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Real-world fuel economy and CO_2 emissions of plug-in hybrid electric vehicles

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Abstract

Plug-in hybrid electric vehicles (PHEV) combine electric propulsion with an internal combustion engine. Their potential to reduce transport related greenhouse gas emissions highly depends on their actual usage and electricity provision. Various studies underline their environmental and economic advantages, but are based on standardised driving cycles, simulations or small PHEV fleets. Here, we analyse real-world fuel economy of PHEV and the factors influencing it based on about 2,000 actual PHEV that have been observed over more than a year in the U.S. and Germany. We find that real-world fuel economy of PHEV differ widely among users. The main factors explaining this variation are the annual mileage, the regularity of daily driving, and the likelihood of long-distance trips. Current test cycle fuel economy ratings neglect these factors. Despite the broad range of PHEV fuel economies, the test cycle fuel economy ratings can be close to empiric PHEV fleet averages if the average annual mileage is about 17,000 km. For the largest group of PHEV in our data, the Chevrolet Volt, we find the average fuel economy to be 1.45 litres/100 km at an average electric driving share of 78%. The resulting real-world tank-to-wheel CO_2 emissions of these PHEV are 42 gCO_2/km and the annual CO_2 savings in the U.S. amount to about 50 Mt. In conclusion, the variance of empirical PHEV fuel economy is considerably higher than of conventional vehicles. This should be taken into account by future test cycles and high electric driving shares should be incentivised.

Keywords: electric vehicles, plug-in hybrid electric vehicles, real-world fuel economy, utility factor

Highlights:

- real-world fuel economy of about 2,000 PHEV is analysed
- fuel economy and electric driving shares differ widely among users
- influencing factors for PHEV fuel economy are identified
- battery size, annual mileage and driving regularity impact PHEV fuel economy
- PHEV enable CO_2 emission reductions depending on electricity generation

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1 Introduction

Plug-in hybrid electric vehicles (PHEV) combine electric propulsion with an internal combustion engine. They are more efficient than conventional internal combustion engine vehicles and can help to reduce greenhouse gas (GHG) emissions from the transport sector (e.g. Bradley and Frank 2009, Arar 2009 and Vliet et al. 2010). However, their GHG emissions reduction potential strongly depends on their actual usage and the underlying electricity generation (Hawkins et al. 2012a and 2012b, Messagie et al. 2010, Lane 2006). In a PHEV, both drive trains can be used for propulsion in parallel, in series or in a combination of the two (e.g. Bradley and Frank 2009). We distinguish the following two operation modes: In charge depleting mode the electric engine is responsible for propulsion and the combustion engine is switched off. In charge sustaining mode (usually applied when the battery has been fully depleted), the combustion engine is (mainly) used to keep the battery state-of-charge within a small window. Even though there are several names for and variants of hybrid electric vehicles which combine combustion engine, electric motor, and onboard charger (e.g. range extended electric vehicle, REEV), we refer to all as PHEV in the following.

The official emission and fuel economy values of passenger vehicles are currently measured by standard driving cycles such as the New European Driving Cycle (NEDC) in Europe or the Federal Test Procedure (e.g. FTP-75) in the U.S. They are the basis for CO_2 emission targets or vehicle taxation and regulations have been extended to include PHEV (e.g. UNECE 2014). However, recent studies show an increasing difference between test cycle and empirical real-world fuel economy (Mock et al. 2014, Ligterink et al. 2014). For PHEV, the differences are expected to be even higher due to the possibility of different operation shares of the two drive trains. The share of distance driven electrically in charge depleting mode is denoted as electric driving share or utility factor (UF). Therefore, for empirical fuel consumption, the charging frequency and the daily mileage are relevant factors.

One approach to analyse PHEV fuel economy is a computational simulation of PHEV operations using test cycles or driving data of conventional vehicles from mobility surveys. This approach is widely applied in research (e.g. Elgowainy et al. 2009, Neubauer et al. 2013, Moawad et al. 2009, Axsen et al. 2011, Bradley and Quinn 2010). Some studies already incorporate the impact on CO_2 emissions (e.g. Karabasoglu and Michalek 2013 and Millo et al. 2014). Elgowainy et al. (2009) estimate electric driving shares based on the US

National Household Transportation Survey (NHTS) and obtain an average UF of 23.2% for a PHEV with an all electric range (AER) of 10 miles. For an AER of 20, 30, 40, and 60 miles they obtain an UF of 40.6%, 53.4%, 62.8%, and 74.9%, respectively. Neubauer et al. (2013) use GPS-data of a traffic choice study (398 profiles with 3 months observation period) to simulate the economics of different vehicle concepts. They calculate fuel savings of PHEV usage for different vehicle designs and charging scenarios that can be interpreted as UF and find 50% for 15 miles (60% if work charging is added) and 70% to 80% for 35 miles AER. Analogously, using over 100 one-day driving profiles from Kansas city, Moawad et al. (2009) find fuel savings to be 48% for a PHEV with a battery capacity of 4 kWh, 62% for 8 kWh and 88% for a 16 kWh battery. Axsen et al. (2011) on the other hand use driving reports of 877 car buyers in California and find an UF of PHEV with an AER of 20 miles to be 35% for home charging and 43% for home and additional work charging as well as an UF of 70% and 79% for an AER of 40 miles. The influence of the UF on PHEV's fuel economy has been further analysed by Bradley and Quinn (2010). They calculate the sensitivity of the average UF with respect to vehicle type, age, mileage and garage availability as well as charging behaviour. A PHEV with an AER of 42 miles was found to have an UF of 64% if fully charged once a day compared to 86% if fully charged before every trip. As expected, the UF strongly depends on mileage as with higher trip length UF decreases. To conclude, several studies have simulated UF of PHEV with different AER but a systematic understanding of the importance of individual factors is lacking.

Real-world-driving data on PHEV usage patterns and fuel economy is rare. Ligterink et al. (2013 and 2014) analyse Dutch refuelling data and find an UF of 24% which includes an important group of business users who hardly charge. Excluding them, the UF raises to 33%. The Toyota Prius PHEV and Opela Ampera are found to have an effective fuel economy of about 4.5 l/100 km (52 MPG) compared to 5.3 l/100km (44 MPG) for the Volvo V60 PHEV and 6.6 l/100km (36 MPG) for the Mitsubishi Outlander PHEV (Ligterink et al. 2014). The corresponding UF were estimated from the fuel savings compared to a similar conventional vehicle and amount to 18% for the Toyota Prius PHEV, 30% for the Chevrolet Volt/ Opel Ampera, 31% for the Mitsubishi Outlander, and 16% for the Volvo V60 PHEV. Davies and Kurani (2013) report results on 25 converted Toyota Prius and find fuel economy to be between 2.1 and 4.5 l/100km (52 – 112 MPG) in charge depleting mode and between 4.3 and 6.5 l/100km (36 – 55 MPG) in charge sustaining mode for an AER of 40 to 60 km. In a second step, using the obtained data to simulate different PHEV usage scenarios, they calculate an UF of 30% for a PHEV with an AER of 24 km for charging at home only, which rises to 50% if workplace charging is added. In summary, studies of PHEV fuel economy up to now are only based on data from simulation and little real-world data which rely, however, on small sample sizes (with the exception of Ligterink et al. (2014) who do not provide details characterising their sample, e.g. in terms of annual mileage).

In this paper, we analyse the real-world fuel economy of PHEV in detail including factors influencing their fuel economy and the related CO_2 emissions. We use vehicle usage data from about 1,800 Chevrolet Volt PHEV observed in North America over more than one year. This main data source is enriched and compared to data from several other PHEV with different electric driving ranges (cf. Table 1). We also contrast PHEV usage in terms of annual mileages. This study differs in at least two aspects from previous work. First, it presents empirical results based on the largest data set of real-world fuel consumptions of different PHEV. Second, it analyses main explanatory factors of PHEV fuel consumption variation (annual mileage, regularity of driving, and AER).

The outline of the paper is as follows. The different data sources are presented and compared in section 2.1 followed by the methodology in section 2.2. Results are presented in section 3 and discussed in section 4. We close with a summary and policy conclusions.

2 Data and Methods

2.1 Data

We use different sources representing real-world driving behaviour. Our main source of data is a large online collection of driving and fuel economy data from about 1,800 Chevrolet Volt driven in the US and Canada (voltstats.net). This data source is compared to and enriched by smaller samples of different PHEV used in Germany from the online database spritmonitor.de. All models analysed here are mass market vehicles from major manufacturers. Finally, to analyse factors influencing UF of PHEV in detail, we simulate PHEV with driving patterns of conventional vehicles. Driving data with several days of observation is decisive for a realistic simulation. Therefore, we do not use the US National Household Travel Survey (NHTS) for the simulation but the German mobility panel (MOP), one of two German national travel surveys. While Table 1 summarises the PHEV data source used in this study, Table 2 provides summary statistics of the main variables.

Table 1: Overview of PHEV fuel economy data sources.

	voltstats.net	**spritmonitor.de**
Available Data	Total miles, electric miles, different fuel economy values, (all monthly), residence	Fuel economy and distance driven between refuelling
Derivable data	Annual mileage, utility factor	Annual mileage, utility factor
PHEV Models and sample size	Chevrolet Volt (N = 1,831)	Toyota Prius PHEV (N = 81), Mitsubishi Outlander PHEV (N = 33), Opel Ampera (N = 23), Volvo V60 PHEV (N = 13)
Data collection	Collected via interface to On-Star (telematic system)	Fuel quantity and odometer reading after each refuelling reported by driver
Data availability	2012-2014	2007-2014 (PHEV subset)
Fleet structure	Mainly private cars	Mainly private cars

2.1.1 Voltstats.net

Voltstats.net is an online database that collects real-world fuel economy performance data of Chevrolet Volt, mainly in the U.S. but also in Canada. Aggregated travel and performance data for every vehicle is freely accessible. Data is collected by interfacing with Onstar, a subsidiary of General Motors that provides inter alia subscription-based communications, in-vehicle security and remote diagnostics (GM 2015). All data is transferred from the vehicles two times a day to the Onstar online database. The voltstats.net website has access to total miles driven, electric miles driven, and total fuel consumption. The electric driving share UF, miles per gallon (MPG) and MPG in charge sustaining mode (MPGcs) are calculated automatically.

The website provides monthly data of total miles, electric miles, MPG, and MPGcs for every user. We programmed a wrapper, to automatically access and download all monthly data of all users (Voltstats 2014). The data has been downloaded from the website on December 17, 2014, and contains fuel economy and driving data of 1,831 Chevrolet Volt. Please note that our sample thus contains 2.5% of all North American Chevrolet Volts (about 72,800 Chevrolet Volt are registered in the US and Canada according to Cobb (2014)).

The average total monthly miles were extrapolated to annual mileage. The individual electric driving share UF is obtained by dividing all electric miles by total miles driven. The average number of days observed per vehicle is 442 days with a minimum of 17, median 382 and maximum of 1,327 days. The individual total fuel consumption c_{tot} is the product of fuel consumption in charge sustaining mode c_{cs} and the share of conventional driving, i.e. $1 - UF$.

2.1.2 Spritmonitor.de

Spritmonitor.de is an online web service for car drivers to calculate real-world kilometre cost including all operating cost. Among other information, registered car drivers report their fuel demand in litres and the corresponding cost as well as the vehicle mileage after each refuelling. The resulting average fuel economy and cost are calculated automatically. Detailed information on distances travelled and the respective fuel economy for every registered driver are accessible freely on the website. Mock et al. (2013) show a good representativeness of the German car fleet within the spritmonitor.de database.

In this work, we use a subsample which includes only PHEV within the database (0.2%). This proportion is in line with the current German market conditions (KBA 2014). We obtain a dataset of 150 PHEV reported since 2007 (downloaded on December 5, 2014 and vehicles with more than 2000 km for a single trip removed as implausible). Since the data sample is small, we should be careful with conclusions from this data set. Furthermore, only vehicles with a reported mileage of at least 1,500 kilometres were analysed to ensure sufficiently long observation time. Additionally, we use data aggregated for specific vehicle models, therefore requiring a minimum number of driving profiles per vehicle model. Information is available for the Toyota Prius PHEV ($N = 81$), Opel Ampera[1] ($N = 23$), Mitsubishi Outlander PHEV ($N = 33$) and Volvo V60 PHEV ($N = 13$). Despite the few observations, we analysed the Volvo as it is the only Diesel PHEV in the database. Other PHEV on the website were not considered due to their limited number of observations. Since the actual electric driving range is unavailable in the data, we use their EPA rating as good approximation for their real-world electric driving range (EPA and DOE 2014) or 0.75 of the NEDC value if no EPA range is available.

In spritmonitor.de average fuel economy for PHEV is reported in two different ways. Most of the users report total fuel economy c_{tot} related to distance driven.

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1 Some Chevrolet Volts are reported, too. As it is identical to the Ampera, we subsume the Chevrolet Volt for this database under the Opel Ampera. In the following, we refer to the European driving data when talking about the Opel Ampera and to the U.S. data (voltstats.net) when talking about the Chevrolet Volt.

Others report average fuel economy in charge sustaining mode c_{cs}. Drivers with more than 30 l per 100 km (7.8 MPG) in charge sustaining mode have been removed from the data as outliers. Yearly mileage is calculated as extrapolation from the average daily mileage. For drivers that state only their total fuel consumption (mixed charge sustaining and depleting mode) we have to estimate their charge sustaining mode fuel consumption in order to arrive at an UF. We take a user's maximal (of all his stated values) total fuel consumption as proxy for his charge sustaining mode fuel consumption c_{cs}. If this value is lower than the inter-user average maximal total fuel consumption, e.g. because the user had only short distance trips between recharges, we replace it by the inter-user average maximal total fuel consumption. The user's UF is then calculated as $= 1 - c_{\text{tot}}/c_{\text{cs}}$, that is the difference between unity and the ratio of average c_{tot} and estimated charge sustaining mode fuel consumption c_{cs}. By using the highest possible denominator here, the calculated UF represents a conservative estimate.

2.1.3 German Mobility Panel (MOP)

In order to study the effect of different factors on electric driving shares of PHEV individually we conducted a simulation of PHEV driving with mobility data of conventional vehicles. Due to the high irregularity of vehicle usage patterns, we need a reliable data basis with an observation period of several days. This requirement excludes many national household travel surveys such as the US NHTS. Here, we use the German Mobility Panel (MOP). The MOP is one of two national travel surveys for monitoring everyday travel in Germany. The survey is annually commissioned since 1994 by the German Federal Ministry of Transport and Digital Infrastructure (MOP 2010). In the annual survey about 1,000 households report their daily travel patterns over a period of one week in autumn. The survey collects data about all trips of the household members including start and end times, trip purposes, distances, and means of transportation used. Moreover, socio-demographic data of households and household members are gathered.

Since MOP is a household travel survey which focuses on people and their trips, we have to assign trips to vehicles if unambiguously possible (see Plötz et al. 2014 for details). We use data from 1994 until 2010 and limit our analysis to vehicles with stated annual mileage with less than 20% difference between the stated annual mileage and the annual mileage as extrapolated from the observed weekly mileage. This ensures that the observed driving week can be used to simulate realistic UF and reduces the sample to $N = 780$ vehicles with

5,140 non-zero daily travel distances. The mean annual mileage is 13,785 km and the median 12,000 km.

2.2 Methods

The European test cycle fuel economy of PHEV is based on regulation 101 of the UN ECE (UNECE 2014). The total fuel consumption of a PHEV in that regulation is given by $c_{\mathrm{tot}} = c_{\mathrm{cs}} \cdot 25\,\mathrm{km}\,/(L_e + 25\,\mathrm{km})$. Here, c_{cs} denotes the consumption of fuel in charge sustaining mode and L_e the electric driving range. The regulation assumes that users drive 25 km in addition to their electric driving range between two recharges. The UF of a PHEV according to the regulation is thus $UF = L_e\,/(L_e + 25\,\mathrm{km})$. Whenever empiric driving data is available, we calculate the electric driving share or UF for all PHEV as ratio between the distance travelled in charge depleting mode and the total distance travelled. The real-world fuel economy and PHEV usage data are further analysed with standard statistical methods such as kernel density estimates and kernel regression. Confidence intervals of several statistics are calculated via bootstrapping (Efron and Tibschirani 1994).

For conversion of units, we assume 8,887 grams of CO_2 per gallon of gasoline corresponding to 2,348 gCO_2/l or 23.4 gCO_2/km (Federal Register 2010). Similarly, 10.2 Kilograms of CO_2 are contained in one gallon of diesel corresponding to 2,690 gCO_2/l or 26.9 gCO_2/km (Federal Register 2010). Furthermore, MPG are converted to l/100 km. Please note, that the conversion between MPG and l/100 km is non-linear. Accordingly, the mean of transformed variables is not equal to the transform of the mean of a variable. When average fuel consumption values are stated in MPG and l/100 km both means have been calculated individually.

When simulating PHEV driving based on data of conventional vehicles, we assume a complete recharge every night, electric driving until the electric driving range has been reached and conventional driving thereafter. Thus, we calculate for every user the mean UF as the ratio of distance in charge depleting mode and total distance travelled. The individual UF are then analysed by a logit regression model.

3 Results

3.1 PHEV fuel consumption and CO_2 emissions

The annual mileage and the UF, i.e. the electric driving share, are the main variables characterising PHEV usage and influencing fuel economy. The summary statistics of these variables is shown in Table 2. We observe a wide range of annual vehicle kilometres travelled by all PHEV analysed. This is also indicated by the large standard deviations (SDs). Similarly, the UF cover a wide range of values. Notably, only the PHEV with the smallest electric driving range of about 18 km, the Toyota Prius PHEV, has a minimum UF below 10% and a mean UF below 50%.

Table 2: Summary statistics of PHEV data annual mileages and electric driving shares.

	Variable	min	median	**mean**	SD	max
Chevrolet Volt (N = 1,831)	Annual mileage [km]	660	16,317	**17,422**	8,269	106,286
	UF (EV share) [%]	11.72	81.89	**78.50**	15.38	100.00
Toyota Prius PHEV (N = 81)	Annual mileage [km]	6,879	17,955	**21,404**	11,920	62,821
	UF (EV share) [%]	5.64	31.97	**38.84**	21.42	90.02
Mitsubishi Outlander PHEV (N = 33)	Annual mileage [km]	2,735	23,281	**23,896**	13,566	70,887
	UF (EV share) [%]	23.90	53.85	**54.01**	14.67	80.08
Opel Ampera (N = 23)	Annual mileage [km]	6,676	16,077	**18,682**	10,202	49,228
	UF (EV share) [%]	21.40	84.37	**77.67**	24.25	100.00
Volvo V60 PHEV (N = 13)	Annual mileage [km]	10,301	23,982	**24,218**	9,538	39,637
	UF (EV share) [%]	31.43	42.54	**49.37**	12.69	71.42

For the main source of data and largest sample, the Chevrolet Volt, we analyse the annual mileage distribution in more detail. Figure 1 shows a kernel density estimate of the probability density function (PDF) of the annual mileage. Shown is the estimated density function of the Chevrolet Volt (blue line) and conventional hybrid vehicles (HEV, red line) from the US NHTS (NHTS 2009) for comparison. The inset shows the cumulative distribution functions (CDFs). The average annual mileage of the Chevrolet Volt in the data set is approximately 17,400 km (10,811 miles) compared to 24,000 km (14,913 miles) of HEV in the NHTS data (the median values are 16,300 km and 19,300 km respectively). This average Chevrolet Volt mileage is close to the average mileage in the US of 10,614 Miles or 17,082 km (FHWA 2011) but different from the other PHEV analysed here.[2] Interestingly, both distributions have their maximum around 15,000 – 18,000 km (9,000 – 11,000 miles) but the Chevrolet Volt distribution is clearly more peaked than the annual mileage distribution of conventional hybrids. This could be explained by the economics of PHEV driving: regular driving behaviour with little or no long-distance trips is required to economize the higher invest in PHEV. Thus, with little or no long-distance trips, very high annual mileage is difficult to obtain, possibly explaining the more pronounced peak in the Chevrolet Volt annual mileage distribution.

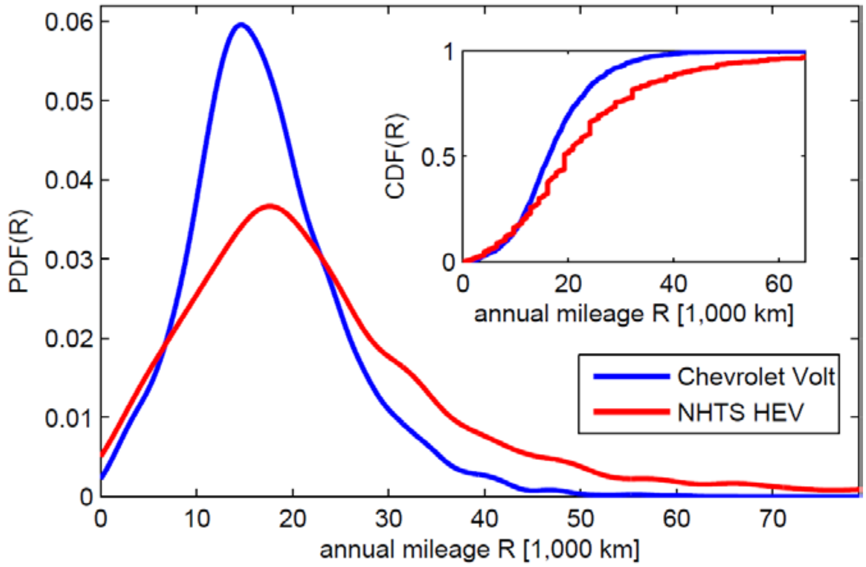

Figure 1: Probability density function of annual mileage.

The individual fuel economy during the charge sustaining mode (MPG_{cs} and c_{cs}) together with individual UF allow us to compute each vehicle's effective or total fuel consumption (c_{tot}) as well as the tank-to-wheel CO_2 emissions. We thus obtain individual UF, effective fuel economies and CO_2 emissions for all considered 1,831 Chevrolet Volt. The same variables were obtained for the other PHEV and the remainder of this section is devoted to an analysis of these variables.

The average fuel consumption in charge sustaining mode of the Chevrolet Volt is 34.9 ± 0.2 MPG_{cs} (at a 95% confidence level) and the median is 35.5 ± 0.2 MPG_{cs} corresponding to 6.88 ± 0.06 l/100km and 6.62 ± 0.04 l/100km re-

2 A two-sample t-test and Wilconxon rank sum test reject the null hypotheses of equal means and medians of the Volt and Ampera annual mileages versus the Outlander, Prius, and V60 annual mileages at 5% significance level. We used logarithms of the mileages since the distributions are right-skewed.

spectively. The median total fuel consumption is 1.23 ± 0.05 l/100km or 191 ± 8 MPG. Table 3 gives an overview of the average electric driving shares (UF), total fuel consumptions and tank-to-wheel CO_2 emissions for all PHEV. The values are real-world fuel economy statistics of PHEV and represent a main result of our study.

Table 3: Average fuel economy and CO_2 emissions of PHEV.

Average Fuel Economy of analysed PHEV	Electric driving share (UF)			Total fuel consumption c_{tot}			CO_2 emissions**		
Unit	**%**			**l/100km**			**gCO_2/km**		
	Estimate	*Lower bound**	*Upper bound**	***Estimate***	*Lower bound**	*Upper bound**	***Estimate***	*Lower bound**	*Upper bound**
Chevrolet Volt (N = 1831)									
NEDC Value	**76.9**			**1.2**			**28**		
Median	**81.9**	81.1	82.7	**1.23**	1.18	1.29	**29.0**	27.8	30.2
Average	**78.5**	77.8	79.2	**1.45**	1.40	1.49	**34.0**	32.9	35.1
VKT Average	**75.4**	73.8	76.8	**1.74**	1.63	1.84	**40.8**	38.3	43.2
Opel Ampera (N = 23)									
NEDC Value	**76.9**			**1.2**			**27**		
Median	**84.4**	73	96	**0.73**	0.3	2.2	**17**	8	52
Average	**77.7**	66	86	**1.23**	0. 8	1.8	**29**	18	41
VKT Average	**73.6**	60	95	**1.41**	0.8	2.7	**33**	19	64
Toyota Prius PHEV (N = 81)									
NEDC Value	**50**			**2.1**			**49**		
Median	**32.0**	27	51	**4.32**	3.1	4.8	**101**	72	113
Average	**38.8**	34	44	**3.98**	3.7	4.3	**93**	86	101
VKT Average	**37.1**	32	44	**4.10**	3.5	4.9	**96**	82	114
Mitsubishi Outlander PHEV (N = 33)									
NEDC Value	**67.5**			**1.9**			**44**		
Median	**53.9**	47	60	**4.31**	3.6	5.0	**101**	85	117
Average	**54.0**	50	60	**4.31**	3.9	4.8	**101**	92	113
VKT Average	**50.7**	43	58	**4.71**	3.7	7.2	**110**	86	168
Volvo V60 PHEV (N = 13)									
NEDC Value	**66.7**			**1.8**			**48**		
Median	**42.5**	41	62	**4.29**	3.9	5.3	**101**	91	124
Average	**49.4**	43	57	**4.54**	4.0	5.1	**106**	95	119
VKT Average	49.4	39	63	**4.54**	3.5	5.8	**107**	82	135

* Lower and upper confidence interval limit obtained via bias corrected and accelerated (BCa) bootstrap from 1,000 bootstrap samples. Values have been rounded to one meaningful digit.

** CO_2 emissions refer to tank-to-wheel only here. See section 3.3 for more details.

Several types of averages or descriptive statistics are relevant for the analysis of fuel economy data. Table 3 states the median, the arithmetic average (abbreviated as “average” in Table 3) and the annual mileage weighted average (abbreviated as “VKT average” in Table 3) of the Chevrolet Volt, Opel Ampera, Toyota Prius PHEV, Mitsubishi Outlander PHEV and Volvo V60 PHEV. The mileage weighted average is used to calculate e.g. the nationwide average of fuel economy since vehicles with high annual mileage are operated differently and show different fuel economies. These three statistics are stated in Table 3 together with the NEDC values for the UF, total fuel economy and tank-to-wheel CO_2 emissions. Also shown in Table 3 are the lower and upper bound of these statistics (95% confidence interval) obtained from 1,000 bootstrap samples via bias corrected and accelerated (BCa) bootstrap.

For the Volt and Ampera, the observed average UF are close to the expected UF from NEDC. For all other PHEV UF from the test cycle are above the empiric UF and even outside of the confidence interval. Part of this difference might be explained by the high annual mileage of these PHEV which implies more frequent long-distance driving and lower UF. We will compare the annual mileage corrected by the UF to the test cycle values in section 3.2. Correspondingly, the total fuel economies are all larger than the fuel economies expected from test cycle values. They are within the confidence bands only for median fuel economy of the Volt and – due to the very broad confidence intervals – for the Ampera. The same holds for the tank-to-wheel CO_2 emissions as a function of effective fuel economy. The fuel economies of all PHEV analysed here are better than those analysed by Ligertink et al. (2014).

Descriptive statistics and average values provide a useful summary of the data, but the distribution of the variables can yield interesting insights. Figure 2 shows the distribution of the UF by the Chevrolet Volt. The inset shows the cumulative distribution function (CDF) of the same data. The average UF of 78% stated in Table 3 is below the most frequent value, i.e. the peak of the distribution at around 85 – 90%. Furthermore, a noteworthy share of vehicles reaches UF above 95%. Only a very low fraction of vehicles electrifies less than 40% of their mileage.

The distribution of UF is similar to a distribution of total fuel economies. Figure 3 shows the distribution of Chevrolet Volt total fuel economies compared to the test cycle fuel economy of 1.2 l/100km. We observe a very broad distribution of total fuel economy ranging from less than one tenth to up to four times the test cycle fuel consumption. Furthermore, a box plot in Figure 3 indicates that the median and average are surprisingly close to the test cycle fuel economy. The box encompasses the 25% and 75% quartiles, the whiskers bound the 9% and 91% quantiles and '+' indicates the mean. Despite the broad overall distribution of fuel economy values, the mean and median are close the test cycle value (100% in Figure 3).

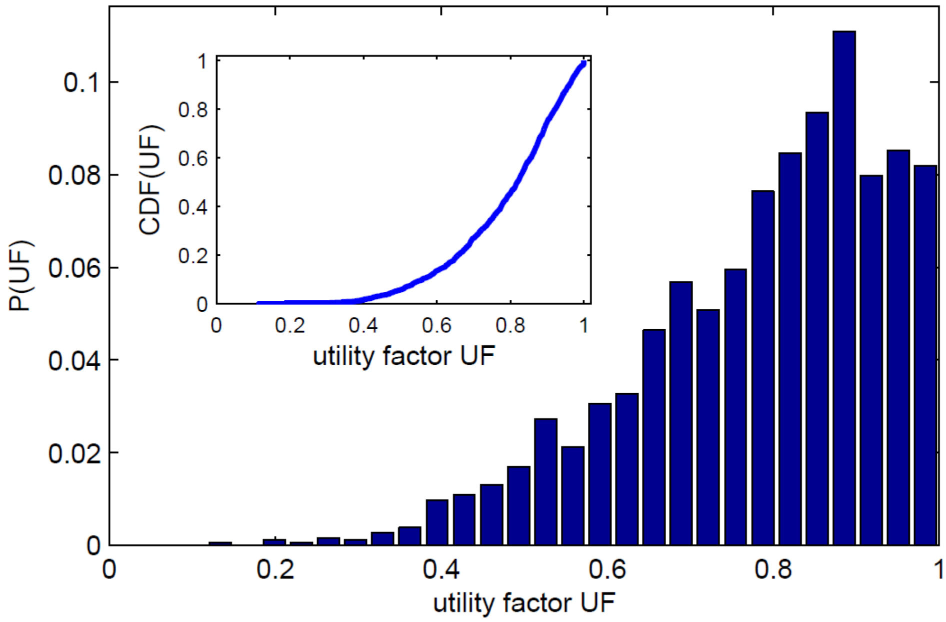

Figure 2: Distribution of Chevrolet Volt electric driving shares UF. *Inset*: CDF of the same data.

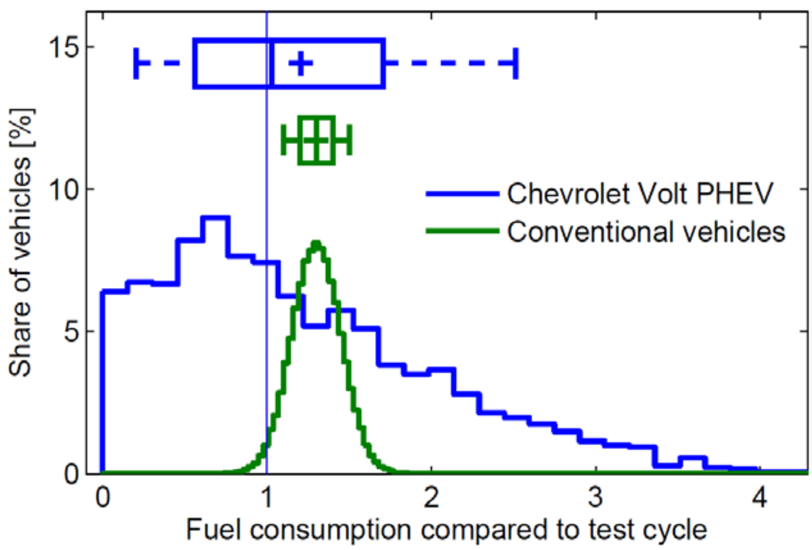

Figure 3: Distribution of fuel economies as compared to test cycle fuel economy for the Chevrolet Volt (blue) and conventional vehicles (green).

For comparison, we show a synthesised real-world fuel economy distribution of conventional vehicles. Following Mock et al. (2014), we use a Gaussian distribution of conventional fuel consumptions with an offset of 30% compared to test cycle consumption and a standard deviation of 15%. This distribution with the corresponding box plot is also shown in Figure 3. We conclude that the fuel economy of both conventional and PHEV differ from the test cycle values. However, the empirical range of the fuel economy by PHEV is much broader than for conventional vehicles but the median and average values can be close to the test cycle values.

The broad range of possible fuel economies raises the question of which factors cause the differences between individual users. As stated earlier, high annual mileage should make long-distance trips and thus low UF more likely. To test this hypothesis, Figure 4 shows a scatter diagram of the UF and annual mileage of the Chevrolet Volt.

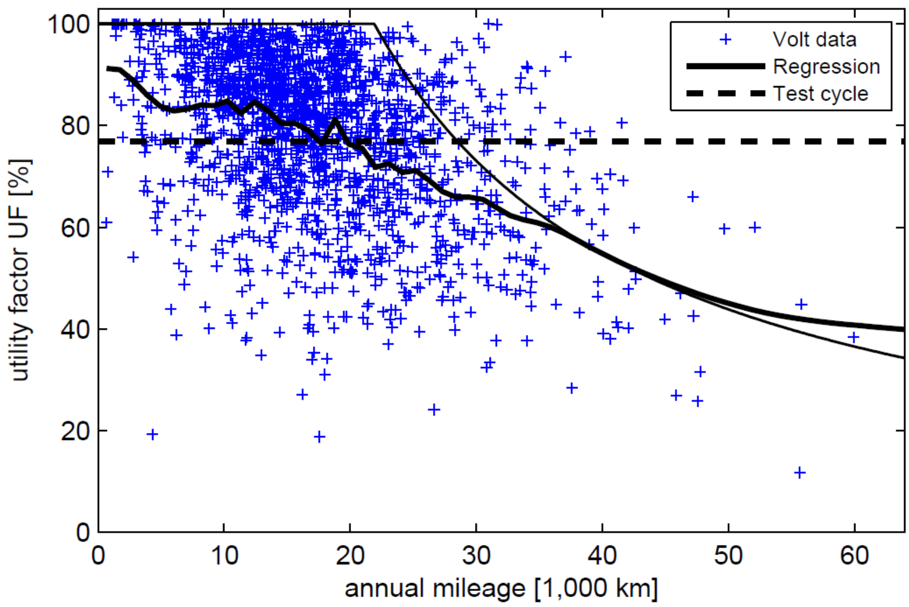

Figure 4: Electric driving shares UF and annual mileages of Chevrolet Volt data (crosses). The thick solid line is a non-parametric regression between UF and the annual mileage and is contrasted by the test cycle value (dashed line). We also indicated the maximum driving share of Chevrolet Volt restricted to only overnight charging (thin line).

We observe a broad distribution of UF even for fixed annual mileage. In order to measure the influence of the annual mileage on UF a non-parametric kernel regression is shown as thick solid line in Figure 4. We use a Nadaraya-Watson kernel regression over $\sqrt{N} = 43$ nearest neighbours to analyse the dependence without a particular assumption on the functional dependence. The kernel regression indicates that the expected UF decrease with increasing annual mileage. A linear regression yields the same negative dependence with high significance (the coefficient is negative with p-value < 10^4). This negative effect of high annual mileage is easily understood as frequent long-distance driving clearly reduces the average UF. However, UF and fuel economy values from test cycles neglect this factor so far. The UF by the NEDC for the Chevrolet Volt is 77% irrespective of the annual mileage (indicated by a dashed line in Figure 4).

The frequency of PHEV recharging is another aspect that influences PHEV fuel economy. Frequent recharging, e.g. during day time at work, can increase the number of miles electrified and thus lower the consumption of conventional fuel. Using the Chevrolet Volt data, we identify lower bounds for the share of users that recharge more than once per day. Assuming an AER of 61 km for the Chevrolet Volt, the maximal annual distance that can be driven electrically with only a single full recharge per day is 365.25 · 61 km = 22,280 km (13,844 miles). If a vehicle has an annual mileage of 30,000 km, the maximal UF with a single full recharge per day is 22,280 km / 30,000 km = 74%. Such an upper bound for the UF with a single recharge per day can be constructed for all annual mileages and is shown as thin solid line in Figure 4. We observe a noteworthy number of users (6.2%), which exceed this upper bound of UF. These users must recharge more than once per day. The assumption to use the vehicle each day a year is utopian. If the vehicle is used on six out of seven days per week, this share of frequent rechargers increases to 13.7%. In summary, our rough estimate provides lower bounds for the frequency of recharging. It indicates that at least about 5 – 10% of the users recharge their PHEV more than once per day at least on some days of the year.

3.2 Simulated electric driving shares and explanatory factors

The share of miles electrified or UF of PHEV is a key factor for its economics. Regular daily driving with almost complete utilisation of the vehicle's electric driving range strongly reduces fuel costs. Assuming only charging at night, a mileage beyond this driving range limitation decreases the average UF. Thus, the regularity of driving and the annual mileage are two factors influencing PHEV fuel economy. In the present section, we analyse factors influencing PHEV fuel economy in more detail.

In general, many factors impact vehicle fuel economy. We focus on factors that are specific to PHEV and related to direct vehicle usage. We discard factors such as aggressiveness of driving or the use of auxiliaries since these are similarly relevant for conventional vehicles. Instead our emphasis is on usage patterns and driving profiles. For example, we try to answer the question which factors during vehicle usage phase lead to different UF and fuel economy for fixed annual mileage. We use driving data of conventional vehicles with several days of observation to simulate UF of PHEV. This allows us to study the effect of different vehicle usages in terms of different daily travel distances and their day-to-day variation. Furthermore, we can simulate various battery sizes (range limitations) and analyse the impact of different factors individually. The simulation does not necessarily reproduce the correct distribution function of UF but renders a controlled variation of influencing factors possible.

We study a sample of 780 conventional vehicles with their reported daily travel distances during one week (MOP data – see section 2.1). We simulate each driving profile as PHEV with use of the full electric driving range of 60 km first and the conventional engine for the additional kilometres. We assume a full recharge of the PHEV every night. The resulting electric driving share or utility factor UF is a quantity between zero and one for each user.

We measure the regularity of driving by the standard deviation σ of the vehicle's daily mileages. A high standard deviation implies irregular driving and a low standard deviation regular driving. Furthermore, despite the variation of daily mileages alone, the tendency to low or high daily mileages might be relevant. If days with low mileage occur more frequently than days with high mileage, a PHEV would reach higher electric driving shares. This is measured by the skewness $\gamma = (1/n)\sum_i (r_i - \bar{r})^3/\sigma^3$ of the vehicle's daily mileages r_i with $i = 1, \dots, n$. A negative (positive) skewness indicates an individual left-skewed (right-skewed) distribution of daily vehicle distance that is small-distance driving days are more (less) likely than long-distance driving days.

Since the electric driving shares are metric variables between zero and one, we perform a logistic regression of the simulated electric driving shares UF to measure the impact of the (natural logarithm of) annual mileage (VKT), the regularity of driving measured by the standard deviation σ of daily driving distances, and the skewness γ of daily driving distances:

$$\text{logit}\,(UF) = \beta_0 + \beta_1 \ln \text{VKT} + \beta_2\, \sigma + \beta_3\, \gamma + \varepsilon$$

The regression results are summarised in Table 4 and form another major finding of our analysis. All explanatory factors are highly significant and have the expected signs. High annual mileage and irregular driving reduce the UF. Similarly, an increased likelihood of long-distance travel days decreases PHEV fuel economy.

Table 4: Regression results for the simulated electric driving shares.

	Estimate	**SE**	**t-statistic**	**p-value**
Constant	24.52	2.78	8.84	$<10^{-4}$
Annual mileage lnVKT	-2.19	0.28	-7.76	$<10^{-4}$
Regularity of driving σ	-1.33	0.27	-5.00	$<10^{-4}$
Tendency to long-distance trips γ	-0.79	0.14	-5.48	$<10^{-4}$

N = 780 observations, df = 776,
χ^2-statistic vs. constant model: 154, p-value = $3.5 \cdot 10^{-33}$.

We study the explained variance R^2 as share of the total variance $R^2 = 1 - \mathrm{Var}(\mathrm{res})/\mathrm{Var}(UF)$ where res are the residuals and UF the electric driving shares. We used different measures such as the adjusted R^2 and obtained similar results. Using only the (log of the) annual mileage explains about 38% of the total variance compared to 33% when using only the regularity of driving or 29% when using only the skewness of the individual daily distances travelled. The annual mileage and regularity of driving together explain 63% of the variance compared to 80% of explained variance of the full model. We attribute the remaining variance mostly to factors that impact fuel economy of conventional vehicles as well such as aggressiveness of driving, share of inner city driving, or the use of auxiliaries.

We performed similar regressions for the full data set without the restriction to representative annual VKT as well as with other electric ranges for the PHEV. The results are similar: high annual mileage, irregular driving and a high likelihood of long-distance travel reduce the electric driving share and thus negatively impact PHEV fuel economy in our case study. The annual mileage and the regularity of driving explain large shares of the variance of the electric driving share.[3]

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3 Their contribution depends on the assumed electric driving range (the annual mileage has the largest explanatory power for small electric driving ranges and the regularity of driving explains about 30% of the variance for more than 30 km AER). Using the full sample without the restriction to maximally 20% offset between stated and observed mileage reduces the explained variance and the explanatory power of the annual mileage but the qualitative regression results are stable.

The electric driving range AER is a technical factor affecting PHEV fuel economy. Figure 5 shows the mean UF (with 95% confidence bands) of all five PHEV (blue symbols) as a function of their actual electric driving range contrasted by their NEDC test cycle values (red symbols). Also shown are the mean electric driving shares from the simulation of the conventional vehicle MOP data (dashed line). Since the regression showed that annual mileage impacts electric driving shares, we corrected all mean electric driving shares by assuming the same average mileage of 17,400 km as the Chevrolet Volt.[4] In Figure 5, the electric range of the Opel Ampera has been offset by 2 km to see the difference between the Ampera and Volt data.

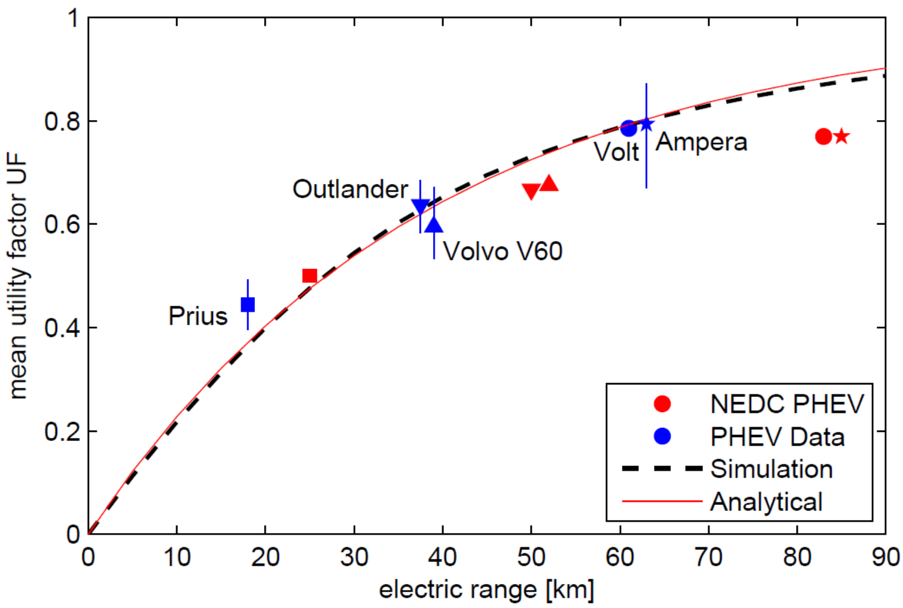

Figure 5: Electric driving shares of PHEV with different electric driving ranges. The electric range of the Opel Ampera has been offset by 2 km to see the difference between the Ampera and Volt data.

Figure 5 indicates (in contrast to Table 3) that the average electric driving shares of PHEV are close to their test cycle values if they had an annual mileage of about 17,000 km such as the North American Chevrolet Volt analysed here. Furthermore, Figure 5 shows that a simulation of conventional

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4 We performed a linear regression with simulated PHEV. For example, the log of the Outlander annual mileage has a coefficient of -0.31. With the difference between the logs of average annual mileages of -0.32 we corrected the electric driving share for the Outlander by 9.7 percentage points.

vehicle driving data as PHEV can yield good estimates for the means of electric shares if several days of observation are used. Also shown in Figure 5 is a simple analytical approximation (thin red line) to the simulated mean electric driving shares $UF = 1 - \exp[-L_e/L_0]$, where L_e is the electric driving range and L_0 = 38.8 is a constant that has been obtained by the method of least squares. We observe very good agreement between the simulation results and this simple analytical expression.

3.3 Real-world CO_2 emissions of the Chevrolet Volt

The fuel economy of PHEV directly impacts their CO_2 emissions. Several studies have analysed potential CO_2 emissions based on small PHEV fleets or simulations of conventional vehicle usage as PHEV. Here, we use the real-world fuel economy results from section 3.1 including mileage weighted fuel economy averages for realistic calculations of PHEV well-to-tank CO_2 emissions. We combine our real-world driving data with CO_2 emissions from electricity generation. Several studies already indicate that the CO_2 intensity of electrified passenger cars strongly relies on the underlying power plant portfolio for electricity provision (e.g. Hawkins et al. 2012a and 2012b, Vliet et al. 2010). Whereas charging electric vehicles with electricity from power plants based on nuclear and renewable energy sources leads to only very few specific emissions of less than 10 g CO_2 per km (Jacobson 2009), oil or coal power plants provoke even more specific emissions than current conventional cars of about 170 g CO_2 per km (274 g CO_2 per mile) (Jochem et al. 2014). Therefore, different national power plant portfolios lead to heterogeneous specific emissions (cf. IEA 2013). Following Jochem et al. (2014), three different accounting methods can be distinguished:

- average national electricity mix (for a certain year),
- marginal electricity mix (provoked by the 'additional' power plant capacity), and
- balancing emissions through policy instruments (e.g. by the EU ETS).

While our focus is on the electricity sectors in the US and Germany, we consider additionally the power plant portfolios of the three US states where most of our vehicles are registered. In California (CA) our data sample shows 239, in Texas (TX) 96 and in Michigan (MI) 89 out of 1,322 registrations where the state is indicated. Whereas the US electricity generation is dominated by hard coal, natural gas and nuclear power, Germany's main shares are coming from lignite, hard coal and renewable energies (DoE 2014, BMWi 2014). In CA generation by natural gas and renewable energy sources are dominating. MI is focusing on nuclear and coal and TX is concentrating on natural gas and coal. The corresponding average specific CO_2 emissions (in gCO_2 per kWh) are 574 for MI, 566 for the US average, 552 for TX, 546 for Germany and 374 g CO_2 per kWh for CA.

Our first scenario refers to the average specific emission values, the second scenario to the emissions values of the identified marginal power plants and the third scenario assumes that the complete electricity demand by EV is generated by renewable energy sources. Furthermore, we assume an annual mileage of 17,500 km (10,874 miles). The total fuel consumption is 0.2 kWh/km (0.32 kWh/mile) and for the charge sustaining mode 6.79 litres gasoline per km (35.2 MPG) are assumed (the mileage weighted average of the Chevrolet Volt).

For calculating the specific emissions of the Chevrolet Volt we take the (mileage weighted average) empiric share of both drive chain technologies during vehicle usage from the data base, which is 0.75 for the electric engine (see above).

$$\mathrm{CO2}_{\mathrm{Volt}} = 0.75 \ \cdot \mathrm{CO2}_{\mathrm{elec}} + 0.25 \cdot \mathrm{CO2}_{\mathrm{cs}}$$

The specific CO_2 emissions in grams per km result from the specific CO_2 emissions in the electric mode ($CO2_{elec}$, depending on the electricity mix) plus the specific CO_2 emissions in the charge sustaining mode ($CO2_{cs}$). The resulting CO_2 emissions range from 42 g CO_2 per km for the green electricity scenario up to 190 g CO_2 per km in the marginal mix scenario for Germany (cf. Table 5).

Table 5: Specific CO_2 emissions for Chevrolet Volt and total annual emission savings.

	Green electricity	Mix	Peak load power
Specific emissions for Chevrolet Volt			
USA	42 g CO_2/km	US: 115 gCO_2/km CA: 76 gCO_2/km MI, TX: 116 gCO_2/km	Natural gas (CA, TX): 99 gCO_2/km Hard coal (MI): 167 gCO_2/km
Germany	42 g CO_2/km	111 g CO_2/km	Lignite: 190 gCO_2/km
Total 2014 emission savings Chevrolet Volt with respect to conventional vehicle with 36 MPG			
USA (73,000 Volt)	140 Mt p.a.	50 Mt p.a.	natural gas (CA, TX): 67 Mt p.a. hard coal (MI): -20 Mt p.a.
Germany (1,500 Ampera)	4.0 Mt p.a.	1.1 Mt p.a.	-1 Mt p.a.

The differences from these specific emission factors and the specific emission factors of comparable conventional combustion engine vehicles (with fuel consumption of 6.5 litres per 100 km) are the specific emission savings per km. We multiplied these differences with the empiric annual mileages and the national number of Chevrolet Volt registrations for the US (Cobb 2014) and Germany. The emissions savings mount up to 144 Mt of CO_2 per year for the green electricity scenario. In the peak load scenario, however, even an increase of emissions might occur (cf. Table 5).

Looking to the future development of specific CO_2 emissions from electricity generation, the CO_2 emission reductions for the average electricity mix might increase. Until 2040 the share of generation by renewables and natural gas in the US will increase from currently 12 to 16% and 25 to 30% respectively, coal and nuclear is going to decrease from 42 to 35% and 19 to 17%, respectively (EIA 2013). This will lead to a decrease of specific CO_2 emissions from currently 100 to 85 g CO_2 per km. For Germany this effect is stronger. The share of electricity generated by renewable energy sources is going to increase from 25 to 60% and all other primary energy source inputs are going to decrease considerably. Coal is decreasing from 35 to 30%, natural gas from 11 to 5% and nuclear from 16 to 0% (Babrowski 2015). The specific CO_2 emission factors per kWh imply a decrease from 111 to only 57 g CO_2/km.

4 Discussion

We used public available data for analysing real-world PHEV fuel economy. Hereby, our results depend on the representativeness and quality of the datasets used. The sample size of the datasets is limited. However, due to the low market diffusion of PHEV our samples represent a remarkable share of the actual PHEV fleet. The analysed Chevrolet Volt sample comprises more than 2% of the total Volt fleet in the U.S. Furthermore, the datasets might be biased to higher fuel economy as users reporting their fuel economy could be more aware of their driving behaviour.

Some parameters, as the annual mileage, have to be derived from data directly available in the datasets. To do so, we assume the reported car usage in the reporting period to be representative for the overall driving behaviour of the user. Due to mainly long reporting periods of more than a year this assumption seems justifiable. Notwithstanding, the high averages of some annual mileages in the databases are remarkable and might be interpreted as rebound effect (Frondel, Peters and Vance 2008).

In the simulation of PHEV usage based on conventional travel data (section 3.2) we use the total dataset whereas the actual mileage distribution of PHEV could be different. Indeed, for descriptive statistics that go beyond measures of location such as the mean or median such as, e.g. quartiles, the simulation performs not as good since the distribution of annual mileages of PHEV differs from the distribution of the full vehicle stock (cf. Figure 1). The narrow peak of the annual mileage distribution leads to an overestimation of the variance of UF by PHEV when simulating conventional vehicles as PHEV.

Finally, we calculate annual emission savings by the Chevrolet Volt. As a reference car, we use a conventional vehicle with fuel economy close to the charge sustaining fuel economy of the Volt. We make this assumption as we expect the effect of the higher mass of the Volt due to the battery and a more efficient smaller engine on fuel economy to mostly balance out. For the calculation of emissions in charge depleting mode we use three different scenarios on electricity generation. A more detailed analysis of actual specific emissions of the electricity used as fuel might be interesting for further research, especially for political action.

5 Summary and Conclusion

We analysed empiric fuel economy of PHEV. The main finding is that test cycle values of PHEV fuel economy and utility factors can be good estimates for the averages of a vehicle fleet if the fleet average annual mileage is about 17,000 km. However, data of individual vehicles differs significantly. The heterogeneous usage patterns of passenger cars have a considerable impact on individual fuel economy.

Our analysis is based on empiric driving patterns of about 2,000 actual PHEV that have been observed for more than a year in the U.S., Canada and Germany. For the largest sample, Chevrolet Volt PHEV, the average annual mileage is 17,422 km (10,826 miles) with a considerable variance (SD = 8,269 km) and the share of kilometres electrified is 78.5% with an SD of 15.4%. The high variance of real-world fuel economies is mainly explained by the regularity of daily driving, annual mileage, and the likelihood of long-distance travel. We proved these findings by a kernel and logit regression of actual and simulated PHEV usage data. Furthermore, we demonstrated that even though the current test cycle fuel economy ratings neglect all three identified influencing factors, the resulting values of average fuel efficiency can be good estimates for average users.

The average empiric fuel economy of the Chevrolet Volt (1.45 litres/100 km or 162 MPG) is only somewhat higher than the official NEDC value of 1.2 litres/100 km (196 MPG). This leads to well-to-wheel CO_2 emissions of 42 – 190 gCO_2/km depending on the underlying electricity generation. The total annual CO_2 savings amount to 144 Mt in an optimistic scenario.

Concluding, due to the higher variance of empirical PHEV fuel economy compared to conventional vehicles, a more sophisticated policy instrument (e.g. considering the main individual usage patterns as regularity of daily driving, annual mileage, and affinity to long-distance trips) would correspond better to the polluter pays principle as the current policy does. This might be taken into account by the future World Light Test Procedure (WLTP), which is currently under development. Furthermore, frequent recharging with low-carbon electricity should be incentivised.

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