncertainty due to the data used in the model and (c) an uncertainty caused by parameters. The uncertainty due to model design in Section 4.4 and data uncertainty was discussed in Section 3. This part focuses on the parameters that were considered in the model and their related impacts on model results.

In Section 5.2.1 the results of market diffusion are shown for three scenarios: pro-EV, medium and contra-EV. Although small variations between scenarios were considered, the difference between results is noteworthy. This arises from small utility differences between propulsion technologies (cf. Section 5.2.1). Especially for fleet vehicles, market shares can vary largely when monetary or non-monetary factors change. The display of utility gaps allows to interpret the changes caused by small differences in monetary and non-monetary factors. Since the data sample is limited, results are shown with confidence bands which cover the uncertainty due to data. Furthermore, the exact numbers of market diffusion results should permit to understand the range of results and what influences them most, yet they are no exact forecast. Under the assumptions made for the scenarios, PEVs enter the market also in the contra-EV scenario. This might be different, if, e.g., battery prices do not decline as much as assumed when PEV sales are low [Nykvist and Nilsson, 2015]. Also the composition of combining favoring and hampering factors for PEVs in the scenarios might be discussible, yet the combination of positive and negative factors for PEVs should show the range of results.

All scenarios show a high share of fleet vehicles in registrations, which is slightly decreasing over the years, in favor of a rising share of private vehicles and, delayed, a small share of company cars. The large number of private PEVs in vehicle stock stems from their diffusion in the secondhand car market after their first holding time. This assumption is based on the current registrations in the second car market of conventional vehicles and may be different for PEVs. While the large potential of fleet vehicles to gain significant market shares has already been discussed in the previous Section 5.1, the small share of company cars has several reasons: (1) there is no publicly available data for the WTPM of company cars, hence the utilities for PEVs and their market shares might be slightly higher. (2) The buying decision of company cars is more complex since the company and the driver participate. This is incorporated into the model (Section 4.2.2), but may differ in reality. (3) The driving behavior of company car drivers is more erratic than for fleet vehicles, but driving distances are higher than for private cars (see Section 5.1). While a certain mileage is important for PEVs to economize against conventional vehicles, several long-distance trips which occur in the week of observation make it difficult for company cars to gain high electric driving shares for PHEVs or to perform the full driving profile with a BEV.

The last point to mention concerning vehicle distribution is the ratio of BEVs and PHEVs, since the high shares of large PEVs in registration and stock was already discussed in Section 5.2.1. In all scenarios, PHEVs gain higher market shares than BEVs in the early market diffusion, while BEVs catch up until 2030. This certainly stems from battery capacities assumed in this thesis which for BEVs are difficult to economize in the beginning. However, developments in several large car markets suggest a similar evolution, since PHEVs allow to perform the common driving profile without behavioral changes [Mock and Yang, 2014]. The re-use of individual charging points may be criticized as well, yet other options were discussed thoroughly in the text.

As framework conditions have a large impact on results, several parameters were varied separately in a sensitivity analysis in Section 5.2.2. The most influential factors in utility calculation were chosen for variation. Still, several robust results on PEV market evolution and their influence factors could be obtained as a monte-carlo-simulation demonstrated (cf. Section 5.2.2). These are summed up in the following Section 5.2.5. Aside from framework conditions, user acceptance has a large impact on market diffusion but is difficult to measure and predict. Surveys clearly show that some user groups are willing to pay a premium for new technologies in general and PEVs in particular. Thus, the inclusion of a higher or smaller willingness to pay of some users is necessary to model future market diffusion of PEVs. Future research could put emphasis on retrieving more quantifiable data for the WTPM, especially for its evolution over time. Moreover, the future development of battery technology is unclear and might change results significantly if new battery technology generations are introduced [Thielmann et al., 2012].

The influence of individual charging infrastructure is analyzed in Section 5.2.3 and shows that additional charging points at work for private vehicle users can increase market shares.[98] It is questionable, whether a vehicle owner would have to pay for the installation of a charging point at work, but the employer is very likely to turn over the cost to the employee. The individual choice per user to install one or two charging points (at home and at work), which was not modeled, could increase PEV market shares even more.

[98] See [Kley, 2011, Björnsson and Karlsson, 2015, Gnann et al., 2012a] for similar results for additional charging points at work.

Furthermore, it is assumed that the electricity charged at work has not to be taxed by PEV users, although this might be considered as a fringe benefit of the company to the employee. Apart from additional individual charging points to increase the electric range of PEVs, the option to use rental cars for occasional long-distance trips has been analyzed in Section 5.2.3. Results show that the influence of such an offer decreases to almost zero until 2030. However, the assumed increasing battery sizes allow longer distances over the years. These were chosen as a reaction of car manufacturers to decreasing battery cost and users' demand for higher ranges. Further, results are based on techno-economical calculations and the effect of such an offer on vehicle purchase was not analyzed.

Lastly, results should be discussed in light of other studies on the same topic. In the introduction of Section 5.2 a comparison to [Mock et al., 2009, Propfe et al., 2012a, Redelbach et al., 2013, Hacker et al., 2011b, Kihm and Trommer, 2014] was suggested. In [Mock et al., 2009, Propfe et al., 2012a, Redelbach et al., 2013] the model VECTOR21 is used, a discrete choice model that bases on a large consumer survey. While assumptions for cost and vehicles differ in the three studies, some results are observable in all of them: a declining share of diesel vehicles and a larger share of PHEVs compared to BEVs in [Mock et al., 2009, Redelbach et al., 2013]. This confirms the same findings in this thesis. Results are not directly comparable to those of this thesis as also NGVs and FCEVs are considered in the scenarios which also amount to a large share of new registrations and user groups are not explicitly distinguished in the papers. While results in [Propfe et al., 2012a] seem moderate and comparable to this thesis, market shares in [Redelbach et al., 2013] of AFVs in 2030 amount to 80% which seems moderate compared to other works. Hacker et al. (2011) studied the market penetration of PEVs based on [infas and DLR, 2008] in the project OPTUM [Hacker et al., 2011b]. Although this work does only consider private vehicles, some results are comparable too. Also in this study, PHEVs gain larger market shares than BEVs and vehicles with garages are better suited than those without.[99] Kihm and Trommer (2014) use the model TREMOD for the development of a PEV market penetration [Kihm and Trommer, 2014]. They find a higher share of PHEVs compared to BEVs as well, yet other results differ largely to this thesis: In [Kihm and Trommer, 2014] private households dominate the vehicle sales and also company cars gain relevant market shares. Apart from different assumptions for techno-economical parameters, their reasoning for a non-consideration of VAT exemption is unclear and no evidence for an introduced "eco-factor" is given. Further, the individual analysis of driving profiles is based on [WVI et al., 2010] and [infas and DLR, 2008] which contain only one day of observation. Since vehicles are simulated individually and electric driving shares as well as BEV feasibility are based on the one observation day, the results of [Kihm and Trommer, 2014] can be considered uncertain.

The comparison to other model results shows that several results and trends of this thesis are confirmed by other research. Yet, a PEV simulation with the differentiation of user groups and the use of driving profiles with long observation periods has to the best of the author's knowledge not been performed to this point. This analysis permits to retrieve several new results summed up in Section 5.2.5.

[99] Although this is a premise of this thesis and users without a garage have to pay a premium for charging infrastructure, the general assumption that the hurdle of buying a PEV when not owning a garage is confirmed here.

5.2.5 Summary

This section analyzed the market evolution of PEVs in Germany until 2030 with non-public charging infrastructure. An analysis of the main monetary and non-monetary influence factors was followed by the influence analysis of additional individual charging points. The following findings should be maintained:

- The results of market diffusion demonstrate a great deal of uncertainty regarding the market evolution of PEVs because it heavily depends on external framework conditions such as price developments for batteries, crude oil and electricity prices, which may double results via small changes (±25%) of relevant input parameters. Also non-monetary factors do have considerable influence as e.g. the willingness to pay more for a new technology may cut the PEV stock in 2020 to half when it is not reflected.

- Nevertheless, the target of the German government of one million PEVs by 2020 can be reached under favorable conditions for PEVs without monetary support for the purchase of PEVs. In 2030 about 20% of of the PEV-stock could be (partly) electrified with favorable assumptions for PEVs while also in unfavorable conditions about 1.5-2 million PEVs in stock are possible until 2030. The most promising user group for PEV adoption are commercial fleet vehicles, followed by private PEVs which gain equal market shares until 2030.

- Further, results suggest a high share of PHEVs. This might derive from the strict exclusion of BEVs, if they cannot perform all of their driving electrically. Yet, no significant changes in the results were found when adding the possibility to use rental cars for long-distance trips [Plötz, 2014]. Further analyses could involve car-sharing vehicles or substitute vehicles in a multi-car household (see e.g. [Khan and Kockelman, 2012]).

- Additional charging points at work increase the number of PEVs in stock even when users have to pay for it. Charging only at work is not sufficient for the majority of private PEV users. Hence, a home or primary charging point is currently a premise for the operation of a PEV.[100]

[100] See [Zhang et al., 2013] for a similar evaluation.

5.3 Interactive plug-in electric vehicle and infrastructure market diffusion

While the diffusion of PEVs with non-public charging infrastructure was analyzed in detail in the previous section, this last part of results focuses on the interaction of PEV diffusion and public charging infrastructure. The influence of non-public charging points as well as framework parameters on PEV diffusion was performed with driving profiles of MOP and REM2030. These profiles also contain information about the vehicle size and several socio-demographic attributes of vehicle and driver. However, these driving profiles do not contain geographic information about the trips, like geographic coordinates of starting and stopping points, which makes it impossible to simulate a joint use and occupancy rate of public charging points. The data set MOPS and REM2030S (both introduced in Chapter 3) contain geographic information (departure and arrival zones of each trip) and will be used for the joint analysis in the following. Although these data sets only contain trips for the region of Stuttgart, all results for PEV and public CP market diffusion are converted to Germany as described in Section 4.3.6.[101]

In the literature analysis in Chapter 2, no model was found that treated the co-diffusion of PEVs and their charging infrastructure which required special features (charging time and frequency as well as a distinction of charging infrastructure accessibility types) that are not considered in the discussed models. For this reason, a comparison to models from the literature is not possible and several sensitivity calculations are performed instead.

This section is organized in the following way: First, a static analysis of public parking spots, duration and frequency after each trip of the driving profiles is performed in Section 5.3.1. Second, a detailed analysis of three scenarios for subsidizing public charging points is conducted in Section 5.3.2. Several variations are performed to analyze the influence of different parameters (5.3.3) followed by a separate analysis for fast charging points (5.3.4). A discussion (5.3.5) and summary (5.3.6) rounds up this section. As described in Table 5.1, only the medium scenario for framework parameters will be used in this section.

5.3.1 Static analysis of geographically distributed driving behavior[102]

Before starting the simulation a minimum need for infrastructure per zone in the region of Stuttgart is defined (cf. Section 4.2.4). In [Funke et al., 2015] differences in a geographical coverage and a user-oriented charging infrastructure set-up were discussed, finding that a user-oriented approach would need less charging infrastructure than an approach based on a predefined geographical coverage (defined number of charging points per square meter for three types of population densities). Still, if public authorities set up charging infrastructure because of their public supply mandate, a geographical coverage is of interest. Since there is information about user behavior and geography in the data sets, it is possible to combine both approaches. As the option to recharge publicly is given when a vehicle is parked in public places, the total vehicle minutes parked publicly per zone in

[101] This conversion will be discussed in Section 5.2.4.

[102] This section is based on [Gnann et al., 2015c].

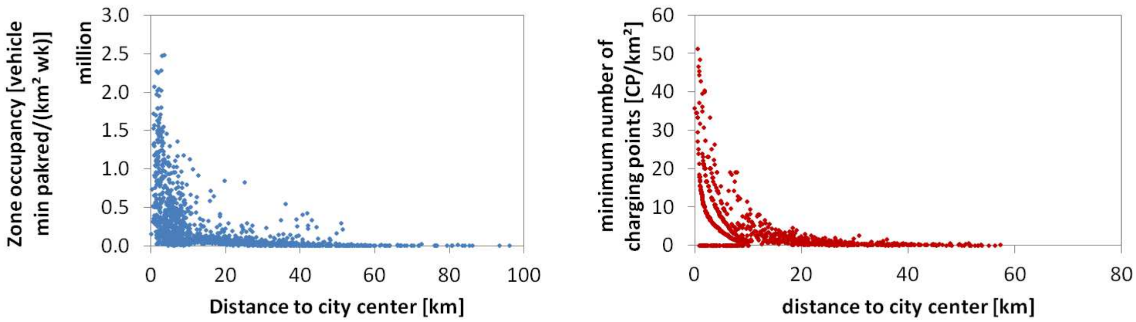

Figure 5.13: Specific zone occupancy and minimum number of public charging points in different zones in the region of Stuttgart. *Left panel:* Specific zone occupancy in different zones in relation to distance to city center. Every point corresponds to one zone. *Right panel:* minimum number of public charging points in different zones in relation to distance to city center. Every point corresponds to one zone.

the driving profiles divided by the area are summed up and defined as the specific zone occupancy. Thus, this indicator describes how many vehicles are parked how long over the full observation period while discrepancies in surface area are reflected. The indicator is shown on the left panel of Figure 5.13 with respect to the zone's distance to the city center (central station). It is visible that zones which are closer to the city center are more likely to have a higher zone occupancy. That implies the further one approaches the city center the more vehicles are parked publicly. A further analysis shows that most zones have a zone occupancy lower than 500,000 vehicle minutes parked/(km^2·wk).

To transform this variation of specific zone occupancies to charging points, it is assumed that users wish for a charging point within every 300 meters. This assumption is based on the average distance people are willing to accept to walk to the next public transport stop, which is also 300 meters according to [KVV, 2006]. With three circles that intersect in one point, the highest coverage with lowest overlap is possible, which results in 4.28 charging points per km^2 (see e.g. [Rune, 2001]). When this average charging point necessity is multiplied by the total area, the result would be the minimum number of public charging points for the geographical coverage approach [Funke et al., 2015]. Instead the zone occupancy and area are used to weigh the minimum number of public charging points:

$$CPN_z = A_z \cdot \overline{CPN} \cdot \frac{occ_z}{\overline{occ}} \tag{5.1}$$

With CPN_z being the minimum number of public charging points in zone z, A_z the area of zone z and $\overline{CPN}$ the above mentioned average minimum number of charging point, the vehicle occupancy occ_z of zone z and the average $\overline{occ}$ include the user-oriented approach to the analysis. The result of this formula for each zone can be found on the right panel of Figure 5.13 with respect to its distance to the city center. To give an example: In zone z_1, two vehicles are parked publicly for half an hour and the area of zone z_1 is 10 km^2. Zone z_2 covers 1 km^2 and one vehicle is parked for five hours. The specific zone occupancy occ_{z_1} for zone z_1 would be $occ_{z_1} = 2 \cdot 30$ min/10 km^2 $= 6$ min/km^2 and for z_2: $occ_{z_2} =$ 300 min/1 km^2. The average zone occupancy $\overline{occ}$ would be $\overline{occ} = 153$ min/km^2. Using the same distance between two charging points, the minimum number of charging points in the two zones would be $CPN_{z_1} = 10$ km^2 $\cdot$ 4.28 CP/km^2 $\cdot$ 6 min/km^2/153 min/km^2 $=$

1.67 CP/km $\approx$ 2CP/km and CPN_{z_1} = 8.37CP/km $\approx$ 8 CP/km which is much less than a full coverage with 4.28 CP/km$^2 \cdot$ 11 km$^2 \approx$ 47 CP.

One can clearly observe that zones which are further away from the city center ($<$ 40 km) need less charging points than those which are 10-40 km away while small zones in the city center also need less charging points because of their size. When considering that zones are larger the further they are away from the city center (cf. Figure A.1), the low occupancy in the zones further away from the city center weighs larger than their area.[103] Also the total sum of charging points necessary for the observation area (3,168 charging points) is significantly lower than with the geographical coverage (15,632 charging points). This zone-specific minimum number of public charging points will be used in the individual battery simulation where users are expected to only recharge their vehicle when the number of charging points in the zone they are stopping is equal or higher than the minimum number of public charging points ($n_{CP_z} \geq CPN_z$). Note that this constraint is not considered in the PEV stock simulation where vehicles stop at a charging point and charge their vehicle if it is not in use (and the battery's SOC is below 50%).

5.3.2 Public charging infrastructure evolution

With this pre-analysis determining the minimum number of public charging points, the simulation can be performed. Three subsidy scenarios with home and public charging points with 3.7 kW are analyzed in detail in this section: In subsidy scenario S1 public charging points are not subsidized while in subsidy scenario S2 the charging points are subsidized until 2020 and in S3 until 2030. The annuities of charging point costs and their subsidies are summarized in Table 5.6. A large subsidy for each charging point is considered for the first five years in subsidy scenario S2 while in subsidy scenario S3 it is phased out linearly until 2030.

Table 5.6: Cost and subsidies for public CPs with a charging power of 3.7 kW in three subsidy scenarios. All costs in EUR$_{2014}$ without VAT.

subsidy scenario	option	2015	2020	2025	2030
S1 - no subsidy	real CP annuity	700	596	508	434
	annual subsidy	-	-	-	-
S2 - subsidy until 2020	assumed CP annuity	100	100	508	434
	annual subsidy	600	496	-	-
S3 - subsidy until 2030	assumed CP annuity	100	100	267	434
	annual subsidy	600	496	241	-

Simulation results for the PEV and CP stocks in three subsidy scenarios for Germany can be found in Figure 5.14 (S1 in red, S2 in blue and S3 in green). This figure uses a double-logarithmic scale (like Figure 2.4) to compare small and large values more easily. Several years are shown to indicate the evolution over time - every marker is equal to one year in the simulation. The first interesting result is that public charging points are not

[103] Zones in the outer area, where none of the vehicle users in the data sample lives, are not considered for a charging point setup, which explains the missing minimum numbers of charging points for zones further away than 60 km from the city center.

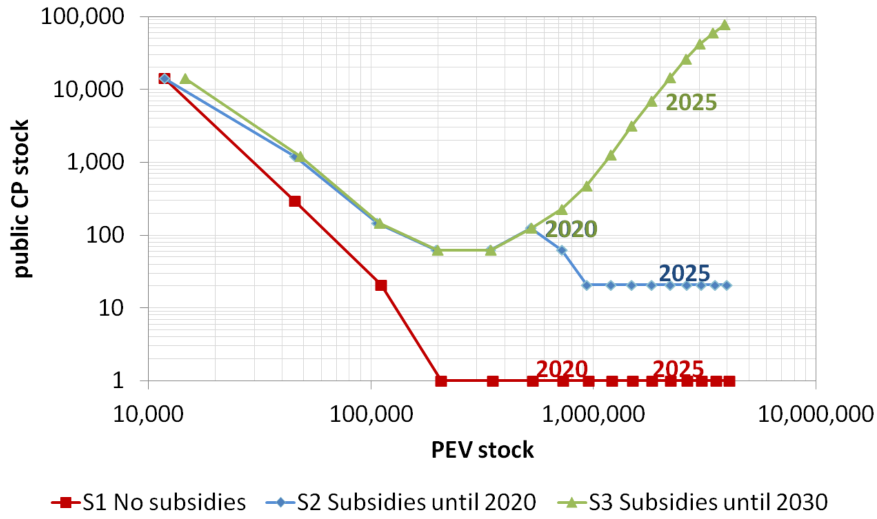

Figure 5.14: Simulation results for Germany for PEV and public CP stock with different subsidies. Axes with logarithmic scales. Results without subsidies with red squares, for subsidies until 2020 with blue circles and for subsidies until 2030 with green triangles. If the CP stock is 0, it is set to 1 because of logarithmic scales.

able to economize when they are not subsidized (subsidy scenario S1).[104] Already in 2018, all charging stations are taken out of order since they cannot economize. This is certainly due to the number of PEVs that are in stock at this time (about 200,000 PEVs), as the charging points have to be subsidized until a sufficient number of PEVs is in place.

Taking a look at subsidy scenario S2, the public CP stock is not falling as much as in subsidy scenario S1, however it is much lower (about 800 public CPs in 2020) than in the beginning (about 14,000 public CPs). After 2020, the slope is declining too, since the amount of charging by the PEV stock at these charging stations is not sufficient for a take up thereafter. Only some public charging points can be maintained for subsidy scenario S2 until 2030. From 2015 until 2030, about 11 million EUR would have to be paid for subsidies in S2. In the last subsidy scenario (S3) results differ in terms of public charging points. The number of public CPs is rising when subsidies are still in place until 2030. Although the slope of the curve is declining, it remains positive until 2030 and supposedly thereafter. Thus, a tipping point is reached in this subsidy scenario and the system becomes self-sustaining. Subsidies only double (26 million EUR) when compared to subsidy scenario S2 as the subsidy per charging point decreases after 2020. When comparing the three subsidy scenarios the difference in public CP stock is obvious, yet the number of PEVs in the vehicle stock does not differ at all. For all three subsidy scenarios, about 4 million PEVs diffuse into the PEV stock until 2030 independent of the public charging options. That implies an impact of the PEV stock on public charging points (a sufficient number of PEVs has to be reached to pay of public charging points), yet an influence of public charging points on the PEV market diffusion can not be found in results. Also, the share of PHEVs in stock is similar for all three subsidy scenarios at about 70%. These results are largely driven by the energy charged at the different charging options which will be analyzed next.

[104]Since zeros are not possible to display on a logarithmic scale, results for the public CP stock are set to one when they are actually zero.

Distribution of energy charged

The number of public CPs is directly linked to the energy charged at these charging options. Figure 5.15 shows the total energy charged[105] at public charging points (abscissa) with respect to the number of public charging points (ordinate) for the three subsidy scenarios. In this display the number of charging points as well as the energy charged is shown for the observation area (the region of Stuttgart).

While all three subsidy scenarios start at 688 public charging points and about 25,000 kWh charged at public charging points (in one year), they differ already in 2016 where in the non-subsidized scenario only 15 charging points are affordable compared to 50-60 in subsidy scenarios S2 and S3. In subsidy scenario S1 only few vehicles can charge at the 15 charging points remaining in 2016 which leads to a decrease in energy charged publicly to about 1,000 kWh. With a public charging price of 0.40 EUR/kWh and an electricity price of 0.30 EUR/kWh that is used in Formula 4.15, 0.10 EUR/kWh remain to cover the price for public charging points. Since 1,000 kWh multiplied by 0.10 EUR/kWh is lower than the cost for one charging point per year in S1 in 2017 (656 EUR/yr), no charging points remain in the stock after 2017. This also means that no vehicles can charge publicly from 2017 on and the number of charging points cannot increase anymore. The subsidies for subsidy scenarios S2 and S3 allow to keep a certain number of charging points in the CP stock, so charging in public remains possible after 2017. However, the sudden suspension of subsidies in S2 in 2020 decreases the number of charging points (and the amount of energy charged).[106] Since the prices for public charging points decrease over the years the decrease of S2 to one charging point is not as sudden as in subsidy scenario S1. Also here, it is possible to keep one charging point until 2030 with a slightly increasing amount of energy charged at this charging point. In subsidy scenario S3 instead it is possible to keep maintain the slightly increasing cost for charging points after 2020 lower than the additional earnings from energy sold at public charging points. Remembering that formula 4.15 reads as follows:

$$n_{cp}(t+1) := \frac{p_{pc}(t) + p_{el}(t)}{a_{cp}(t+1)} \cdot W_{pc}(t).$$

For the above mentioned case, let the public charging price $p_{pc}(t)$ and the price for electricity $p_{el}(t)$ be constant, then the number of charging points n_{cp} stays stable if $\Delta n_{cp} = n_{cp}(t+1) - n_{cp}(t) = 0$ or $\Delta a_{cp} = \Delta W_{pc}$, the change in additional cost for charging points is compensated by the additional energy charged. It increases if the change in public energy charged is larger than the change in cost and subsidies respectively. However, this is no trivial connection as the amount of energy charged depends on the number of charging points and PEVs and it is not possible to draw a simplified form of this connection.

Further, slightly differing results between subsidy scenarios S2 and S3 between 2015 and 2020 can be noted. Although the cost for public charging points is equal in both

[105]For a classification of amounts of energy: a medium sized BEV with a consumption of 0.2 kWh/km and an annual mileage of 20,000 km would need 4,000 kWh per year, an average household has an electricity consumption of about 3,200 kWh per year and the total electricity consumed in Germany in 2014 amounts to $578.5 \cdot 10^9$ kWh [AGEB, 2015].

[106]In 2020 about 7,000 kWh are charged publicly in S2 which allows a number of charging points $n_{cp} = \frac{7{,}000 \text{ kWh/a} \cdot 0.10 \text{ EUR/kWh}}{100\text{EUR/a}} = 7$ charging points.

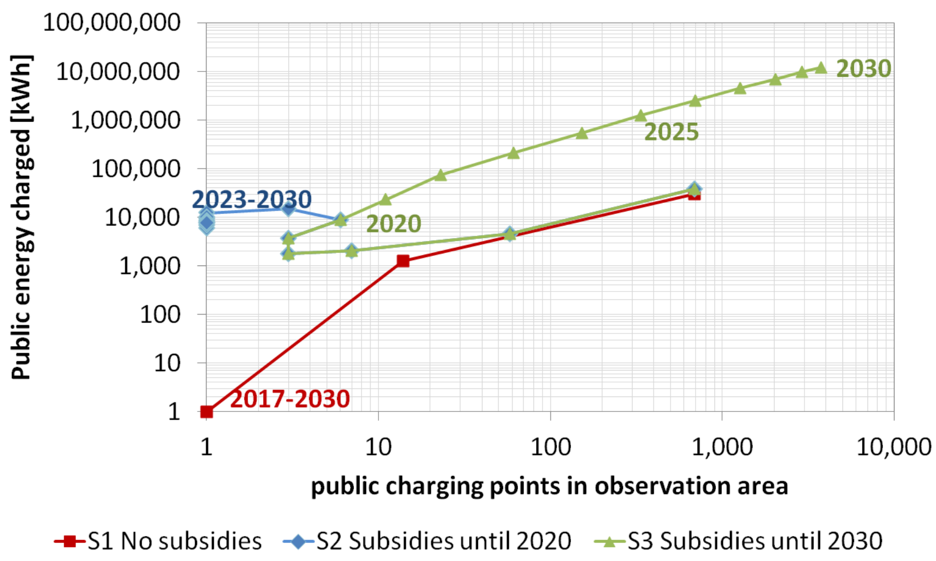

Figure 5.15: Simulation results for the region of Stuttgart for energy consumed at public CPs and public CP stock with different subsidies. Axes with logarithmic scales. Results without subsidies with red squares, for subsidies until 2020 with blue circles and for subsidies until 2030 with green triangles. If the CP stock is 0, it is set to 1 because of logarithmic scales.

subsidy scenarios, there are differences in the amount of charging and charging stations. This stems from the two random processes in the simulation: (1) Because of the limited availability of PEVs, a limited number of PEVs is randomly chosen to diffuse into the vehicle stock every year (cf. Section 4.2.3). However, this limitation decreases over the years and (2) the random order of PEVs at public charging to charge may have a greater influence. Consider a vehicle that stops at a public charging point and needs to recharge 10 kWh which takes about 2.7 hours, yet the vehicle is parked there for 10 hours. At the same time more vehicles could have been charged while the charging point was blocked. This could have been the case for one of the simulations and the other way round for the other. Especially the second random process could lead to differences in charging point usage, yet these differences decrease when only reflecting the later years with higher amounts of PEVs and CPs where positive (higher usage of individual CPs) and negative (lower usage) effects should cancel each other. To sum up, the subsidy to charging points depends on their cost, the number of public CPs and the PEVs charging at them and no trivial logic can be extracted from results to determine this number.

However, the energy charged at public charging points in relation to the full energy consumed by PEVs in combination with the number of PEVs could be a good proxy. Figure 5.16 shows the energy consumed at domestic, commercial and public charging spots in subsidy scenario S3 for one week in 2030 in the observation area (region of Stuttgart). The left panel of Figure 5.16 shows the distribution to accessibility types as stacked area plots and the right panel as lines with domestic charging in red, commercial charging in green and public charging in blue. Although commercial PEVs in subsidy scenario S3 amount to one third of the PEV stock in 2030, their higher mileage results in about 56% of the total energy consumed. Domestic charging accounts for 41% and public charging for about 3% of total energy consumed. Further, the characteristic evening peak for private vehicles (when returning home) is visible as well as the decreased peaks on

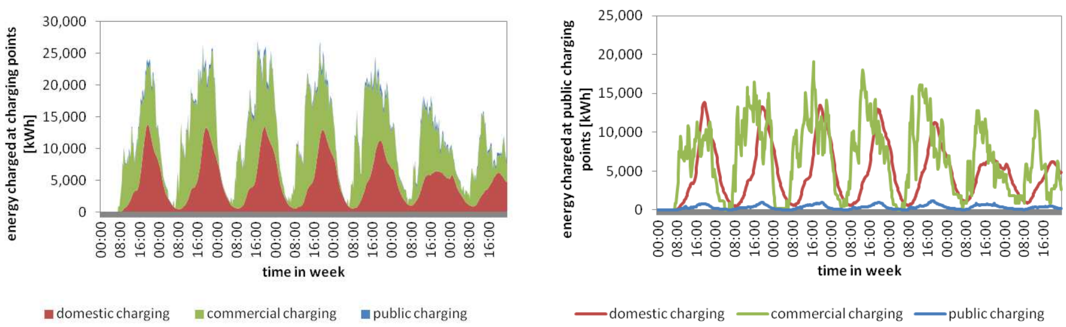

Figure 5.16: Simulation results for the region of Stuttgart for energy consumed by PEV stock over one week in subsidy scenario S3 (subsidies until 2030) in 2030. Energy charged at domestic charging locations in red, at commercial charging spots in blue and at public locations in green. *Left panel:* Total energy consumed as stacked area plot. *Right panel:* Energy consumed at different locations (non-stacked).

the weekend (last two days/peaks) (see e.g. [Dallinger and Wietschel, 2012]). Commercial charging is slightly more erratic and distributed over the day while public charging also has the small peaks in the afternoons or early evenings. Since the locations of these peaks are similar to those of domestic charging spots, a price independent load shift due to public charging points cannot be drawn from results. However, comparing the height and amount of energy charged at public charging points and in total, the impact of public charging on the energy system is small compared to domestic and commercial charging according to these results.

Finally, it is possible to analyze if the location of charging points has an impact on energy consumed at public charging spots. In Figure 5.17 two results are shown: the number of charging points with respect to their distance to the city center on the left panel and the energy charged at these charging points in 2030 on the right panel. The left panel of Figure 5.17 shows the timely evolution of charging points over the years. While most charging points are built in the city center at the moment (see blue graph for 2015), first charging points in 2020 are built further away from the city center. In 2025, several charging points are created closer to the city center, however the majority remains at about 10–20 km away. The peaks for the graph of 2030 (turquoise) indicate this finding even more. As the optimization of charging point setup changes in 2027/2028 from covering the minimum number of public charging points to the setup of charging points with high PEV occupancy (cf. Section 4.2.4), these high numbers stem from the demand for charging points in these zones.

Turning to the right panel of Figure 5.17, the usage of charging points (in 2030) is considered as well. In this figure every charging point gets assigned the average energy consumed by the charging points in its zone and the zone's distance to the city center. For example, in zone z there are ten public charging points, the energy charged in zone z is 340 kWh in the simulated week and zone z is 13 km away from the city center. Accordingly, ten charging points with a 34 kWh/wk and 13 km away from the city center are used for the display of the right panel of Figure 5.17. A lot of charging points (about 200) are found within a distance 12-15 km away from the city center and an average energy of 20 kWh/CP in one week. Yet, which amount of energy is needed for charging stations to pay off? The simulation of subsidy scenario S3 returns a public charging

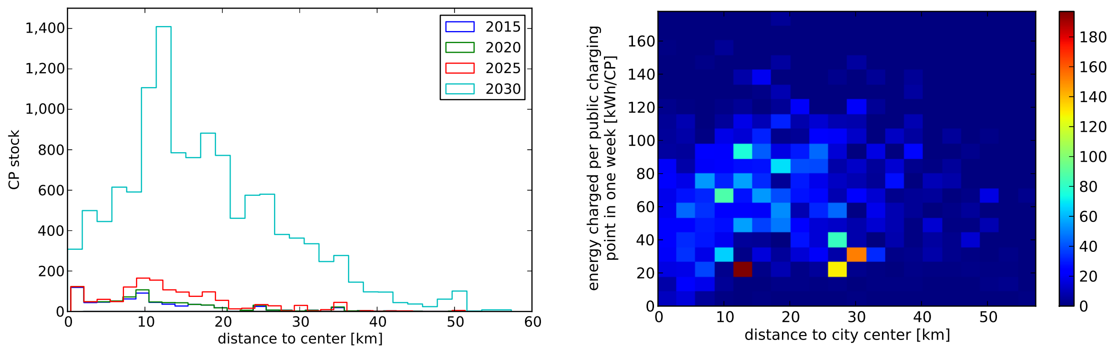

Figure 5.17: Simulation results for the region of Stuttgart for public CP stock over time and energy consumed at public CPs in 2030 with respect to distance to city center in subsidy scenario S3 (subsidies until 2030). *Left panel:* Simulation results for public CP stock with respect to distance to city center in subsidy scenario S3 (subsidies until 2030) in observation area. Results are shown for different years as contours of histograms. *Right panel:* Shown is the the absolute frequency (color bar) of charging points described by their average energy consumed per charging point [kWh/CP] and the zone's distance to the city center in kilometers in a 2D-histogram.

price of 0.44 EUR/kWh in 2030 (resulting from the energy charged at and number of all public charging points). With the electricity price of 0.32 EUR/kWh about 65 kWh/wk (3,338 kWh/yr) have to be charged for a public charging point to disburse. Several charging points are above this level, however, no best location for charging points can be found on the right panel of Figure 5.17. In combination with the left panel, the best locations should be 10–20 km away from the city center, since most charging points are built there and the usage would even be higher with a lower number of charging points in these zones.

Hence, it can be retained that charging points within a distance of 10–20 km away from the city center obtain the highest usage in the simulations and can pay off most easily. This may have to do with the home locations of first PEV users in the simulation who will be analyzed in the following.

Where do PEV users live?

In this last part of Section 5.3.2, the geographical location of homes of PEV users is analyzed. For this analysis only private PEV users are analyzed since the number of commercial driving profiles is too small for a further geographical distinction.

Figure 5.18 shows the distribution of homes of private PEVs (left panel) and all vehicles (right panel) in the vehicle stock with respect to the distance to the city center. While the left panel holds simulation results for several years, the right panel contains the distribution of homes of all vehicles in MOPS. Starting with the left panel of Figure 5.18, the simulation results of the private PEV stock are shown for 2018 until 2030 in three-year steps. While for 2018 no clear pattern can be found, the distribution is peaked at a distance of 20 km away from the city center in 2021. This peak is even more distinctive in later years with more than 50% of PEV user's homes between 10–30 km distance from the city center in 2020. When comparing the distributions to those of all private vehicles in stock (right panel of Figure 5.18), the image is even more clear: Potential PEV users living in a distance between 10–30 km away from the city center are better suited for

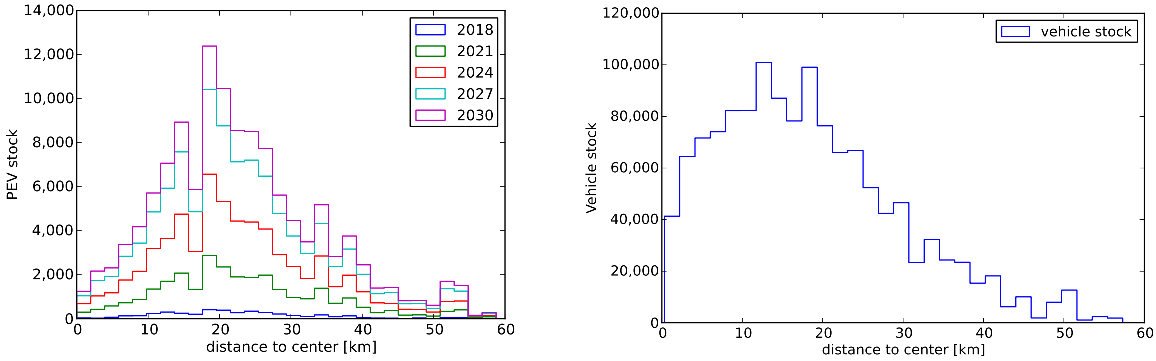

Figure 5.18: Simulation results for the region of Stuttgart for PEV and total vehicle stock with respect to distance of home (private) or company (commercial) to city center in subsidy scenario S3 (subsidies until 2030). Results are shown as contours of histograms. *Left panel:* PEV stock for different years. *Right panel:* Total vehicle stock.

PEVs than those living closer to the city center. Vehicle owners living further away from the city center perform higher mileages on average than users living in the inner city and high mileages are needed for PEVs to economize against conventional vehicles. This argumentation is supported by other studies as well [Plötz et al., 2014b, Newman et al., 2014]. Combining the results of the distances of PEV homes (1, Figure 5.18), CP locations (2, Figure 5.17) and vehicle zone occupancy public parking (3, Figure 5.13), the following picture seems conceivable: Most PEV users live further away from the city center (1). They drive into the center during the day (probably for work) (3) and go shopping or to sports on their way home. Then they probably recharge publicly (2) in some distance to the city center before returning home.

To sum up this section, the following findings should be recorded: (1) The availability of public charging points has neither an influence on PEV market diffusion, nor on the ratio of BEVs and PHEVs from a techno-economical point of view. (2) Public charging points cannot pay off when they are not subsidized until 2030 and some public charging points have to be retained until the number of PEVs and the energy charged publicly is sufficient. (3) Only 3% of the total energy for PEVs is charged at public charging points, the distribution over the day is similar to those of home charging points. (4) Public charging points with highest usage are within 10-30 km away from the city center as are the homes of most PEV users. The robustness of these results will be analyzed in the following subsection.

5.3.3 Variation of assumptions

The results presented in the previous section are subject to a number of assumptions. Several of these assumptions are varied in the following to test their influence. The following variations are tested and results are displayed for Germany: increasing charging power, changing the charging availability with additional charging at work, varying the individual limit to recharge, changing the initial charging price, varying the (de-)construction strategies for the CPO and changing the battery sizes.

Increasing charging power

The first variation is to increase the charging power. Two variations are compared to the subsidy scenario S3 with 3.7 kW chargers subsidized until 2030: (Power1) A variation with 22 kW chargers that are also subsidized until 2030 and (Power2) a variation with 50 kW charger and subsidies until 2030. In both variations, the assumed annual costs for both charging options are cut down to 100 EUR/yr and subsidies are calculated thereof.[107] Results for both variations and subsidy scenario S3 are displayed in Figure 5.19 which the PEV and CP stock using the same display as Figure 5.14.

Starting with the 22 kW variation, a slight decrease of charging points can be observed until 2017 which increases until 2021 and stays almost equal until 2030. Remembering the calculations for the differences of additional energy charged and change in subsidies, the amount of additional energy charged after 2021 is enough to compensate the higher cost of charging points. When comparing this variation to S3, a lower number of charging points is found in 2030 (34,000 vs. 78,000) and the fluctuation is not as high as in S3. However, the number of PEVs in stock is unaffected of this change in power.

Turning to the 50 kW charging option, a decrease in public charging points until 2018 can be observed with a slight increase until 2020. Thereafter, the number of charging points is not able to pay off, though subsidized until 2030, and decreases to zero in 2026. The high costs of the 50 kW charging points cannot be compensated by the amount of energy charged after 2020. Also in this variation, the number of charging points has no influence on the number of PEVs (and the share of PHEVs) and the subsidies for public charging points only determine the total number of public CPs. Hence, it can be stated that the power at public charging points does not influence the market diffusion of PEVs and only determines the number of public charging points due to their cost.

Additional charging at work

The second variation is to change the availability of charging options. Here, three different charging options are compared to subsidy scenario S3: Charging at home-only (and at commercial charging spots for fleet vehicles respectively), charging at home and at work for private vehicles and charging at home, work and in public. Since public charging infrastructure is only contained in subsidy scenario S3 and the variation with home, work and public charging, these are shown on the left panel of Figure 5.20 with the same display as in Figures 5.14 and 5.19. On the right panel, the total number of PEVs in stock in 2030 for all four options is visualized instead.

On the left panel of Figure 5.20 the green graph is used for subsidy scenario S3 and the orange one for the home, work and public charging variation, i. e. in the orange variation all private users are able to recharge at work additionally (cost for charging points at work in Table 4.2). All assumptions for subsidies to public charging points are equal in both variations. One observes a slightly higher starting point in terms of PEVs in 2015 for the orange graph due to the higher registrations of private PEVs. Also the number of public charging points in the home, work and public charging variation does not decrease as much as for home and public charging since the number of PEVs and their amount of public charging is higher. Most interesting, the number of PEVs in 2030 is higher when additional charging at work is possible for private users (4.7 million vs. 3.9 million

[107] See Table B.6 for all cost assumptions.

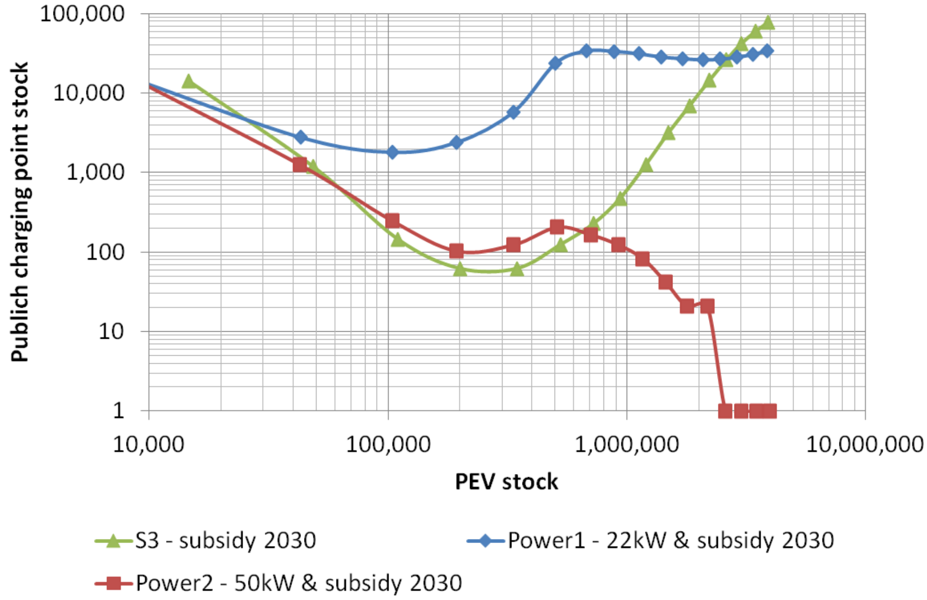

Figure 5.19: Simulation results for Germany for PEV and public CP stock with variation of charging power. Axes with logarithmic scales. Results for subsidy scenario S3 with 3.7 kW (subsidies until 2030) with green triangles, charging power of 22 kW (with subsidies until 2030) with blue diamonds and for 50 kW charging power (with subsidies until 2030) with red squares. If the CP stock is 0, it is set to 1 because of logarithmic scales.

PEVs in S3) and also the number of public charging points differs slightly with a higher number of public CPs in subsidy scenario S3. While the latter can be explained with the less frequent use of public charging points when additional work charging is available, the change in PEV stock has to be further analyzed. The question is, whether the additional charging spot at work or the combination of home, work and public charging is responsible for the change in the number of PEVs?

On the right panel of Figure 5.20 the amount of PEVs in 2030 for all four charging availability options is analyzed. Here, it is possible to compare whether public charging may help to increase the number of PEVs in stock. By comparing the green (subsidy scenario S3) and red bars (home-only charging), it can be confirmed that additional charging in public has no positive influence on the PEV stock when added to home-only charging. It even decreases the number of PEVs slightly due to some users that may incorporate public charging in their buying decision although charging at home would have been more economical for them. Then, the utility values for PEVs for these users may be higher than for conventional fuels and the number of registrations decreases. Although this effect should not be overstated as variations are only low, the non-existence of an influence of public charging points can be approved. Considering the blue (home and work charging) and orange bar (home, work and public charging), the same effect is visible as for the other two variations - additional public charging slightly decreases the number of PEVs. For all PEV options the share of PHEVs does not change significantly. While the same explanation holds for this comparison as given earlier, there are two main results from this part of the analysis: (1) no influence of public charging points on PEV diffusion results can be found and (2) charging at work increases the number of PEVs.

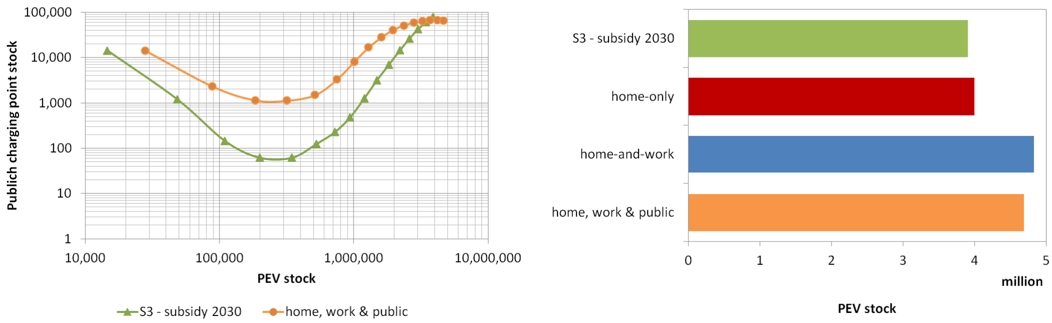

Figure 5.20: *Left panel:* Simulation results for Germany for PEV and public CP stock with variation of infrastructure availability. Axes with logarithmic scales. Results for subsidy scenario S3 (subsidies until 2030) with green triangles, additional charging at work (home, work & public) with orange diamonds. *Right panel:* PEV stock in scenario S3 (home&public, green), and variations home-only (red), home-and-work (blue) and home, work & public (orange).

Varying individual recharging limits and changing the initial charging price

After analyzing the influence of charging power and charging point availability, two more model assumptions are checked for their influence of simulation results: the limit of PEVs to recharge and the initial charging price.

As explained in Section 4.2.1, BEVs are always assumed to recharge when their battery's SOC is below 50%. The same holds for PHEVs for which driving with publicly charged electricity has to be cheaper than driving with conventional fuels additionally. This limit is changed to 70% and to 30% for two more calculations, which can also be understood as the range anxiety level of PEV users. Subsidies to public CPs are equal to subsidy scenario S3. Results for this analysis are shown on the left panel of Figure 5.21.

Surprisingly, results are almost equal for both variations and all public charging points are taken out of service until 2018. How can these very different assumptions return the same results? Turning to the variation with a limit of 30% at first. This variation assumed that vehicles are only recharged publicly when their battery's SOC is below 30%. Considering a case where a BEV arrives at a charging point with the battery SOC at 45% and it would not recharge although this would not be sufficient to return home. This may exempt several users from buying a BEV, if the individual simulation a BEV could not fulfill all his trips. Thus, only users that could fulfill their trips without public recharging would buy a BEV in this variation in the beginning, leading to a low amount of energy charged publicly and a deconstruction of charging points. Also the PEVs in vehicle stock would recharge only at a SOC of less than 30%, hence the amount of energy charged publicly would decrease even further. The variation with a 70% recharging limit suffers from a different problem: Vehicles that could return home to recharge now charge at public charging points. This increases their TCO for BEVs and they buy a PHEV or conventional car instead. In fact, results for BEVs decrease in the early years of market diffusion which decreases the amount of public charging. A higher subsidy to charging points would have been needed to keep them in stock.

Another option to increase the profitability of public CPs would be an increase of the public charging price to cover the cost for public charging points. A variation of an initial public charging price of 0.50 EUR/kWh is tested and results are shown on the right panel of Figure 5.21. Results are even more drastic than before, as now all PHEVs do

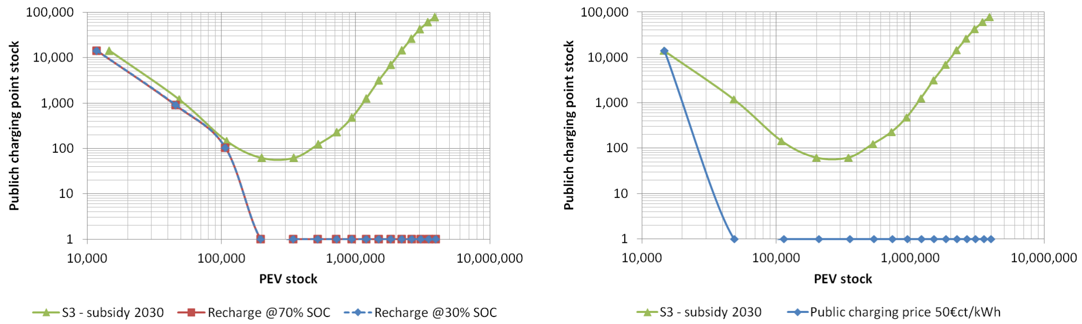

Figure 5.21: Simulation results for Germany for PEV and public CP stock with variation of recharging level when vehicles are expected to recharge and initial public charging price. Axes with logarithmic scales. *Left panel:* Variation of recharging level. Results for subsidy scenario S3 (subsidies until 2030) with green triangles where PEVs are assumed to recharge publicly at an SOC of less than 50%, an increased limit of 70% with red squares and a decreased limit with blue diamonds. *Right panel:* Variation of initial public charging price. Results for subsidy scenario S3 (subsidies until 2030) with green triangles where the initial public charging price is at 0.40 EUR/kWh and an increased price of 0.50 EUR/kWh with blue diamonds. If the CP stock is 0, it is set to 1 because of logarithmic scales.

not charge in public anymore since it is cheaper to drive with conventional fuels. This simply decreases the amount of public charging and the number of public charging points close to zero in the first years. A change to less than 0.4 EUR/kWh is not considered as the difference between the price for public charging ($p_{cp}(t)$) and electricity ($p_{el}(t)$), used to pay of public charging points, is already small.

These analyses showed that the initial public charging price as well as the level to recharge for public charging points have a major impact on the number of public charging points, yet the number of PEVs diffusing into the vehicle stock remains unaffected.

Changing the CPO strategies for charging point deconstruction and setup

As in all variations analyzed so far the deconstruction of public charging points has a major influence on the number of charging points. Hence, two further variations are tested in which a deconstruction is not considered: a variation without any subsidies for charging points (shown in blue on the left panel of Figure 5.22) and with subsidies until 2030 and a recharging level of 70% (in red). Results for the variation without subsidies show that the public CP stock stays equal until 2030 without changing the number of PEVs. This means that the energy charged at the public charging points is not sufficient for them to economize until 2030. The total energy charged at public charging points in the observation area is 2.5 million kWh/yr which is sufficient for 570 charging points (12,000 public CPs in Germany) to economize in 2030.[108] Thus again, public charging points do not diffuse into market without subsidies. This is also visible in the second variation without deconstruction that incorporates subsidies until 2030 and a higher SOC-limit (or level of concern) to recharge (70%). In this variation, the number of charging points increases for the first time in 2023 and reaches a higher number of public charging

[108] With a public charging price of 0.42 EUR/kWh and the price for electricity of 0.32 EUR/kWh, 0.10 EUR/kWh can be used to cover the cost for public charging points. This leads to $n_{cp} = \frac{0.10\text{EUR/kWh}\cdot 2.5\text{GWh}}{434\text{EUR/(CP yr)}} = 576\text{CP}$.

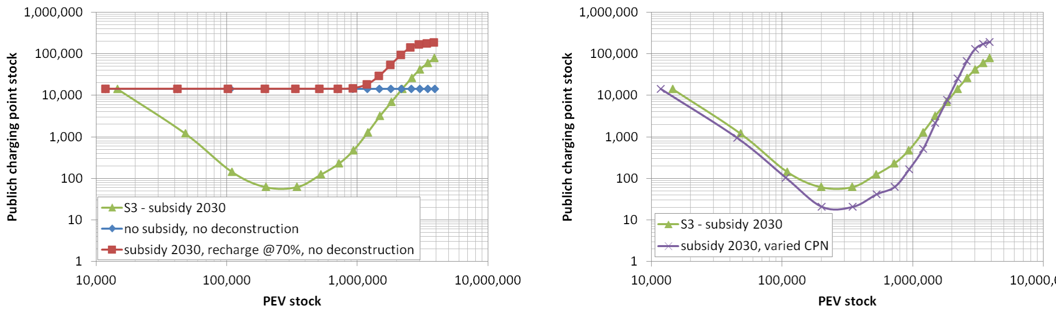

Figure 5.22: Simulation results for Germany for PEV and public CP stock with variation of charging point setup strategies. Axes with logarithmic scales. *Left panel:* Results for subsidy scenario S3 (subsidies until 2030) with green triangles, a variation where a deconstruction is not considered (no subsidies) with blue diamonds and a variation with non-consideration of deconstruction, necessity to recharge at 70% SOC and subsidies until 2030 with red squares. *Right panel:* Results for subsidy scenario S3 (subsidies until 2030) with green triangles and variation with a changed setup strategy with violet crosses.

points (185,000) than subsidy scenario S3 (78,000) because of the changed SOC-limit to recharge which increases the amount of public charging.

Although these results suggest a very clear picture, the location of initial charging points may not be well chosen and thus the amount of energy charged publicly could depend on the initial CP placement. Hence, on the right panel of Figure 5.22 a variation with a changed setup strategy is tested shown in comparison to subsidy scenario S3. In this variation, the minimum number of public charging points per zone is set to one. This allows a faster setup in zones with high demand for charging points and a lower minimum level of service. This variation shows similar results for the PEV stock like other variations as it does not change compared to subsidy scenario S3. In contrast to that, the CP stock is much higher (188,000 CPs) than in other variations (e.g. 78,000 CPs in S3). Thus, a different strategy for the setup of charging points could lead to a higher number of charging points or to a lower need for subsidies. However, it has no influence on the market diffusion of PEVs.

Variations of BEV battery sizes

Lastly, the model results are tested with a variation of battery sizes. Since the level to recharge also depends on the battery size, this assumption may influence results for charging infrastructure as well. While in subsidy scenario S3 a battery size of 40 kWh is assumed, it is changed to 24 kWh in the first variation and increasing from 24 kWh (2014) to 40 kWh in 2020 and remaining stable afterwards in variation 2. In all variations, charging points are subsidized until 2030 and results are shown on the left panel of Figure 5.23.

A higher starting point of PEVs in stock can be observed in both variations and the typical decrease in the number of public charging points (until 2018/2019) as well. However the number of PEVs is higher in the variation with a 24 kWh BEV battery as a higher share of potential users can afford a PEV. In this variation, the number of PEVs in 2030 is 6.5 million PEVs and the number of charging points is higher as well (315,000 CPs). This stems from the affordability of BEVs for a large number of users

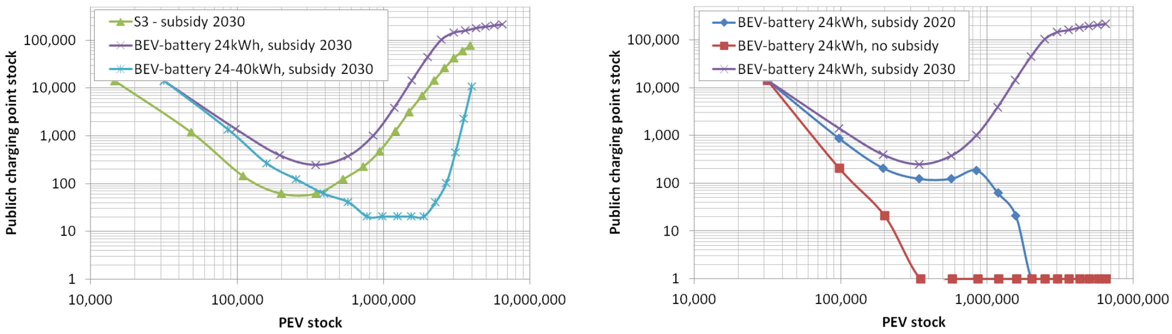

Figure 5.23: Simulation results for Germany for PEV and public CP stock with variation of BEV battery sizes. Axes with logarithmic scales. *Left panel:* Results for subsidy scenario S3 (subsidies until 2030) with green triangles where the BEV battery capacity is 40 kWh, a variation with BEV battery capacities of 24 kWh and CP subsidies until 2030 with blue diamonds and a variation with BEV battery capacities of 27 kWh in 2015 rising to 40 kWh in 2020 and remaining stable afterwards plus CP subsidies until 2030 with red squares. If the CP stock is 0, it is set to 1 because of logarithmic scales.

and the PEV stock changes ratios from two thirds PHEVs in S3 to two thirds BEVs in the 24 kWh BEV battery variation. The variation with changing battery sizes returns the same number of PEVs as subsidy scenario S3 although the number of public CPs is different. The PEV stock changes from mostly BEVs in this variation in the beginning to a higher number of PHEVs which might explain the variation in the CP stock.

Having found a variation with more PEVs, the influence of public charging points should be tested again. On the right panel of Figure 5.23 three different subsidies are shown for the 24 kWh battery: (B1) no subsidies for public CPs (with red squares), (B2) with subsidies until 2020 (blue diamonds) and (B3) with subsidies until 2030 (with violet crosses). The results are similar to those shown in Figure 5.14: (1) The height and timing of subsidies changes the amount of public charging points in 2030. (2) Subsidies have to be granted also after 2020 to reach a tipping point where they economize on their own. Although the number of charging points varies (3) no influence of public charging infrastructure on the market diffusion of PEVs can be found as results for PEVs in stock are equal in 2030.

Having changed various assumptions for charging infrastructure and PEVs, it can be retained that the market diffusion of public charging points has no influence on the market diffusion of PEVs as well as the ratio of PHEVs and BEVs. The number of PEVs instead determines the profitability of public charging points. For this reason, public charging infrastructure has to be subsidized until a critical mass of PEVs with the respective amount of public energy charged is in the vehicle market. According to various calculations this tipping point is after 2020.

5.3.4 Estimation of fast charging need

In the previous subsection, the influence of different power levels was analyzed. Charging stations with 50 kW were analyzed and could not economize until 2030. However, in the combined market diffusion approach for PEVs and their charging infrastructure, it is assumed that PEVs are connected to the charging points whenever they are parked.

Since the charging time at 3.7 kW or 22 kW chargers is frequently exceeding the parking time this assumptions seems to be in order for so-called slow-charging options [BMWE, 2015]. For fast charging options, like the 50 kW charging stations, the charging time per charging event often exceeds the time connected to a charging point. With a higher amount of energy necessary to amortize, this approach could underestimate the potential for fast charging stations. Further, the possibility to interrupt a trip and recharge if the battery capacity is sufficient, is not considered in this approach.

In Section 5.2.3, an approach was introduced in which BEVs could replace their vehicles by rental or car-sharing cars if the battery capacity was exceeded. This approach bases on the methodology of [Plötz, 2014] that permits to estimate the days on which the BEV battery capacity is exceeded. Instead of rental cars, long-distance trips could be covered by recharging at fast charging points as well (cf. [Lin and Greene, 2011] for a similar approach). A simple assumption is used for a rough calculation: For every day on which the electric range of a BEV is exceeded, a potential BEV buyer would once have to pay 10 EUR (for 20 kWh of public charging, i. e. a public charging price of 0.50 EUR/kWh) to cover his mobility need. The additional range from recharging of about 100 km is sufficient for most profiles. PEV simulations with ALADIN are run with parameters of the medium scenario and the profiles of MOP to test this option.

The total number of PEVs increases with the fast charging approach by about 15% from 4.8 million PEVs to 5.5 million PEVs, thus this approach returns more PEVs. The BEVs in stock need to refuel 30 times per year on average, thus the total amount of money that could be earned with such an offer would sum up to 2.0 billion EUR between 2015 and 2030. While of the 0.50 EUR/kWh, 0.30 EUR/kWh would have to be subtracted for electricity, the remaining 0.20 EUR/kWh or 800 million EUR would serve to cover the cost for charging infrastructure. In [Plötz et al., 2013, p.158,159] the average terminal value[109] for a fast charging point is on average 70,000 EUR (between 2015 and 2030), so about 12,000 such charging points could be covered with the assumed costs.[110] Thus, the fast charging option can be considered a more economic charging option than the slow-charging point. Yet, what would the usage rate of such charging facilities be?

The vehicle stock in 2030 contains about 1.2 million BEVs in the variation calculated with additional cost for fast charging. If these vehicles recharge 30 times per year at public fast charging stations, about 36 million fast charging events would take place over the year or about 96,000 per day. If these were equally distributed to the fast charging stations that contain three charging spots, then at every charging spot, 3.2 BEVs would recharge per day taking 1.25 hours. This charging time seems possible, yet it is based on the assumption that fast charging events are equally distributed over the year and between all charging stations. Since this approach does not analyze any simultaneous arrival at charging stations, it can only be considered a rough estimate. However, in contrast to slow charging stations, the PEV stock can be increased with such fast charging options and the economics seem more favorable than for slow charging points.

[109]Here the terminal value of the cost is considered which combines investments and running costs of charging points to the TCO and transfers them to their end point.

[110]For charging points with a 50 kW, costs are taken from [Plötz et al., 2013, p.152].

5.3.5 Discussion

In the following, the data used for the analysis, several specific assumptions for public charging and the main results with respect to other studies are discussed.

For the co-diffusion of PEVs and their charging infrastructure a set of driving profiles has been used that contains geographic information of the vehicle trips. This information is decisive to determine the usage of public charging points, however, the data set lacks some socio-demographic attributes that could have been used in the simulations or for the assignment of a WTPM. For this reason, the following adjustments were made (cf. Section 4.3.6): (1) The WTPM was randomly assigned to private driving profiles. (2) Company car users were assigned to the private vehicle profiles based on the attributes: sex, occupation, household size, cars in household and driving behavior. (3) Garage ownership was randomly assigned to driving profiles based on the settlement structures of their homes and [infas and DLR, 2002]. By comparing market diffusion results of simulations with the two data sets and home-only charging, the influence of these assignments can be tested. Table 5.7 shows the results of the German PEV stock in 2030 for simulations with home-only charging for both data sets.

Table 5.7: Comparison of results with data for Germany and Stuttgart. All results for PEVs in vehicle stock in Germany in 2030 based on the medium scenario and home-only charging.

	German data		Data for region of Stuttgart	
data sets	MOP & REM2030		MOPS & REM2030S	
total number of PEVs	4,839,000	100%	3,991,000	100%
private PEVs	3,388,000	70%	2,685,000	67%
company car PEVs	273,000	6%	0	0%
private PEV garage owners	3,039,000	63%	2,219,000	56%
PHEVs	2,946,000	61%	2,830,000	71%

Results for both data sets differ in terms of total PEVs in stock in 2030 while the share of private vehicles is about equal. Company car PEVs are not found in the results simulated with MOPS & REM2030S at all and private PEVs are less frequently bought by garage owners for the data from Stuttgart. In contrast to that, the share of PHEVs is higher with the data from Stuttgart. How can these changes be explained? As shown in Section 5.2.2, a random allocation of the WTPM to private driving profiles decreases results until 2020 by about 10% and 5% in 2030. Thus, decreasing the total number of PEVs in stock in 2030 by 5% (of private vehicles) would return 4,577,000 PEVs. By further subtracting all company car PEVs (273,000 PEVs) the total number reduces to 4,304,000 PEVs in 2030 which is very close to the results with the data from the region of Stuttgart and certainly within the 90%-confidence bands due to limited sample sizes (cf. Figure 5.5). Thus, the results for PEVs presented in Section 5.3 should be about 20% higher, however, the conclusions do not change. The slightly lower vehicle mileage in the MOPS-data (cf. Section 3.2.2), the differentiation of vehicle sizes as well as the changing battery sizes[111] may influence the PEV garage ownership as well as the share of PHEVs. Also garage ownership for PEV users could be correlated to the WTPM and hence cause an error. Yet, these effects have not been quantified up to now.

[111]The simulation of the German data (MOP, REM2030) was performed with a battery size of 27 kWh in 2015 for medium sized BEV increasing to 40 kWh in 2020 and thereafter.

Several assumptions for charging points were discussed in Section 5.3.3 in which the influence of charging power, charging infrastructure availability, SOC-limits for users to recharge or another initial charging price were discussed. Also different strategies for the CPO for CP deconstruction and setup as well as different battery sizes were investigated. The minimum number of public charging points also influences results as the first charging points to be built are created based on the (driving and) parking behavior of conventional vehicles. It could be better to focus on the parking of PEVs, however in the beginning the limited number of PEVs is not expressive for the zone occupancy and a CPO would focus on the congestion and zone occupancy of conventional vehicles. With a certain number of PEVs his focus would change to PEVs. Another option would be to combine the two setup strategies, however no good mechanism was found to combine the occupancy of a small number of PEVs (e.g. 0.5 million in 2020) and a large number of conventional vehicles (45 million conventional vehicles), since their occupancy rates differ largely. A different initial charging infrastructure could also be used, e. g. a randomly distributed. Yet, the current public CPs in the observation area are already in place and should not be neglected. Moreover, in all variations most of this initial charging infrastructure is deconstructed.

Further, the more general assumption every user needs one home-charging point may be doubted. Yet, in Section 5.2.3, it was shown that charging at work-only would decrease the number of PEVs by 50%. Since vehicles park even less in public than at work, a frequently used charging point seems to be a valid presumption. Combining investment and variable cost to a TCO for public charging points might be discussible as well. Especially when investments are much higher than running cost, this might be true, although the reproduction of diesel market shares in Section 4.4.1 contradicts this hypothesis. However, at least for slow charging points the operating expenditure often exceeds the annual capital expenditure which also supports the assumption to switch off charging stations when they do no economize.

Apart from all assumptions that would change results for public CP market diffusion, all public slow charging points would have to be subsidized until 2030. The question is: Can a positive correlation of the timely evolution between public CPs and PEVs be triggered with such a subsidy? Figure 5.24 shows the correlation of the timely evolution between public CPs and PEVs with respect to the total subsidies to public CPs until 2030. To compare small and large values of the market diffusion of PEVs and public CPs, the logarithm to the base of 10 of values for PEV stock $S_{m,s}(t)$ (with $s \in \{BEV, PHEV\}$) and public CP stock $n_{CP}(t)$ is used for the correlation. The Pearson correlation coefficient is applied with $\rho = \text{cov}(x, y)/(\sigma_x \cdot \sigma_y)$ with $x(t) = \log_{10}(S_{m,s}(t))$ and $y(t) = \log_{10}(n_{CP}(t))$ (see e.g. [Efron and Tibshirani, 1994]). The correlation coefficient for all subsidy scenarios and variations are displayed with 90%-confidence intervals[112] and the color indicates the duration of subsidies: no subsidies with green, subsidies until 2020 with red and subsidies until 2030 with blue markers. There are two main findings to be observed: (1) No positive correlation can be found when public CPs are not subsidized until 2030. This is visible for all subsidy scenarios and variations that are close to the abscissa in Figure 5.24. (2) Even when public CPs are subsidized, a positive or negative correlation may result from the simulations. There are several subsidy scenarios and variations where a subsidy is granted for every public CP until 2030, yet the stock of public CPs decreases to zero. Also, (3) the

[112]For the determination of confidence bands, the Fisher-transformation is used with $m = \text{arctanh}(\rho)$, $SE = 1/(\sqrt{(n-3)})$ and $z = (x - m)/SE$ (see e.g. [Efron and Tibshirani, 1994]).

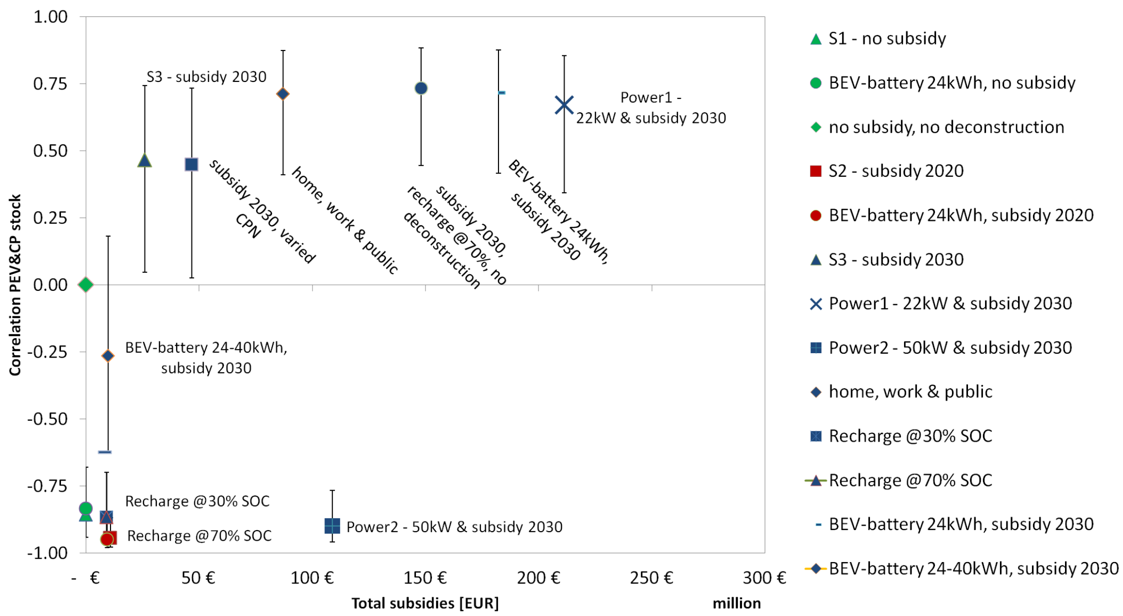

Figure 5.24: Relation between subsidy to public charging points and correlation of timely evolution of PEV and public CP diffusion. Total subsidies on ordinate, correlation of PEV and public CPs on abscissa. Results for all subsidy scenarios and variations of Section 5.3 shown with different markers and whisker for confidence intervals. Subsidy scenarios and variations without subsidies with green, with subsidies until 2020 with red and until 2030 with blue markers.

broad confidence intervals indicate a large uncertainty in the correlation and thus to the effect of subsidies granted (cf. [Schroeder and Traber, 2012] for a similar evaluation).

In earlier works [Plötz et al., 2013, Gnann et al., 2015b, Plötz et al., 2015], the effect of other policy measures was analyzed of which some results are briefly repeated here to set the subsidies for charging points into context. Three of the policy options analyzed in [Gnann et al., 2015b] are shown in Table 5.8: (P1) A flat-rate subsidy given to users which started with 1,000 EUR in 2013 and decreased linearly to 300 EUR in 2020. (P2) A decrease of the interest rate for private users from 5% to 4% and (P3) a tax exemption for PHEVs. For these policy options the market diffusion of PEVs was analyzed until 2020 with slightly different parameters than throughout this thesis. Yet, the relative difference to the medium scenario and the range of subsidies of policy options should be comparable.

The total subsidies that had to be paid for these policy options until 2020 (744 million EUR for P1, 2,493 million EUR for P2 and 68 million EUR for P3) are generally higher than those for public charging points (26 million EUR in S3 and 211 million EUR in Power1).[113] As public charging points are subsidized until 2030 the subsidy per PEV user is obviously lower, yet the the PEV stock does not change when public charging points are subsidized. For an uptake of PEV market diffusion the three other policy options would offer a more effective solution, even when their total subsidies are considerably higher. Which policy option is best for an introduction of PEVs is subject of a controversial public and scientific discussion [Srivastava et al., 2010, Diamond, 2009, Mock and Yang, 2014, NPE, 2014, Gass et al., 2014, Bakker and Trip, 2013, Jin et al., 2014].

[113] Also Dong et al. (2014) state that subsidies to public charging points are generally low compared to other policy options [Dong et al., 2014].

Table 5.8: Financial policy options modeled. Shown are the PEVs resulting from the policy options as well as necessary subsidies in total and per user. All subsidies in EUR_{2014}.

Policy option	PEV stock	total subsidy	subsidy per PEV
Units	*PEVs 2020*	*million EUR*	*EUR/PEV*
Medium scenario	631,000	-	-
(P1) Flat-rate subsidy of EUR 1,000, decreasing	1,118,000	744	1,529
(P2) Lowering private interest rate on investment	1,143,000	2,493	4,873
(P3) Tax exemption for PHEV, REEV	685,000	68	1,248
Units	*PEVs 2030*	*million EUR*	*EUR/PEV*
(S1) No subsidies to 3.7 kW chargers	3,991,000	-	-
(S3) Subsidies to 3.7 kW chargers until 2030	3,896,000	26	7
(Power1) Subsidies to 22 kW chargers until 2030	3,860,000	211	55

For fast charging a rough estimate showed that this charging option might be more promising for CPOs and the PEV market diffusion than slow charging points. This estimate could certainly be extended in further research, since it also covers a general criticism of charging simulations based on driving profiles: the possible interruption of a trip to recharge that is not covered in the PEV simulation of the proposed model.

These results are based on the model proposed in Chapter 4 in which public charging infrastructure is modeled from a mostly techno-economical point of view. In Section 5.3.1, a zone-specific minimum number of public charging points was defined which has to be in place for a vehicle buyer to consider it in his buying decision (see Section 4.2.1). Although minimum number of charging points symbolizes a potential barrier to the adoption of PEVs, the option to potentially recharge could have a greater influence on model results. However, the lack of data in this field of research does not permit a more detailed integration into the vehicle buying decision.

To the best of the author's knowledge, there are no studies treating the interaction of PEVs and their charging infrastructure that could serve for comparison. The studies analyzed in Section 2.2 treated different AFV-types, yet several results could be generalized to all AFVs. Köhler et al. (2010) found that only a small subsidy is needed for the initial refueling infrastructure and infrastructure was not a major barrier for the diffusion of FCEVs [Köhler et al., 2010]. While the small subsidy to public charging can be confirmed with this analysis, the present study shows that public charging infrastructure is not necessary for a PEV market diffusion when PEV users buy a private or commercial home-charging point. This primary charging point is necessary for a market diffusion of PEVs as stated by [Schwoon, 2007, Stephan and Sullivan, 2004, Melaina, 2003].

5.3.6 Summary

In this subsection the co-diffusion of PEVs and public charging infrastructure has been studied. A 3.7 kW charging option with three subsidy options was studied in detail in Section 5.3.2 with respect to the number of PEVs and CPs, several energy related aspects as well as locations of charging points and PEV users homes. Thereafter a number of variations was analyzed to test the robustness of results. A brief analysis of fast charging points and a discussion rounded up this section. The following findings can be extracted from this analysis:

- No impact of public slow charging points on the market diffusion of PEVs can be determined in any subsidy scenario or variation analyzed. The number of PEVs on the other hand influences the profitability of public charging points. Until a sufficient number of PEVs has diffused into the vehicle stock, a subsidy to charging points is needed to cover the expenses. A tipping point will most likely be beyond 2020.
- The energy charged at public charging points will not have a significant impact on the energy system, since the load shift potential from private load to public charging stations is low as both are most occupied at the same times. Also the energy charged at public charging points is only around 3% of the total energy charged by PEVs.
- Charging points with the highest use rates and PEV owners' homes are located 10–30 km away from the city center.
- An increase of power, a variation of the minimal SOC before recharging and the initial public charging price have no influence on the PEV market diffusion.
- Decreasing the battery sizes of PEVs or offering additional charging points at work to private users increases the number of PEVs in stock. However, this increase is not connected with public slow charging infrastructure.
- First calculations indicate that public fast charging points could increase the number of PEVs and offer a more economic public charging point option. More effort needs to be spend on their investigation.

5.4 Synopsis of simulation results

This chapter aimed at analyzing the market diffusion of PEVs and their charging infrastructure using the model proposed in Chapter 4. Three parts were presented with a rising model complexity: the market potential of PEVs as private or commercial vehicles (Section 5.1), the market evolution of PEVs with non-public infrastructure (Section 5.2) and the co-diffusion of PEVs and their infrastructure (Section 5.3). Here, results are compared to each other and their implications are discussed.

Commercial fleet vehicles are the most important user group for PEV sales, followed by private and lastly company cars. Commercial fleet vehicles show a higher market potential for PEVs than private vehicles. The larger shares of commercial vehicles in new registrations in Germany as well as the reimbursement of VAT and depreciation allowances for commercial vehicles increase the market potential for PEVs in general. The analysis of commercial fleet driving profiles collected for this thesis also shows a favoring higher mileage and regularity compared to private driving profiles. This results in higher PEV market shares in registrations for fleet vehicles than for private vehicles. That also influences the need for public charging infrastructure, as commercial PEVs charge less often in public.

Framework conditions have the largest impact on PEV diffusion, followed by battery sizes and charging options at work. Public (slow) charging points have no impact on PEV market diffusion. While market shares are larger for commercial fleet vehicles, the stock is dominated by private users in which PEVs diffuse through the second-hand car market. The market diffusion of PEVs is strongly dependent on framework conditions, especially on energy and battery prices. Results for three scenarios range from 2 to 10 million PEVs in Germany in 2030. This is also visible on the left panel of Figure 5.25 which shows a comparison of results for the market diffusion of PEVs that were shown in Section 5.2. Non-monetary factors like a WTPM or the cost for individual charging infrastructure have an influence on PEV market diffusion in the beginning (cf. Section 5.2.2 and [Gnann et al., 2015b]), yet it decreases over time (as assumed ex ante). Apart from framework conditions, only additional charging points at work have a considerable influence on the diffusion of PEVs in the simulations without public charging infrastructure.
The interaction of PEVs and their charging infrastructure is complex, since charging options for PEVs have to be divided into three groups: domestic or commercial, work and public charging points. Section 5.3 especially focused on the interaction of public CPs and PEVs. The right panel of Figure 5.25 shows all simulation results of Section 5.3 with the number of public CPs in 2030 on the ordinate and the number of PEVs in stock in 2030 on the abscissa. This figure again demonstrates that most subsidy scenarios and variations are on a horizontal line, indicating that the number of public charging points has no influence on the PEV diffusion. Only two options increase the PEVs in stock in 2030: A decrease of BEV battery sizes (raises the PEV stock by about 2.5 million additional PEVs) and additional charging points at work (about 700,000 PEVs). Also the decrease of BEV battery sizes raises the PEV stock independent of the number of charging points.

For a PEV diffusion, most important are domestic and commercial charging points, followed by charging points at work and lastly in public. Results show that the availability of domestic or commercial charging points has the most impact on market diffusion of PEVs which is cut to half when only charging at work is possible and to zero with public

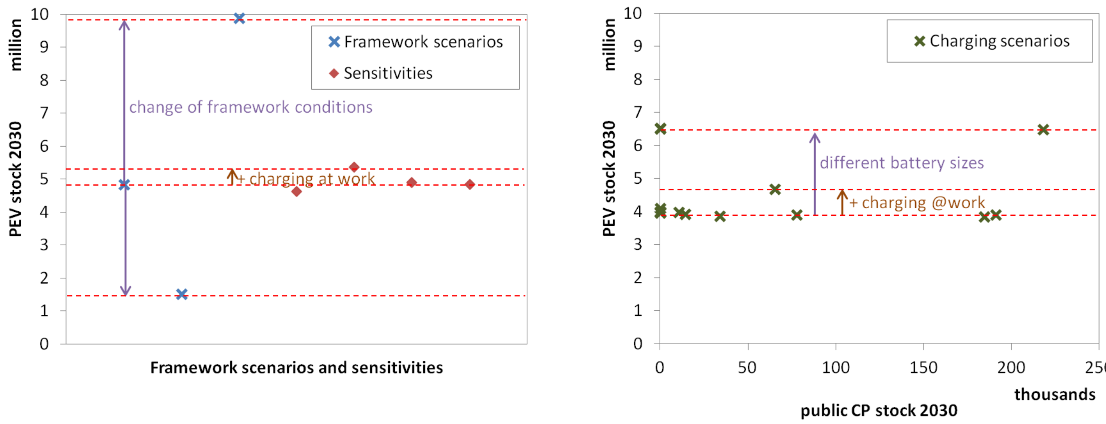

Figure 5.25: Comparison of simulation results. *Left panel:* Results of PEV market diffusion without public charging infrastructure from Section 5.2. Framework scenarios with blue crosses and sensitivity calculations with red diamonds. *Right panel:* Results of PEV and public CP market diffusion in 2030. Calculations of Section 5.3 shown with green crosses.

charging points only. The number of PEVs can be increased with additional charging points at work, also when users have to pay for it. Public slow charging points (≤22 kW) can not increase the number of PEVs, independent of their exact configuration, while public fast charging points (>22 kW) indicate slight increases in a rough estimate. Lin and Greene (2011) come to similar conclusions for charging power (cf. [Lin and Greene, 2011]). The market diffusion of PEVs has a noteworthy impact on the diffusion of charging points on the other hand. For the assumed one-to-one allocation of individual charging points this connection is predefined, yet the number of PEVs is also decisive for the diffusion of public charging points. Public (slow) charging infrastructure needs to be subsidized until reaching their tipping point. In all calculations made in this thesis, this tipping point is beyond 2020.

The problem of a limited range of BEV users can best be addressed by a switch to PHEVs, then by a increase of battery sizes. Additional charging options and rental cars are less important from a techno-economical point of view. Resuming the possibilities to increase the assumed range of BEVs in Section 5.2.3, four possibilities were discussed: (1) switch from BEV to PHEV, (2) use substitute vehicles, (3) raise charging options and (4) increase a BEVs battery size. In Section 5.2.3, the alternative use of rental cars for long-distance trips was discussed (case 2), which might help in the beginning of a market diffusion, yet not in the long term. Additional charging options (case 3) would help to increased the BEV range if created at work and increase the PEV stock in 2030. Also public fast charging points may be an option, yet slow charging in public does not increase the PEV stock in 2030. Increasing the battery size (case 4), to simply gain range, may not be affordable for a large number of vehicles (cf. Section 5.3.3). Thus, offering affordable BEVs with an user-accepted range will be the key task for the automotive industry in the next years. Switching to a PHEV (case 1) does not increase the range of the BEV, but it may be the favorite option for a large number of potential PEV customers during the next years. Almost all results throughout this thesis confirm this statement.

Chapter 6

Conclusions and further research

6.1 Summary and conclusions

Plug-in electric vehicles are a means to reduce greenhouse gas emissions and the dependency on fossil fuels from the transportation sector. However, their diffusion depends, among other factors, on the prevalence of a charging infrastructure and vice versa. Hence, the aim of this thesis was to answer the following question: *"How do the diffusion of plug-in electric vehicles and the diffusion of their charging infrastructure mutually influence each other?"*

For this purpose, an agent-based model has been developed that simulates potential PEV buyers individually with the existing charging infrastructure and jointly simulates PEV users and their interaction at public charging points for Germany until 2030. A charging infrastructure agent decides about the setup or deactivation of public charging points based on the publicly charged energy and associated revenues. The individual analysis permits to examine charging at different infrastructure facilities - at home (domestic or commercial), at work and in public - which is decisive since the usage of one charging facility influences the other [Schroeder and Traber, 2012].
The model is based on driving profiles with an observation period of at least one week to cope with the variation in driving between users and days. Two household travel surveys with an observation period of one week were used to extract the driving behavior of private vehicles. As for commercial vehicles, driving profiles with an observation period of more than one day were not publicly available, more than 500 commercial vehicle driving profiles with an observation period of three weeks have been collected for this thesis. Further, two types of PEVs are distinguished in the analyses - PHEV and BEV - that have different needs for the charging infrastructure since PHEV can refuel conventionally as well.
Three scenarios were defined with different prices for the most important framework conditions: electricity, fuel and battery prices. A scenario with favorable conditions for PEVs (pro-EV) and a scenario with unfavorable conditions (contra-EV) were completed by a medium scenario in between the two. None of the scenarios makes extreme assumptions, e.g. the oil price lies between 115 $\$_{2014}$/bbl and 180 $\$_{2014}$/bbl in 2030. The following scenario-independent findings respond to the initially proposed research questions (Chapter 1). They are divided into contentual and methodological results and conclusions.

There is no lock-in in the co-diffusion of PEVs and their charging points for countries *with a large availability of home charging points.* Model results show that, a domestic or commercial charging infrastructure has a strong influence on PEV diffusion results and covers the needs of most PEV users. A simulation of charging only at work showed that the PEV stock was cut by half and charging only at public charging points would return even fewer PEVs since parking durations at these sites are too short. Thus, charging at home is a prerequisite for a large number of PEVs. Additional charging at work could increase the number of PEVs since this would effectively increase PEVs' electric ranges. Additional charging at public slow charging points ($\leq$22 kW) has no influence on market diffusion results of PEVs which was demonstrated in multiple scenarios. Parking times are either not sufficient or public charging is not necessary to be able to drive PEVs. Additional calculations with a slightly adapted approach for public fast charging points (>22 kW) indicate a potential stimulation of PEV diffusion, though further research on this topic is needed.

The diffusion of public charging points follows the diffusion of PEVs. The influence of PEVs on home and work charging points was not analyzed since their one-to-one allocation (one home and/or work charging point per vehicle) was a prerequisite of the model. For public charging points a strong influence of the number of PEVs was found. The number of PEVs and their usage determines the profitability of public charging points. Until there is a sufficient number of vehicles charged with a good amount of public energy charged, public charging points have to be subsidized in large measure. Yet, the most important charging infrastructure type for PEV diffusion are charging points at home (domestic or commercial), followed by charging points at work and lastly by public charging points.

Framework conditions are more important than public charging points. With charging infrastructure only at domestic and commercial sites, a PEV market diffusion of 2-10 million PEVs, depending on assumptions, is possible for Germany until 2030. However, the diffusion of PEVs is largely influenced by framework conditions, such as oil, electricity and battery prices. While the influence of a PEV diffusion on energy prices is supposedly low until 2030, potential policies to foster PEV market diffusion should be dynamically adaptable to react to changing framework conditions. Further, the configuration of vehicles (especially battery sizes) influences the total number of PEVs. Thus, car makers have to find the right balance between vehicles with high ranges and their affordability to the customer. All simulations show a higher share of PHEVs and commercial vehicles which both have a limited need for a public charging infrastructure. It can be confirmed that "inadequate recharging availability will not be the key barrier in holding back the near-term penetration of BEVs-PHEVs" [Lin and Greene, 2011]. This statement may also apply to public charging points in the medium-term if battery technology keeps developing and electric ranges are extending.

In countries with home-charging options, an extensive public charging infrastructure roll-out is not necessary from a techno-economical point of view. As a result, policy makers should focus on facilitating the access to home charging points for potential PEV buyers with monetary or non-monetary instruments. Similarly, regulatory barriers for charging at work may be reduced, e. g. a tax exemption for charging at work which could be considered a fringe benefit to the employee (see also [Trigg et al., 2013]). For public charging points the focus should lie on fast charging which is not an unusual situation to the user because of the similarity to conventional refueling stations and fewer charging points are needed. Here, the terms of billing, like the exact measurement of energy charged, could be facilitated. Investments in public charging infrastructure remain a risk though [Schroeder and Traber, 2012]. In EU directive 2014/94/EU, which deals with the deployment of an alternative fuels infrastructure, 150,000 public charging points in Germany by 2020 were proposed [EC, 2014], while the BMWE suggested 35,000 public charging points by 2020 [BMWE, 2015]. The model results contradict these numbers from a techno-economical point of view as the availability of home charging options and actual user behavior should to be taken into account.

The distinction of different access types for charging infrastructure - at home, at work, in public - is obligatory for a model development. The analysis of the co-diffusion of PEVs and their charging infrastructure is different to studies for other alternative drive trains, since the usage of different charging options depends on each other. Especially the public charging infrastructure diffusion should not be analyzed independently of home charging infrastructure diffusion which covers high shares of charging needs.

Driving behavior differs between drivers, days of individual drivers and user groups. While most studies focus on the typical mileage of a user on an average day, this is neither sufficient to identify early niche markets, nor does it reflect the requirements for PEVs to become economically viable. High annual mileage paired with regular driving within the electric range require a detailed analysis of individual driving behavior in different user groups. This requires driving profiles of more than one day.

The differentiation between BEVs and PHEVs is important. While BEVs are limited to the use of (public) charging points, PHEVs can also use refueling stations for range extension. The use of public slow charging points by PHEVs will most likely be opportunity charging only, while it may be a requirement for some BEVs. The large share of PHEVs throughout all model results indicates the necessity for their consideration.

Agent-based simulation models fit best for these various modeling requirements. The previously mentioned aspects make agent-based models the most promising approach to gain insights into the co-diffusion of PEVs and their charging infrastructure, since agent-based models are useful "when the population is heterogeneous, when each individual is (potentially) different." [Bonabeau, 2002]

Studies which analyze driving profiles individually should use driving profiles with long observation periods. Driving profiles are often used to cope with the variation in driving between different vehicle users. When driving profiles are used for an individual analysis of PEVs, a long observation period is decisive. This lowers an eventual overestimation of PEV-potentials as it covers the variation in driving.

Commercial vehicles should be analyzed individually when they have significant market shares. In Germany, commercial users account for more than half of the vehicle market and thus represent an important market segment for PEVs. Since special rules apply to their buying decision which differ from private vehicles, e. g. the exemption from VAT, they should be modeled separately. This applies for other vehicle markets as well if market shares have a relevant size or accounting rules differ between private and commercial vehicles.

6.2 Discussion and further research

Discussion

Different approaches to the diffusion of PEVs and the diffusion of their charging infrastructure are conceivable, e.g. modeling of coupled differential equations in a top-down approach. However, as mentioned in the last section, charging infrastructure should be divided into subgroups and their usage depends on each other. Also a distinction between PHEVs and BEVs is necessary, since the ability of PHEVs to refuel conventionally incorporates another option to refuel. The diversity of users and the task to identify a niche with convenient attributes for PEVs make such top-down approaches inadequate for this research question. Since no overall objective function can be formulated for this research question (PEVs could be maximized, however the number of public charging infrastructure may be maximized or minimized), an optimization model does not seem useful either. The individual rules that can be formulated for this large number of differently behaving users favor the use of a simulation model which is confirmed by previous modeling approaches (cf. Chapter 2). Further, the analysis is a model-based assessment and no probabilities of occurrence of the three scenarios can be given. Hence, conclusions are drawn related to the influencing factors of the diffusion of PEVs and their charging infrastructure, but not on their absolute number.

Concerning data, driving profiles with a "long" observation period were used. Although driving profiles with an observation period of one week or three weeks are more reliable for an individual analysis, they still do not cover all aspects of driving behavior, e.g. long-distance travels. This issue was addressed with an estimated number of days that exceed the electric range of PEVs in Section 5.2.3. Further, the number of driving profiles is limited, yet their representativeness was discussed in Chapter 3 and some results are shown with confidence bands due to the sample size (see Section 5.2.1). Like most studies, the analyses performed in this thesis could be improved with larger data sets. This especially applies to commercial fleet vehicle and company car profiles, but also to the magnitude and evolution of the WTPM. Since the joint simulation was performed with data for the region of Stuttgart, their results should not be directly transferred to less populated areas. However, the transferability to Germany was discussed in Section 5.3.5, finding comparable results for the market diffusion of PEVs for Germany. A projection to other countries might be a further field of research (see e.g. [Pasaoglu et al., 2014, Seixas et al., 2015]), but was beyond the scope of this thesis.

Moreover, results are based on scenarios and assumptions that were discussed thoroughly throughout this thesis. Yet, not all aspects influencing this topic could be incorporated into the model and some important facets should be mentioned: The simulations for the co-diffusion of PEVs and their charging infrastructure are performed for Germany from 2015 until 2030. This is an early market phase of PEVs in a highly industrialized country, and, e.g., not comparable to a complete replacement of conventional vehicles by plug-in electric vehicles. Results might differ for countries in which the electricity grid is not as elaborated and stable as for Germany. Several aspects could affect results in the long term, but are not incorporated into the model: Improvements in battery technology [Nykvist and Nilsson, 2015] are currently unknown and results for studies vary largely. Three evolutions were chosen that were discussed thoroughly with a groups of experts in this field [Plötz et al., 2013]. An inclusion of fuel cell electric vehicles like in [Propfe et al., 2012a] could be a model extension for the future, yet the focus of this study was to analyze the connection between PEVs and their charging infrastructure. In addition, an increasing use of car-sharing programs could affect the diffusion of PEVs in the long term, but until 2030 the number of PEVs in car-sharing is expected to not be the main driver for overall PEV diffusion. Rebound effects [Frondel et al., 2012] or a change in mobility behavior would both influence results, yet data on both effects is not publicly available in the desired granularity. Further on, feedback loops for the costs of batteries and vehicles representing economies of scale could also be incorporated into a later version of the model. Further, aspects like the ban on driving in cities due to air pollution, an intensification of European directive 443/2009 [EC, 2009], which treats the regulations of CO_2 emissions in the vehicle fleet, after 2020 or a tax on electricity charged for driving could affect PEV diffusion by large, yet they are beyond the scope of this study. Also, the psychological effect of a (public) charging infrastructure which might increase the need for public charging infrastructure was not the focus of this study.

Further research

This thesis aimed at analyzing the co-diffusion of PEVs and their charging infrastructure. While the author focused on answering this question, several further fields of research could be identified.

Modeling of public charging infrastructure in this thesis focused on techno-economical aspects. The psychological need for charging points for potential users is often stated, yet to the best of the author's knowledge unquantified. Retrieving quantitative data on the vehicle buyer's utility of charging infrastructure and integrating it into his buying decision would certainly improve the model. Also survey data about neighboring effects would ameliorate the interaction in the model and the switch to a multi-agent simulation could be possible. More research is needed that combines psychological and techno-economical aspects in general and for PEVs and their charging infrastructure in particular.

Further, initial calculations were made for the influence of fast charging points on PEVs in this thesis. Results showed that the profitability of fast charging points was higher and also their contribution to PEV diffusion is noticeable. These calculations were made with a different approach since staying connected to a charging point as long as vehicles are parked is appropriate for slow charging, yet not for the interruption of long-distance trips for fast charging. However, this analysis did not consider the simultaneity of charging events. Further research on the interaction of PEV diffusion and fast charging points could be an interesting research topic.

Moreover, energy-related aspects like load shifting, buffering energy for intermittent renewable energy or energy storage for PEVs have a minor relevance for Germany until 2030 [Dallinger and Wietschel, 2012,Heinrichs, 2014]. Yet, these could become relevant in local networks or with a faster increasing number of PEVs which may include additional benefits that make public charging points more profitable. In connection with a public charging infrastructure, this could be a further field of research as well.

Finally, the publicly available information about company cars is scarce. Their buying decision is more complex than for fleet vehicles and private cars, since the company (with a pre-selection) and the private user (with the final choice) are involved. Also data on driving behavior and their WTPM is hardly available. Understanding their buying behavior and their potential to adopt PEVs is an uncovered field of research.

Appendix A

Vehicle usage data

A.1 Extraction of private driving profiles

The private data sets MOP [MOP, 2010] and MOPS [Hautzinger et al., 2013] are both household travel surveys which contain the trips of all members of participating household.[114] Since in this analysis the movement of vehicles is of concern, all vehicle trips have to be assigned to vehicles where unambiguously possibly. The following assumptions are used (see also [Kley, 2011, Chlond et al., 2014]):

1. If there is only one vehicle in the household, trips of all household members as vehicle driver are assigned to the vehicle. In this case the socio-demographic information of the first driver is assigned to the vehicle profile.

2. If the number of vehicles exceeds the number of drivers, the trips of the first household member are assigned to the first vehicle, those of the second driver to the second vehicle until the last driver's trips are assigned. This might overestimate the driving of single vehicles.

3. If the number of vehicles is smaller than the number of household members, the vehicles will be exempted from the further analysis, since the allocation of trips to vehicles is unknown.

These assumptions are valid for both private data sets used in the analysis, MOP and MOPS, while details for both are explained in the following.

Extraction of vehicle driving profiles from MOP

The part of MOP used in this thesis contains mobility behavior of the years 1994 until 2010. For every year, there are four tables in MOP (XX indicates the year):

- *hhXX*: Household table which contains information about the household, e.g. household size, household income, city size, parking situation of vehicles in the household.

- *pXX*: Person table contains information about all members of participating households, e.g. their age, sex or education.

[114] For more details refer to Section 3.2. Note, that MOPS is a synthetic data set, yet the structure of tables is similar to MOP.

- *wXX*: Trip table that comprises all trips performed in the observation period and the means of transport.
- *tank(XX+1)*[115]: Refueling table which includes all information about the vehicles and their refueling behavior.

All files can be connected with their primary keys [MOP, 2010]. To retrieve the above mentioned cases in which an allocation of trips of persons to vehicles is possible, all trips are extracted with a vehicle as means of transport and the person as driver (*wXX.vmdiw=4*). For plausibility reasons, also the possession of a driving license is checked (*pXX.fspkw=1*). Then all households with only one vehicle (case 1) are extracted and all trips are assigned to the vehicle (see Listing A.1). Thereafter, all trips of persons in households with more vehicles than driver (case 2) are assigned to the vehicles while trips of the first stating driver are assigned to the first stated vehicle (*pkwXX.persnr = wXX.persnr*, see Listing A.1).

Listing A.1: MOP vehicle driving profiles extraction part 1

```
SELECT
  pkw10.hhid, pkw10.persnr, w10.jahr AS jahr, w10.wotag, w10.bertag,
  w10.datum, w10.abzeit, w10.zweck, w10.anzeit, w10.km, p10.sex,
  p10.gebjahr, p10.schulab, p10.beruf, hh10.raumtyp, hh10.kreis,
  hh10.ewzahl, hh10.hhtyp, hh10.einko,
  CASE tank11.pkwordnr
    WHEN 1 THEN hh10.parkstr1
    WHEN 2 THEN hh10.parkstr2
    WHEN 3 THEN hh10.parkstr3
    ELSE hh10.parkgar+1
  END AS garage, tank11.privpkw, tank11.nutzung, tank11.marke,
  tank11.baujahr, tank11.hubraum, tank11.benzin, tank11.kmjahr,
  tank11.hub_klas, pkw10.persnr AS pkwno, hh10.hhgro AS hhgro
FROM
  (SELECT
    wege.hhid, 1 AS persnr
  FROM
    (SELECT
      DISTINCT hhid, persnr
    FROM
      (SELECT
          id AS hhid, persnr
      FROM
          w10
      WHERE
          vmdiw = 4
      )
    ) wege,
    (SELECT
        DISTINCT pp.hhid, pp.persnr, pp.hh_pot_drivers, hh.pkwhh
    FROM
      (SELECT
          DISTINCT p1.hhid, p1.persnr, p2.hh_pot_drivers
      FROM
        (SELECT
            id AS hhid, persnr
```

[115] The household, person and trip table use the same year for one survey wave while the refueling table has the following year as connection: *tank11* belongs to *hh10*.

```
        FROM
            p10
        WHERE
            fspkw = 1
        ) p1
        LEFT OUTER JOIN
        (SELECT
            id AS hhid, COUNT(persnr) AS hh_pot_drivers
        FROM
            p10
        WHERE
            fspkw = 1
        group by id
        ) p2
        on (p1.hhid = p2.hhid)
      ) pp, hh
      WHERE
          (hh_pot_drivers > pkwhh AND pkwhh = 1)
      AND
          pp.hhid = hh.id
    ) personen
    WHERE
      wege.hhid = personen.hhid
    AND
      wege.persnr = personen.persnr
  ) pkw10
 , p10, hh10, w10, tank11
WHERE
  pkw10.hhid = p10.id
AND
  pkw10.persnr = p10.persnr
AND
  pkw10.hhid = hh10.id
AND
  pkw10.hhid = w10.id
AND
  pkw10.hhid = tank11.idhh
AND
  pkw10.persnr = tank11.pkwnr
```

Listing A.2: MOP vehicle driving profiles extraction part 2

```
SELECT
  pkw10.hhid, pkw10.persnr, w10.jahr AS jahr, w10.wotag, w10.bertag,
  w10.datum, w10.abzeit, w10.zweck, w10.anzeit, w10.km, p10.sex,
  p10.gebjahr, p10.schulab, p10.beruf, hh10.raumtyp, hh10.kreis,
  hh10.ewzahl, hh10.hhtyp, hh10.einko,
  CASE tank11.pkwordnr
    WHEN 1 THEN hh10.parkstr1
    WHEN 2 THEN hh10.parkstr2
    WHEN 3 THEN hh10.parkstr3
    ELSE hh10.parkgar+1
  END AS garage, tank11.privpkw, tank11.nutzung, tank11.marke,
  tank11.baujahr, tank11.hubraum, tank11.benzin, tank11.kmjahr,
  tank11.hub_klas, pkw10.persnr AS pkwno, hh10.hhgro AS hhgro
FROM
  (SELECT
```

```
    wege.hhid, wege.persnr
  FROM
    (SELECT
      DISTINCT hhid, persnr
    FROM
      (SELECT
          id AS hhid, persnr
      FROM
          w10
      WHERE
          vmdiw = 4
      )
    ) wege,
    (SELECT
        DISTINCT pp.hhid, pp.persnr, pp.hh_pot_drivers, hh.pkwhh
    FROM
      (SELECT
          DISTINCT p1.hhid, p1.persnr, p2.hh_pot_drivers
      FROM
        (SELECT
            id AS hhid, persnr
        FROM
            p10
        WHERE
            fspkw = 1
        ) p1
        LEFT OUTER JOIN
        (SELECT
            id AS hhid, COUNT(persnr) AS hh_pot_drivers
        FROM
            p10
        WHERE
            fspkw = 1
        group by id
        ) p2
        on (p1.hhid = p2.hhid)
      ) pp, hh
      WHERE
          hh_pot_drivers <= pkwhh
      AND
          pp.hhid = hh.id
    ) personen
    WHERE
      wege.hhid = personen.hhid
    AND
      wege.persnr = personen.persnr
  ) pkw10
, p10, hh10, w10, tank11
WHERE
  pkw10.hhid = p10.id
AND
  pkw10.persnr = p10.persnr
AND
  pkw10.hhid = hh10.id
AND
  pkw10.hhid = w10.id
```

```
AND
  pkw10.persnr = w10.persnr
AND
  pkw10.hhid = tank11.idhh
AND
  pkw10.persnr = tank11.pkwnr
```

Since the data structure changed over the years, this allocation has to be adapted for every year. Table A.1 shows the differences between the years with respect to the data of 2010.

Table A.1: Changes between observation waves in data set MOP.

Field	Problem	Concerns years	Solution
hhXX.Parkstr1	not available	1994-2002	hhXX.parkgar+1 as garage
hhXX.Parkstr2	not available	1994-2002	hhXX.parkgar+1 as garage
hhXX.Parkstr3	not available	1994-2002	hhXX.parkgar+1 as garage
tankXX.privpkw	not available	1995-1999	NULL as privpkw
tankXX.nutzung	not available	1995-1999	NULL as nutzung
tankXX.typ_k_a	different coding	1995,1996, 2000-2002	case tankXX.typ_k_a when 2 then 3 when 3 then 5 else tankXX.typ_k_a end as benzin
tankXX.typ_k_a	different coding	1997-1999	case tankXX.typ_k_a when 2 then 5 when 3 then 4 when 4 then 2 else tankXX.typ_k_a end as benzin
tankXX.kmjahr	not available	1995-2003	NULL as kmjahr
tankXX.hub_klas	not available	1995,1996, 2002	NULL as hub_klas
tankXX.id	Combination of HHID and PersNr	1995-2001	hh94.id = tank95.id/10 (div); p94.pkwnr = tank95.id %10 (modulo)
tankXX.pkwnr	not available	1995-2001	tankXX.pkwnr = tankXX.id %10 (modulo)
tankXX.pkwnr	not available	2002	tankXX.pkwnr = tankXX.pkwnrhh
tankXX.marke	ASCII-coding	1994	*coding like 2010*

After the extraction of all driving profiles, trips with 0 km are deleted (three cases) and trips with arrival times prior to departure (two cases). Since the field *tankXX.hub_klas*, which contains the vehicle size, is not completely filled, the size of the vehicles is determined by their cubic capacity: small ($<$ 1,400 ccm), medium (1,400 ccm $\leq$ CC $<$ 2,000 ccm) and large (CC $\geq$ 2,000 ccm). This yields to 6,339 vehicles with 172,978 vehicle trips.

Extraction of vehicle driving profiles from MOPS

A similar procedure is performed for MOPS. This data set is slightly different from MOP as it contains no information about the vehicles used and less socio-demographic information about the households and persons. Thus, there are three tables:

- Haushalt: Contains the information about households, i.e. the four attributes: household-id, zone of the household, household size (persons) and vehicles in household.
- Personen: Information about the persons (nine attributes): household-id, person-id, sex, employment status, possession of a transit pass, possession of a driving license, zone of working place, zone of apprentice position.
- Wege: Information on all trips performed (twelve attributes): household-id, person-id, day of week, departure time, arrival time, duration of trip, starting zone, stopping zone, distance, means of transport, trip purpose, duration of following activity.

Since the number of vehicles is only available in the household table, the allocation of person trips to vehicles runs as in Listing A.1.

Listing A.3: MOPS vehicle driving profiles extraction

```
CREATE TABLE mops_weg_miv AS
(SELECT
   *
FROM
   mops_weg
WHERE
   modus LIKE 'MIV')


CREATE TABLE mops_pkw_hh AS
(SELECT
   hh.hhid AS hhid,
   hh.hh_groesse AS pkw_in_hh,
   count(miv.pid) AS pkw_driving
FROM
   mops_haushalt hh,
   mops_weg_miv miv
WHERE
   hh.hhid = miv.hhid
GROUP BY
   miv.hhid);


CREATE TABLE mops_weg_pkw AS
SELECT
   alltrips.hhid,
   CASE feasible.pkw_in_hh
     WHEN 1 THEN 1
     ELSE alltrips.pid
   END AS pkwid,
   alltrips.wochentag,
   alltrips.abzeit,
   alltrips.anzeit,
```

```sql
    alltrips.dauer,
    alltrips.vz_ab,
    alltrips.vz_an,
    alltrips.strecke,
    alltrips.modus,
    alltrips.zweck,
    alltrips.dauer_aktivitaet
FROM
    (
      SELECT
         *
      FROM
         mops_pkw_hh
      WHERE
         pkw_in_hh = 1
      OR (
         pkw_in_hh > 1
         AND pkw_driving <= pkw_in_hh
       )
    ) feasible,
    mops_weg_miv alltrips
WHERE
    feasible.hhid = alltrips.hhid;
```

In the initial data set, there are 21,949,597 vehicle trips available performed by 1,585,271 vehicles. The allocation reduces the data sample to 20,514,826 vehicle trips of 1,312,817 vehicles. For practical reasons, especially computing time, the time intervals of trips were reduced to 15 min sections, which further decreases the number of trips to 19,100,429. A further partition is described in Section 4.3.6.

A.2 Further information about MOPS

An important advantage of MOPS in comparison to MOP is the availability of geographical information. This information is necessary for the joint simulation of PEVs at public charging points. Yet, the geographic information in the driving profiles are no coordinates, but geographic zones in GIS-format. A map of these zones is shown in Figure 3.2 in Section 3.2, yet the 1,173 zones are hardly visible on the map. For a better interpretation of results, Figure A.1 shows the connection of zone area and its distance to the city center.

Figure A.1 shows the area of the zones on the ordinate and the distance to the city center on the abscissa. Both axes use a logarithmic scale to be able to compare small to large values and every dot corresponds to one zone. It is clearly visible that the area of zones rises with the distance to the city center which was already mentioned in Section 3.2. Also two groups are visible for zones with a distance of 1 to 10 km distance to the city center (inner city zones) and from 10 to 100 km distance (outer city zones).

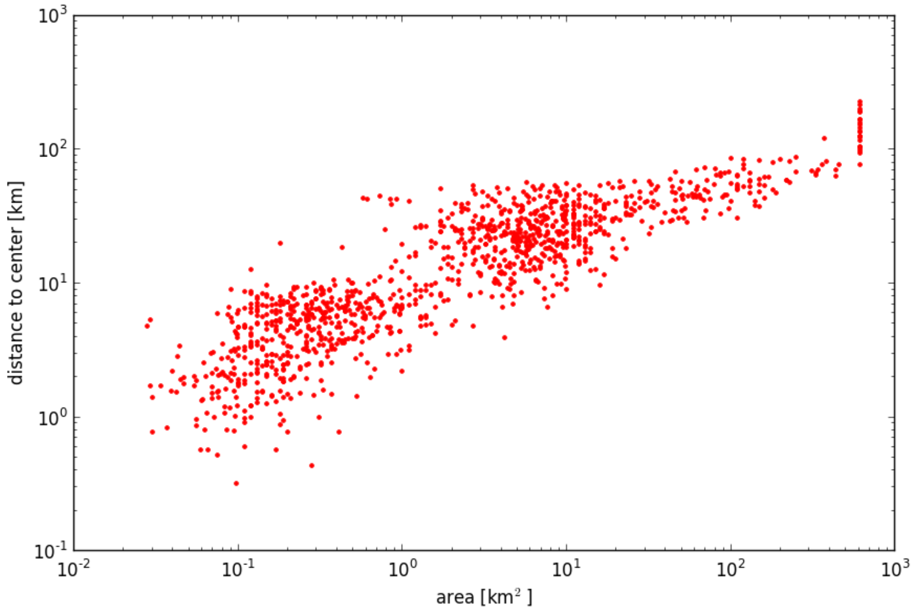

Figure A.1: Distance and area of zones in observation area of MOPS. Both axes with logarithmic scales. Every point corresponds to one zone.

A.3 Collection of commercial vehicle usage data

The data collection of REM2030 was performed from June 2011 until June 2014. The goal was to collect data of commercial vehicles for at least three weeks and to be representative for the distribution of vehicles to commercial branches in commercial vehicle registrations. The data collection was carried out in 13 survey waves with 50 GPS-trackers of which 45 on average were used during the surveys and 40 sent usable data (see next paragraph for data correction). Companies were asked by phone to participate in a data collection for the application of PEVs as commercial vehicles and the rate of participation was at about 20% on average. GPS-trackers were sent to companies who distributed them to vehicle users who were willing to participate in the data collection personally[116]. The vehicle movements were audited in an online portal and companies were contacted in case the cars were not moving. All vehicle trips including their starting and stopping time and geographical coordinates were collected. After 4-5 weeks, participants had to fill out a small questionnaire indicating the vehicles' sizes (small, medium, large, LCVs) and the company size (<10, 11-50, 51-100, 101-250, 251-1,000, 1,001-5,000, >5,000). Since 2014 also the common parking spot ("own parking spot on company site", "varying spots on company site", "no parking on company site"), the number of car users (one/multiple) and the vehicle usage (as fleet vehicle or company car) were requested. These questionnaires were digitized and reports for every company with vehicle-specific recommendations about the PEV-replaceability based on the driving behavior were sent to companies. Additionally the city size of the company's main site, the commercial branch and commercial segment according to [Eurostat, 2008] were collected as additional information.

This procedure allows to pursue the representativity regarding the commercial branches in vehicle registrations. However, incorrect reporting of additional information in the

[116]Participants had to agree personally because of data privacy.

questionnaire cannot be precluded. Several plausibility checks of the trips were performed to correct some technical issues. Since the data recording with GPS-trackers suffers from dead spots of GPS and radio communication, the recorded trips were tested for plausibility and, if necessary, adapted or additional trips were inserted. There were two types of trips that had to be adapted: (1) the distance between starting and stopping point was shorter than the minimal distance extracted from Google-maps and (2) the length of the trips resulted in an average speed below 1 km/h or the duration was below one minute. The first case of incorrect distances concerned 2,585 trips with an mean distance of 4.2 km (SD: 30.3 km). Incorrect driving times (case 2) were found in 2,397 cases with a mean distance of 1.1 km (SD: 13.4 km). Furthermore, additional trips were inserted if the destination of trip i differed from the origin of the trip $i + 1$. Then an additional trip was determined using Google-maps, which concerned 2,597 trips with a mean value of 15.6 km (SD: 67.6 km).

Appendix B

Techno-economical parameters

This annex holds the parameters used for calculations and their references were discussed in Section 4.3. Table B.1 holds the parameters for small vehicles, Table B.2 for medium sized vehicles, Table B.3 for large vehicles and Table B.4 for light commercial vehicles. For all BEVs a maximum depth of discharge of 90% is used, while PHEVs may use 80% of their battery capacity [Plötz et al., 2013].

The limited availability of PEVs as described in Section 4.3.5 is shown in Table B.5. Lastly, the cost and subsidies to public charging points with 22 kW and 50 kW charging power used in Section 5.3.3 are shown in Table B.6.

Table B.1: Parameters for small vehicles. All prices and costs without VAT in EUR_{2014}.

Parameter	unit	2015	2020	2025	2030
battery capacity BEV[a]	kWh	20	20	20	20
battery capacity PHEV[a]	kWh	8	8	8	8
conventional consumption Gasoline[b]	l/km	0.058	0.054	0.051	0.048
conventional consumption Diesel[b]	l/km	0.046	0.043	0.041	0.038
conventional consumption PHEV[b]	l/km	0.054	0.051	0.048	0.045
electric consumption BEV[b]	kWh/km	0.164	0.155	0.146	0.138
electric consumption PHEV[b]	kWh/km	0.153	0.144	0.135	0.127
O&M cost Gasoline[c]	EUR/km	0.026	0.026	0.026	0.026
O&M cost Diesel[c]	EUR/km	0.026	0.026	0.026	0.026
O&M cost PHEV[c]	EUR/km	0.023	0.023	0.023	0.023
O&M cost BEV[c]	EUR/km	0.018	0.018	0.018	0.018
net list price Gasoline[d]	EUR	10,477	10,699	11,033	11,403
net list price Diesel[d]	EUR	12,666	12,888	13,222	13,592
net list price PHEV w/o battery[d]	EUR	14,991	14,556	14,556	14,556
net list price BEV w/o battery[d]	EUR	10,923	10,480	10,480	10,480
vehicle tax Gasoline[e]	EUR/yr	65	50	50	50
vehicle tax Diesel[e]	EUR/yr	139	126	126	126
vehicle tax PHEV[e]	EUR/yr	26	26	26	26
vehicle tax BEV[e]	EUR/yr	0	0	0	0

a: [Hacker et al., 2011b, Gnann et al., 2012a, Linssen et al., 2012, Pfahl, 2013]
b: [Helms et al., 2011]; c: [Propfe et al., 2012b]; d: [Pfahl, 2013]; e: [BMF, 2014]

Table B.2: Parameters for medium sized vehicles. All prices and costs without VAT in EUR_{2014}.

Parameter	unit	2015	2020	2025	2030
battery capacity BEV[a]	kWh	27	40	40	40
battery capacity PHEV[a]	kWh	10	10	10	10
conventional consumption Gasoline[b]	l/km	0.072	0.066	0.062	0.057
conventional consumption Diesel[b]	l/km	0.057	0.053	0.049	0.046
conventional consumption PHEV[b]	l/km	0.066	0.062	0.058	0.055
electric consumption BEV[b]	kWh/km	0.201	0.190	0.180	0.170
electric consumption PHEV[b]	kWh/km	0.189	0.179	0.168	0.159
O&M cost Gasoline[c]	EUR/km	0.048	0.048	0.048	0.048
O&M cost Diesel[c]	EUR/km	0.048	0.048	0.048	0.048
O&M cost PHEV[c]	EUR/km	0.043	0.043	0.043	0.043
O&M cost BEV[c]	EUR/km	0.033	0.033	0.033	0.033
net list price Gasoline[d]	EUR	17,298	17,698	18,298	18,965
net list price Diesel[d]	EUR	19,485	19,885	20,485	21,152
net list price PHEV w/o battery[d]	EUR	21,677	21,116	21,116	21,116
net list price BEV w/o battery[d]	EUR	17,613	17,042	17,042	17,042
vehicle tax Gasoline[e]	EUR/yr	125	101	101	101
vehicle tax Diesel[e]	EUR/yr	226	209	209	209
vehicle tax PHEV[e]	EUR/yr	34	34	34	34
vehicle tax BEV[e]	EUR/yr	0	0	0	0

a: [Hacker et al., 2011b, Gnann et al., 2012a, Linssen et al., 2012, Pfahl, 2013]
b: [Helms et al., 2011]; c: [Propfe et al., 2012b]; d: [Pfahl, 2013]; e: [BMF, 2014]

Table B.3: Parameters for large vehicles. All prices and costs without VAT in EUR_{2014}.

Parameter	unit	2015	2020	2025	2030
battery capacity BEV[a]	kWh	59	80	80	80
battery capacity PHEV[a]	kWh	13	13	13	13
conventional consumption Gasoline[b]	l/km	0.095	0.087	0.080	0.074
conventional consumption Diesel[b]	l/km	0.071	0.066	0.061	0.056
conventional consumption PHEV[b]	l/km	0.084	0.078	0.072	0.067
electric consumption BEV[b]	kWh/km	0.216	0.204	0.193	0.183
electric consumption PHEV[b]	kWh/km	0.204	0.193	0.182	0.171
O&M cost Gasoline[c]	EUR/km	0.074	0.074	0.074	0.074
O&M cost Diesel[c]	EUR/km	0.074	0.074	0.074	0.074
O&M cost PHEV[c]	EUR/km	0.066	0.066	0.066	0.066
O&M cost BEV[c]	EUR/km	0.051	0.051	0.051	0.051
net list price Gasoline[d]	EUR	30,755	31,355	32,255	33,255
net list price Diesel[d]	EUR	32,987	33,587	34,487	35,487
net list price PHEV w/o battery[d]	EUR	34,986	34,351	34,351	34,351
net list price BEV w/o battery[d]	EUR	30,932	30,232	30,232	30,232
vehicle tax Gasoline[e]	EUR/yr	229	193	193	193
vehicle tax Diesel[e]	EUR/yr	349	325	325	325
vehicle tax PHEV[e]	EUR/yr	46	46	46	46
vehicle tax BEV[e]	EUR/yr	0	0	0	0

a: [Hacker et al., 2011b, Gnann et al., 2012a, Linssen et al., 2012, Pfahl, 2013]
b: [Helms et al., 2011]; c: [Propfe et al., 2012b]; d: [Pfahl, 2013]; e: [BMF, 2014]

Table B.4: Parameters for LCVs. All prices and costs without VAT in EUR_{2014}.

Parameter	unit	2015	2020	2025	2030
battery capacity BEV[a]	kWh	32	32	32	32
battery capacity PHEV[a]	kWh	16	16	16	16
conventional consumption Gasoline[b]	l/km	0.119	0.110	0.102	0.095
conventional consumption Diesel[b]	l/km	0.089	0.083	0.077	0.072
conventional consumption PHEV[b]	l/km	0.104	0.098	0.092	0.086
electric consumption BEV[b]	kWh/km	0.324	0.306	0.289	0.274
electric consumption PHEV[b]	kWh/km	0.301	0.285	0.269	0.255
O&M cost Gasoline[c]	EUR/km	0.050	0.050	0.050	0.050
O&M cost Diesel[c]	EUR/km	0.050	0.050	0.050	0.050
O&M cost PHEV[c]	EUR/km	0.044	0.044	0.044	0.044
O&M cost BEV[c]	EUR/km	0.034	0.034	0.034	0.034
net list price Gasoline[d]	EUR	38,000	38,600	39,500	40,500
net list price Diesel[d]	EUR	40,200	40,800	41,700	42,700
net list price PHEV w/o battery[d]	EUR	42,853	42,171	42,171	42,171
net list price BEV w/o battery[d]	EUR	38,215	37,477	37,477	37,477
vehicle tax Gasoline[e]	EUR/yr	161	161	161	161
vehicle tax Diesel[e]	EUR/yr	161	161	161	161
vehicle tax PHEV[e]	EUR/yr	161	161	161	161
vehicle tax BEV[e]	EUR/yr	0	0	0	0

a: [Hacker et al., 2011b, Gnann et al., 2012a, Linssen et al., 2012, Pfahl, 2013]
b: [Helms et al., 2011]; c: [Propfe et al., 2012b]; d: [Pfahl, 2013]; e: [BMF, 2014]

Table B.5: Limited availability of PEVs.

Parameter	unit	2015	2020	2025	2030
limited availability BEV small[a]	-	0.482	0.845	0.970	0.995
limited availability PHEV small[a]	-	0.037	0.650	0.989	1.000
limited availability BEV medium[a]	-	0.480	0.876	0.982	0.998
limited availability PHEV medium[a]	-	0.539	0.982	1.000	1.000
limited availability BEV large[a]	-	0.043	0.184	0.532	0.852
limited availability PHEV large[a]	-	0.273	0.889	0.994	1.000
limited availability BEV LCV[a]	-	0.260	0.632	0.893	0.976
limited availability PHEV LCV[a]	-	0.018	0.461	0.976	0.999

a: Assumptions based on press announcements summed up in [Plötz et al., 2013, Ch. 7.4].

Table B.6: Cost and subsidies for public CPs with a charging power of 22 kW and 50 kW. All costs in EUR_{2014} without VAT.

scenario	option	2015	2020	2025	2030
Power1 (22 kW)	assumed CP annuity	100	100	466	883
	annual subsidy	1,254	1,114	557	-
Power2 (50 kW)	assumed CP annuity	100	100	1,840	3,580
	annual subsidy	6,693	5,196	2,444	-

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List of Abbreviations and Variables

Abbreviations	Full Expression
ABS	Agent-based Simulation
ABM	Agent-based Model
AC	Alternating Current
AFV	Alternative Fuel Vehicle
AG	Argentina
ALADIN	Alternative Automobiles Diffusion and Infrastructure (ALADIN-model)
ASTRA	Assessment of Transport Strategies (ASTRA-model)
BEV	Battery Electric Vehicle
BMWE	Federal Ministry of Economics Affairs and Energy (Bundesministerium für Wirtschaft und Energie; formerly: Federal Ministry of Economic Affairs and Technology, Bundesministerium für Wirtschaft und Technologie)
BR	Brazil
CAGR	Compound Annual Growth Rate
CH	Switzerland
CNG	Compressed Natural Gas
CO_2	Carbon Dioxide
CP	Charging Point
CPO	Charging Point Operator
CV	Conventional Vehicle
DC	Direct Current
DE	Germany
EC	European Commission
ENTD	National survey on transport and movements (Enquête Nationale des Transports et des Déplacements)
EREV	Extended-range Electric Vehicle (see also REEV)
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gas
GPS	Global Positioning System
HEV	Hybrid Electric Vehicle
IT	Italy
KBA	Federal Motor Transport Authority (Kraftfahrt-Bundesamt)
KiD	Motor Traffic in Germany (Kraftfahrzeugverkehr in Deutschland)
LCV	Light Commercial Vehicle

LPG	Liquefied Petroleum Gas
LPGV	Liquefied Petroleum Gas Vehicle
MAS	Multi-agent Simulation
MiD	Mobility in Germany (Mobilität in Deutschland)
MOP	German Mobility Panel (Deutsches Mobilitätpanel)
MOPS	Mobility Panel for the region of Stuttgart
NGV	Natural Gas Vehicle
NHTS	National Household Travel Survey
NL	Netherlands
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
REEV	Range-Extended Electric Vehicle (see also EREV)
REM2030	Regional Eco Mobility commercial vehicle driving profiles
REM2030S	Regional Eco Mobility commercial vehicle driving profiles for the region of Stuttgart
SCMD	Swedish Car Movement Data
SD	Standard Deviation
SOC	State of Charge
TCO	Total Cost of Ownership
VAT	Value Added Tax
VKT	Vehicle Kilometers Traveled
VRI	Vehicle to Refueling station Index
WTPM	Willingness To Pay More

Symbol	Unit	Explanation
a	years	Vehicle age
$a_{cp}(t)$	EUR/a	Annuity for charging point in year t
$a_{i,s}^{\mathrm{CI,opex}}(t)$	EUR/a	Annuity of operating expenditure for individual charging infrastructure in year t
$a_{i,s}^{\mathrm{CP,opex}}(t)$	EUR/a	Annuity of operating expenditure for public charging point in year t
$a_{i,s}^{\mathrm{veh,capex}}(t)$	EUR/a	Annuity of capital expenditure for vehicle
$a_{i,s}^{\mathrm{veh,opex}}(t)$	EUR/a	Annuity of operating expenditure for vehicle
$ACD_i(t)$	km	Average commuting distance of user i in year t
A_z	km^2	Area of zone z
b_i	-	Brand of the vehicle i
$c_{r,s}^c(t)$	l/km	Conventional vehicle consumption
$c_{r,s}^e(t)$	kWh/km	Electric vehicle consumption
$C_i^e(t)$	EUR/a	Annual cost for energy charged by user i in year t
$C_{r,s}(t)$	kWh	Net capacity of vehicle with vehicle size r and propulsion technology s in year t
CPN_z	CP/km^2	Minimal number of charging points in zone z
$d(\Delta\tau)$	km	Distance driven in time period $\Delta\tau$

$d^{el}_{i,s}(t)$	km	Kilometers driven in electric mode by user i with propulsion system s in year t
d_i	km	Kilometers driven by user i
$dep^{\text{veh,capex}}_{i,s}(t)$	EUR/a	Depreciation for vehicle capital expenditure of user i for propulsion system s
$dep^{\text{veh,opex}}_{i,s}(t)$	EUR/a	Depreciation for vehicle operating expenditure of user i for propulsion system s
DR	-	Depreciation rate
$f_{m,s}(t)$	-	Share of driving profiles of users of group m and propulsion system s in year t
$f_{i,m,s}(t)$	-	Share propulsion system s in driving profile i and group m in year t
$g^{\text{veh}}_{i,s}(t)$	EUR/a	Fringe benefit tax for company cars for user i and propulsion system s in year t
i	-	Index for driving profile
$I^{CI}(t)$	EUR	Investment for individual charging infrastructure
$I^{CP}(t)$	EUR	Investment for public charging points
$ITR_i(t)$	-	Income tax rate of user i in year t
$k^{c}_{r,s}(t)$	EUR/l	Costs for conventional fuel
$k^{\text{OM}}_{r,s}(t)$	EUR/km	Costs for operations and maintenance for vehicle of size r and propulsion system s in year t
$k^{\text{tax}}_{r,s}(t)$	EUR/a	Vehicle tax for vehicle of size r and propulsion system s in year t
l	-	Location type index; $l \in$ {domestic, commercial, work, public}
$L(a)$	-	Vehicle survival probability until year a
$lim_{m,s}(t)$	-	Limited availability of vehicle in group m for propulsion system s in year t
$\text{LP}^{G}_{r,s}(t)$	EUR	Gross list price of vehicle of size r and propulsion technology s in year t
$\text{LP}_{r,s}(t)$	EUR	Net list price of vehicle of size r and propulsion technology s in year t
$\text{LP}^{PEV}_{r,s}(t)$	EUR	Net list price of vehicle of size r and propulsion technology s in year t that is a PEV
$n_{cp}(t)$	-	Number of public charging points in year t
$n_{CP,z}(t)$	-	Number of public charging point in year t and zone z
$n_m(t)$	-	Vehicle registrations of group m in year t
$N_{m,s}(t)$	-	Vehicle registrations of group m and propulsion technology s in year t
m	-	Index for vehicle group; $m \in$ {private small, private medium, private large, fleet small, fleet medium, fleet large, fleet LCV, company small, company medium, company large}

occ_z	Vehicle min parked/(km^2·wk)	Specific zone occupancy of zone z
$occ_{z,PEV}(t)$	Vehicle min parked/(km^2·wk)	Specific zone occupancy of zone z by PEVs
$p_s^{batt}(t)$	EUR/kWh	Battery price for vehicle of propulsion technology s in year t
$p_{r,s}^{car}(t)$	EUR	Price for vehicle without battery of size r and propulsion technology s in year t
$p_{cp}(t)$	EUR	Price for a public charging point in year t
$p_{el}(t)$	EUR/kWh	Price for electricity at a public charging point in year t
$p_{i,l}(t)$	EUR/kWh	Charging price for user i at location l in year t
$p_{pc}(t)$	EUR/kWh	Price for public charging in year t
$P_l(\tau, t)$	kW	Power for charging at the location l where vehicle i was parked at τ and year t
$P_{p,z}(t)$	kW	Power for public charging in zone z at time t
$P^{\text{scrap}}(a)$	-	Probability of scrapping a vehicle of age a
r	-	Index for vehicle size; $r \in$ {small, medium, large, LCV}
s	-	Index for propulsion technology; $s \in$ {Gasoline, Diesel, PHEV, BEV}
$s_{i,s}(t)$	-	Electric driving share of vehicle i with propulsion system s
$S_{m,s}(t)$	-	Vehicle stock of vehicle group m and propulsion technology s in year t
$SOC_i(\tau, t)$	kWh	Battery's state of charge of vehicle i at time τ in year t
$\text{SP}_{i,s}(t)$	EUR	Resale price of vehicle i and propulsion technology s in year t
t	years	Year of observation
$T_u^{CI}(t)$	years	Investment horizon of charging infrastructure for user group u in year t
T^{dlim}	years	Maximum depreciation period of vehicles
$T_u^{veh}(t)$	years	Investment horizon of vehicles for user group u in year t
$\text{TCO}_{i,s}^{a,\text{veh}}(t)$	EUR/a	Annual total cost of ownership for vehicle i and propulsion technology s in year t
$\text{TCO}_{i,s}^{a,\text{CI}}(t)$	EUR/a	Annual total cost of ownership for individual charging infrastructure for vehicle i and propulsion technology s in year t
$TE_{r,s}^{PEV}(t)$	EUR	Amount of tax exemption for PEVs of size r and propulsion technology s in year t
u	-	Index for user group; $u \in$ {private, fleet, company}
$u_{i,s}^a(t)$	EUR/a	Utility value of propulsion technology s for user i in year t

$use_z(t)$	kWh/yr	Usage of public charging points in zone z and year t
VKT_i	km/a	Annual vehicle kilometers traveled by vehicle i
$W_{i,l}(t)$	kWh/a	Annual amount of energy charged by vehicle i at location l in year t
$W_{i,l}(\tau, \tau + 1, t)$	kWh/a	Amount of energy charged by vehicle i at location l in year t between τ and $\tau + 1$
$W_{pc}(t)$	kWh/a	Total amount of energy charged at public charging points in year t
$\text{WTPM}^a_{i,s}(t)$	EUR/a	Annuity of willingness to pay more by the owner of vehicle i for propulsion technology s in year t
$\text{wtpm}_{i,s}(t)$	-	Willingness to pay more by the owner of vehicle i for propulsion technology s in year t as a percentage compared to a conventional vehicle
z	-	Index for zones
$z_u(t)$	-	Interest rate for user group u in year t
α_1	-	Parameter for calculation of residual values
β_1	-	Parameter for calculation of residual values (age)
β_2	-	Parameter for calculation of residual values (mileage)
β_3	-	Parameter for calculation of residual values (list price)
β	-	Parameter for stock calculation (shape)
Δn_{cp}	-	Difference between charging points between two periods of time t
$\Delta\tau$	min	Time period between τ_1 and τ_2
$\kappa_{r,s}(t)$	kWh	Gross battery capacity of vehicle with size r and propulsion technology s in year t
τ	min	Time section in observation period
τ_i^0	min	Initial point in time of observation of vehicle i
τ_i^{max}	min	Last point in time of observation of vehicle i
θ	-	Parameter for stock calculation (scale)

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How do market diffusions of plug-in electric vehicles and their charging infrastructure interact? And what is a sufficient number of public charging stations to overcome a potential lock-in? In this thesis, an agent-based simulation model is introduced to answer this question for Germany until 2030. The inclusion of different charging options and electric drive trains allows a realistic picture of the future market diffusion.

The Fraunhofer ISI analyzes the framework conditions for innovations. We explore the short- and long-term developments of innovation processes and the societal impacts of new technologies and services. On this basis, we provide our clients from industry, politics and science with policy recommendations and perspectives for key decisions. Our expertise lies in a broad scientific competence as well as an interdisciplinary and systemic research approach.

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