Total Ownership Cost Projection for the German Electric Vehicle Market with Implications for its Future Power and Electricity Demand

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Abstract

Electric vehicles have a high potential to reduce the greenhouse gas emissions from transportation, but their large-scale introduction would also have a significant impact on power grids and the electricity demand. Reliable estimates of their future market share are therefore of great interest to distribution network operators, electricity producers and vehicle manufacturers alike.

The future market shares of electric vehicles are difficult to predict but purchase prices and fuel costs are generally acknowledged as highly relevant factors. However, the latter are heavily dependent on driving behaviour and the vehicle kilometres travelled which required a detailed analysis. In this paper, we examine the total cost of ownership (TCO) for a distribution of annual vehicle kilometres travelled based on a large data set of driving profiles from Germany rather than the 'average driver', which is a commonly used but misleading entity. Such TCO estimates are an integral part of buying decisions and we compare the TCO for conventional, plug-in hybrid, and battery electric vehicles. We look at four different vehicle size classes to model customer purchase decisions and to derive the future market shares of the three propulsion technologies.

The resulting projections represent an important baseline for models attempting to estimate future market shares and we combine them with a vehicle fleet stock model to obtain projections of the German electric vehicle fleet. The associated increased energy demand is then computed for different fuel price scenarios. Implications for electricity consumption and time-resolved power demand are then derived and discussed.

Keywords: electric vehicle, plug-in-hybrid electric vehicle, total cost of ownership, stock model

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1. Introduction

Electric vehicles have a high potential to reduce green house gas emissions in the transport sector (Pasaoglu et al., 2012; Thomas, 2009, 2012). Their large-scale introduction would also have a significant impact on power grids and the electricity demand. Thus, reliable estimates of their future market share are of great interest to distribution network operators, electricity producers and vehicle manufacturers alike and has received substantial interest in the literature (see Wietschel and Dallinger (2008) and references therein).

The expected market diffusion of new technologies in general has long been studied. Different models and projections for the market diffusion of different future propulsion technologies exist (McKinsey and Company, 2011; Mock, 2010; Mock et al., 2009; Kley, 2011). The future market shares of electric vehicles are difficult to predict but purchase prices and fuel costs are generally acknowledged as highly relevant factors and modelled as part of the adoption decision. However, the latter are heavily dependent on driving behaviour and the vehicle kilometres travelled which required a detailed analysis. In this paper, we examine the total cost of ownership (TCO) for a distribution of annual vehicle kilometres travelled based on a large data set of driving profiles from Germany rather than the 'average driver', which is a commonly used but misleading entity. Such TCO estimates are an integral part of buying decisions and we compare the TCO for conventional, plug-in hybrid, and battery electric vehicles. We look at four different vehicle size classes to model customer purchase decisions and to derive the future market shares of the three propulsion technologies.

The majority of light-duty vehicles is privately owned and accordingly, the potential for private costumers to adopt electric vehicles has been studied extensively (Biere et al., 2009). Here, we study the time-evolution of market shares and stock for electric vehicles as obtained from TCO projections. We will use a time frame until 2050. However, let us emphasise again that the market shares obtained from TCO projections are no predictions for actual sales but rather one important ingredient. The time frame has been chosen rather long, in fact much longer than reliable estimates for prices or technological evolution are available, since the evolution of stocks is rather slow. Thus, the values beyond 2030 are rather meant as an outlook, what might be obtained when current trends are extrapolated and its effect on the German vehicle fleet.

2. TCO Model and Battery Simulation

2.1. TCO Approach and Resulting Market Shares

In the present section, we explain our general approach to compute the total costs of ownership for different vehicle types. The total costs of ownership (TCO) are given by the sum of purchase and usage costs over the vehicle's lifetime. We distinguish between the vehicle, its battery and variable costs. The latter are given by the product between the specific fuel consumption and the annual vehicle kilometres travelled (VKT). The investment is discounted to make the different annual fuel costs and the different vehicle purchase prices comparable. We are now going to develop a single mathematical description for various propulsion technologies. The formalism is general, but we will later limit ourselves to four propulsion technologies (Chan, 2007): the internal combustion engine (ICE), the hybrid electric vehicle (HEV) which has a small high-power battery for efficiency increase but cannot drive fully electrically, the plug-in hybrid electric vehicle (PHEV) which here drives electrically but has an additional combustion engine as an effective range extender, and finally the battery electric vehicle (BEV) which has a rather large battery and a limited driving range.

Treating different VKTs of individual is straightforward when the vehicle is with only one propulsion technology, i.e., either only electrically or only by internal combustion engine. This is different for PHEVs. Here, we assume that the owner of a PHEV uses the total electric driving range available to him or her first and uses the additional combustion engine when the electric driving range is exceeded. As an illustration, we will discuss the formalism for PHEVs first. The TCO for PHEVs are given by the sum of discounted purchase and usage costs

$$\mathrm{TCO} = (I + c_B\kappa)a_n(p) + d \cdot C(L,\kappa). \tag{1}$$

Here, I denotes the purchase costs of the PHEV (excluding the battery), c_B the specific battery cost (in Euro/kWh), $a_n(p) = \frac{p(1+p)^n}{(1+p)^n-1}$ is an annuity factor for n years at an interest rate p. We will use $n = 4$ years and $p = 5\%$ throughout this work. The second term in eq. (1) will be explained in a moment and represents the variable costs of going on a trip of length L with costs $C(L,\kappa)$ on every day (out of d days per year). Since the PHEV can drive electrically or by using its additional combustion engine, we assume that the drivers uses his full electric driving range L_E first, and turns on the combustion engine only when the actual trip length is longer than the electric driving range. We thus have to distinguish daily driving distances smaller or larger than the electric driving range. The variable costs for a single trip of length r with a PHEV with a battery of size κ and an electric driving range $L_E(\kappa) = \kappa/u_E$ (u_E is the specific electric energy consumption in kWh/km) are accordingly given by

$$C(r,\kappa) = \begin{cases} c_E r & \text{for} \quad r \le L_E(\kappa) \\ c_E L_E(\kappa) + c_R(r - L_E(\kappa)) & \phantom{\text{for}} \quad r > L_E(\kappa) \end{cases} \tag{2}$$

Here, c_E (c_R) denotes the specific electric (range extender) driving costs in Euro/km. Using the Heaviside step function $\Theta(x-a) = 0$ for $x < a$ and $\Theta(x) = 1$ for $x > a$, this can be written in a single line as follows

$$C(r,\kappa) = c_E r\Theta(L_E - r) + [c_E L_E + c_R(r - L_E)]\Theta(r - L_E) \tag{3}$$

The idea just outlined can straightforwardly be generalised to several vehicle technologies or vehicle categories. Let us denote the (discounted) total cost of ownership per year t for a vehicle of technology i driving L kilometres per day as

$$\begin{aligned} \mathrm{TCO}_i(L,t) = {} & a_n(p)(I_i + c_B(t)\kappa_i) + \\ & d\Big[c_{E,i}(t)L\Theta(L_{E,i} - L) + [c_{E,i}(t)L_{E,i} + c_{R,i}(t)(L - L_{E,i})]\Theta(L - L_{E,i})\Big] \end{aligned} \tag{4}$$

where we added an index i to all variables to allow individual consumption rates, battery size, etcetera for each vehicle class i. A vehicle class might be a technology, a size class or a combination of both. We will later discuss four vehicle technologies (ICE, HEV, PHEV, BEV) and three vehicle sizes (small, medium, large), such that i runs effectively from 1 to 12. Furthermore, we will later use time-dependent prices and indicated this by adding an explicit time-dependence in the consumption costs for technology i (given by $c_{X,i}$, with $X = B, R, F$) and accordingly to the total costs of ownership. The special case of in ICE which can only drive on fuel is also included in eq. (4) by using an electric driving range of 0 kilometres, i.e., by setting $L_E = 0$ in eq. (4).

Let us now turn to the calculation of market shares based on minimal TCO. We assume that every potential adopter buys the vehicle that has minimal TCO for his annual driving distance. As mentioned before, this is certainly not a realistic model of purchase decisions, but it is an important aspect thereof and one actually observes that the owners of efficient vehicle technologies such as diesel have larger annual VKT (at least for the German market which we consider here). For our TCO comparison we need to find those daily driving distances $L \in (0, \infty)$ for which technology i is the cheapest. This means we are looking for the set $\{L|\forall j = 1 \dots N, j \neq i : \mathrm{TCO}_i(L) < \mathrm{TCO}_j(L)\}$. This can be implemented by using the Heaviside step function $\Theta(x - a) = 0$ for $x < a$ and $\Theta(x) = 1$ for $x > a$. Since a product is different from zero if and only if all factors differ from zero, we can define the characteristic function for technology as

$$\chi_i(L, t) = \prod_{j \neq i} \Theta\left(\mathrm{TCO}_j(L, t) - \mathrm{TCO}_i(L, t)\right). \tag{5}$$

This characteristic function has the desired property: it is one for all L where technology i is cheaper than all other technologies and equal to zero when at least one of the other technologies is cheaper for the given driving distance L. Since we allow the prices to change in time, the characteristic functions are also time-dependent. The formalism described so far might seem somewhat cumbersome, given that the same could have been written as

$$\chi_i(L, t) = \begin{cases} 1 & \text{if} \quad \mathrm{TCO}_i(L, t) = \min_j \mathrm{TCO}_j(L, t) \\ 0 & \quad\quad\quad \text{else} \end{cases}. \tag{6}$$

The advantage of eq. (5) is that it can be used in numerical simulations without time-consuming if-statements.

Having determined the cost-optimal vehicle option for given VKT L, we can now compute market shares, i.e., which fraction of drivers would choose which option for minimal TCO. This market share of technology i is given by the sum over all annual (or daily) vehicle kilometres travelled for which technology i is cost-optimal weighted by the probability of occurrence $P(L)$ for the specific VKT L:

$$p_i(t) = \int_0^\infty \chi_i(L, t) P(L) \mathrm{d}L. \tag{7}$$

In this expression the characteristic function effectively reduces the sum (or integral) to those VKT where the given technology is the cheapest. Please note, that the market shares sum up to unity by when $P(L)$ is normalised and no further normalisation is required.

To summarise, for given cost and vehicle parameters, we developed a single mathematical expression for the market shares of different technologies. We presented it for TCOs of vehicle propulsion technologies, but the formalism is quite general and other use-values than TCO could likewise be implemented.

2.2. Stock Model

Let us use the market shares obtained so far as an input for the vehicle stock evolution. If there are in total $N_{\text{in}}(t)$ new cars per year, the number of new cars of technology i is simply given by $n_i(t) = p_i(t)N_{\text{in}}(t)$. 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 $P_{\text{scrapping}}(t)$. This can also be written with a probability $L(t) = 1 - \int_0^t P_{\text{scrapping}}(s)\mathrm{d}s$ for a vehicle to survive until age t. With this distribution at hand, one can write the stock of vehicles in year t as the sum of vehicles purchased in earlier years that survived until year t:

$$N_i(t) = \sum_{s=t_0}^{t} n_i(s)L_i(t-s). \tag{8}$$

This expression has been used for numerical results that will be shown below with a survival probability obtained from the official German statistics (KBA, 2011).

2.3. Battery State of Charge Simulation

Similar to earlier works (Gnann et al., 2012) we study driving profiles of German drivers to analyse whether their vehicles could be replaced by battery electric vehicles. We use the German mobility panel (MoP, 2008) as data set for driving behaviour. It consists of 12,812 households, who reported all their outdoor movements for one week. Since these movements are person-specific and e. g. also contain movements by foot, train or bicycle, we allocate movement profiles to cars if possible unambiguously (for further details see Kley (2011)). This reduces the data set to a total of 6,629 car-specific driving profiles. As the sample does not contain car size information, we assumed all vehicles to be medium-sized, due to the fact that this is the largest car segment in Germany with almost 55 % of all light duty vehicles (Gnann et al., 2012).

With these driving profiles we may calculate the battery state of charge (SOC) any point in time of the week t as follows:

$$\mathrm{SOC}(t+1) = \left\{ \begin{array}{c} \mathrm{SOC}(t) - d_{\Delta t} \cdot u_e \\ \min\{\mathrm{SOC}(t) + \Delta t \cdot P_{loc_t}, C\} \end{array} \right. \text{for} \quad \begin{array}{c} d_{\Delta t} > 0 \\ d_{\Delta t} = 0 \end{array} \tag{9}$$

where the initial value is given by $\mathrm{SOC}(0) = C$. In this formula $\mathrm{SOC}(t)$ denotes the state of charge at the point of time t. The distance driven between the two points of time t and $t + \Delta t$ is given in km in $d_{\Delta t}$, while Δt in hours is the time difference. The consumption of electric power in kWh/km is denoted as u_e. In addition, P_{loc_t} (in kW) describes the power for charging at the location where the car was parked at t. Here we take charging infrastructure to be available only at the final destination. C in kWh describes the capacity of the battery analysed. Thus, the equation can be read as follows: if the car is driven (case 1), the battery will be discharged by the energy needed for driving distance $d_{\Delta t}$. Otherwise (case 2), it will be charged with the power P_{loc_t} for the time Δt if necessary and charging infrastructure is available ($P_{loc_t} > 0$).

In the following we use time sections Δt of 15 minutes for the profile generation and record starting and stopping time, the stopping location and the distance travelled in this time period. The consumption for all cars is set to $u_e = 0.194$ kWh/km (Helms and Hanusch, 2010).

3. Parameters and German Driving Behaviour

3.1. Vehicle Parameters and Prices

As already mentioned, we will use four vehicle technologies and three vehicle classes. The purchase prices and energy consumptions follow (Helms and Hanusch, 2010; Wietschel et al., 2010; Fraunhofer ISI, 2010) where applicable, others are assumptions for this work. Additionally, the HEV is assumed to be 10% more efficient than the ICE and only slightly more expensive (excluding the battery price). The parameters are summarised in table 1. Please note that the battery sizes are the actually used net capacities. The effect of depth of discharge (DoD) smaller than unity is effectively captured by the high battery prices we will assume, e.g. 75% DoD can be modelled as a 33% higher battery price.

Parameter	Units	**small**	**medium**	**large**
Consumption per km				
fuel consumption ICE	[l/100km]	5.7	7.6	9.5
fuel consumption HEV	[l/100km]	5.1	6.9	8.6
fuel consumption PHEV	[l/100km]	3.8	4.75	7.6
elec. consumption PHEV	[kWh/km]	0.151	0.193	0.242
elec. consumption BEV	[kWh/km]	0.17	0.21	0.26
Battery size				
Battery size HEV	[kWh]	1	1.5	2.0
Battery size PHEV	[kWh]	6	10	14
Battery size BEV	[kWh]	15	20	40
Invest (without battery)				
Invest ICE	[Euro]	9,079	17,358	32,787
Invest HEV	[Euro]	9,179	17,458	32,887
Invest PHEV	[Euro]	10,721	19,114	34,587
Invest BEV	[Euro]	9,597	17,804	32,000

Table 1: Assumed technical parameters for the total cost of ownership calculation for the four vehicle classes (small, medium, large) under consideration and the four vehicle technologies (ICE, HEV, PHEV, BEV).

To compute the variable costs for given VKT, we need assumptions for the time-evolution of fuel, electricity and battery prices. The (annually averaged) fuel price depends both on the oil price and taxes. Oil price and fuel price scenarios are often influenced by short time fluctuations or important reference scenarios. Furthermore, many assumptions for fuel prices are over optimistic and quickly overtaken by time. For example, (Biere et al., 2009) used a fuel price of 1.53 Euro/litre for 2030 in Germany which has been reached already in 2011.

Here, we take a different route to estimate future German fuel prices. We study the inflation-adjusted German fuel prices of the last 40 years (data at an annual basis was not available for years before 1970) and obtain average compound growth rates which

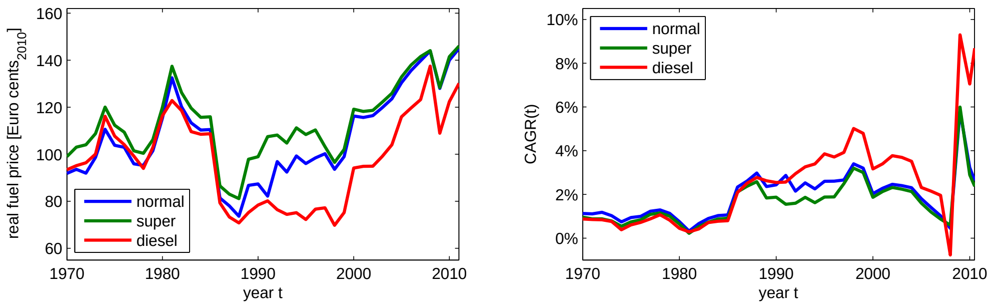

Figure 1: *Left panel*: Inflation-adjusted German fuel price since 1970 (in Euro cent$_{2010}$/litre). The historical oil price shocks and the steady increase over the last decade are clearly visible. *Right panel*: Evolution of compound annual growth rates with each year since 1970 as starting year according to eq. (10).

are then used to compute future fuel prices. The advantage of this method is purely data driven and directly includes both effects of oil price variations and changing taxes.

The left panel of figure 1 shows the inflation-adjusted fuel prices for Germany[1] for three fuel types: normal, super, and diesel fuel. The strong increase in prices in the 1970s and early 80s are clearly visible. Furthermore, the three prices have been growing with some fluctuation since since 1990.

Compound annual growth rates are a useful to calculate average growth rates over longer periods of time. However, taking into account the fluctuation of the fuel prices, it is difficult to decide which year to take as starting year. We thus compute the compound annual growth rate (CAGR) with each of the last forty years as starting year:

$$\mathrm{CAGR}(t) = \left(\frac{p_F(2011)}{p_F(2011-t)} \right)^{1/t} \tag{10}$$

where $p_F(t)$ denotes the inflation-adjusted fuel price in year t. The resulting CAGRs are since 1970 are shown in the right panel of figure 1.

The CAGRs with each of the last forty years as starting year shows a clear dependence on the choice of the initial year. Taking a year between 1970 and 1985 as starting year, the CAGR obtained would be roughly one percent. Taking later starting years between 1985 and 2005, the resulting CAGR is around $2-4$ %. For years later than 2005, the CAGR reflects recent price changes and fluctuates rather strongly. Facing these varying CAGRs, we decide to compute the arithmetic averages and median over the different starting years for CAGR. The results for the three different fuels (normal, super, and diesel fuel) are summarised in table 2. We observe that all average CAGRs vary between 1.6 and 2.5% with a tendency to values larger than 2%. Based on the results, we will thus assume an annual increase in fuel price of 2% for the future fuel prices. That is, we take the fuel price to be 1.50 Euro/litre in 2011 and increase by 2% annually. For the electricity price, 0.22 Euro/kWh in 2011 and 1% annual increase are assumed. This results in an electricity price of 27 Eurocent in 2030. Furthermore, battery costs are

[1]Before 1990 West Germany only.

statistic	**normal fuel**	**super fuel**	**diesel**
Median	2.09%	1.61%	2.41%
Mean	2.50%	2.23%	2.51%

Table 2: Median and mean of annual compound growth rates for computation of CAGRs with different starting years between 1970 and 2010.

Parameter	unit	**value**
fuel price p_F	[Euro/l]	$1.50(1+0.02)^{t-2011}$
spec. elec. costs c_i	[Euro/kWh]	$0.22(1+0.01)^{t-2011}$
battery cost c_B	[Euro/kWh]	$150 + 850\sqrt[9]{350/850}^{\,t-2011}$

Table 3: Assumed time-evolution of fuel, electricity and battery prices.

rather conservatively assumed to drop from 1000 Euro/kWh in 2011 to 500 Euro/kWh by 2020 but never in the future time-evolution below 150 Euro/kWh. These assumptions on future prices are summarised in table 3.

3.2. Segments

As already mentioned, we will distinguish three vehicle classes small, medium, and large that represent coarse-grained versions of the most important vehicle size segments as listed by the German vehicle fleet statistics.[2] Figure 2 shows the share of these classes of the total annual vehicle sales in Germany since 2006. The shares of the three coarse-grained vehicle size classes are more or less constant over time. 2009 forms an exception when the German government offered for a short time financial support for the replacement of existing vehicles.

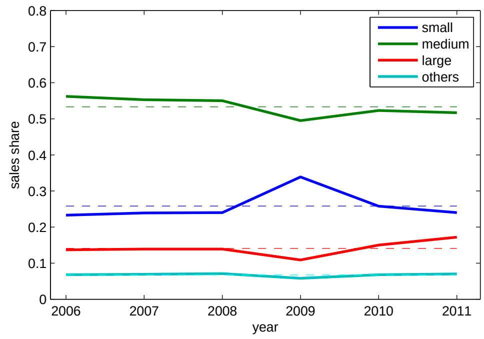

Figure 2: Share of vehicle size class in sales of new vehicles in Germany since 2006. The averages over the last 5 years are shown as dashed lines.

[2]We use small: Mini, Kleinwagen; medium: Mittelklasse, Obere Mittelklasse, Mini-Vans, Kompakt; large: Oberklasse, Grossraum-Vans, Geländewagen; the three remaining segments (Utility, Sportwagen, Wohnmobile) only make up between 6 and 7% of the annual German sales and will be neglected.

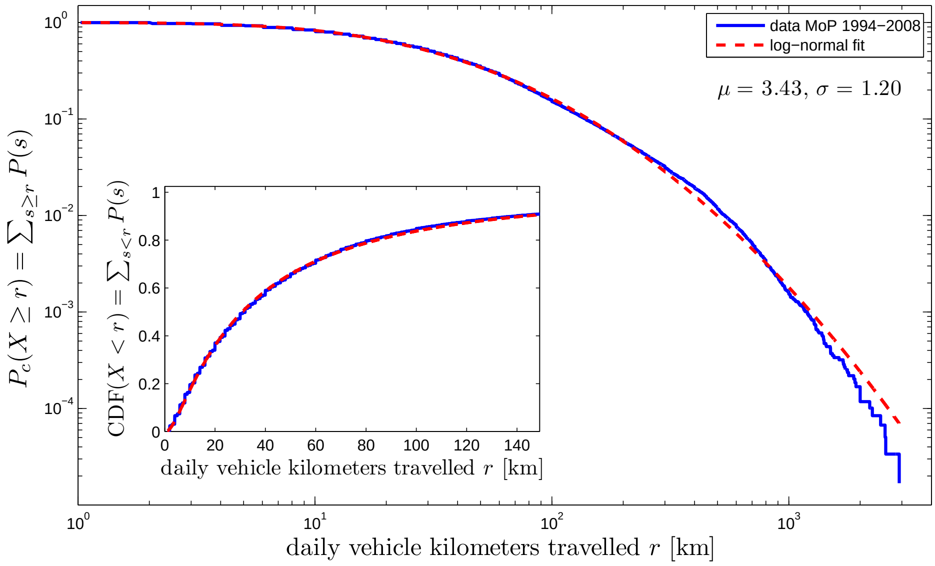

Figure 3: Distribution of daily vehicle kilometres travelled in Germany.

For the following, we will exclude the categories 'others' and treat the average share of each segment as constant in time. The shares, excluding 'others', are given by 27,7% for small, 57,2% for medium and 15,1% for large vehicles respectively.

3.3. German Driving Behaviour

When introducing the market shares in eq. (7) we mentioned the need for using a distribution of VKT for the drivers. To this end, we analysed the daily VKT by for a large set of German vehicle travel data. Figure 3 shows the complementary cumulative distribution function $P_c(x) = \int_x^\infty P(s)\mathrm{d}s$ (main figure) and cumulative distribution function $\mathrm{CDF}(x) = \int_0^x P(s)\mathrm{d}s$ (inset) of the daily vehicle kilometres travelled for Germany (over all segments). The data has been taken from MoP 1994–2008 MoP (2008). We model the distribution of daily vehicle kilometres travelled by a log-normal distribution

$$P(r) = \frac{1}{r\sqrt{2\pi}\sigma}\exp\left[\frac{(\ln r - \mu)^2}{2\sigma^2}\right]. \tag{11}$$

A least square fit of the log-normal distribution (dashed line) is shown in figure 3, as well. We observe excellent agreement between the data and the fitted log-normal distribution. Only at very large travel distances, the curve slightly deviate showing a difference of the order of 10^{-2}. However, since the data refers to Germany and a single day only, this might also be due to the finite day-length.

The inset of figure 3 shows the cumulative distribution function $\mathrm{CDF}(r) = \int_0^r P(s)\mathrm{d}s$, where $P(s)$ is the probability density function of driving s kilometers per vehicle and day, of the daily driving distances. The cumulative distribution function has a simple interpretation: $\mathrm{CDF}(r)$ is the share of vehicle driving up to r kilometres per day. Thus, about 70% of the German vehicles drive less than 60 km per day.

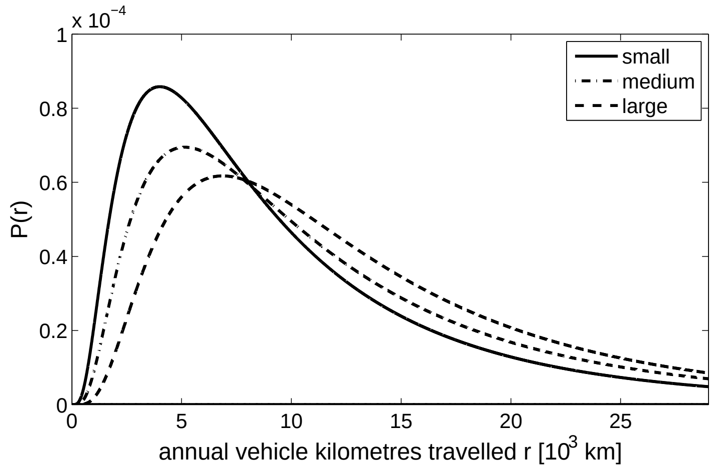

Figure 4: Distribution of annual vehicle kilometres travelled by privately owned vehicles for different vehicle size classes (solid line – small, dashed-dotted – medium, dashed – large). Longer annual driving distances are more likely for larger vehicles.

We will use the log-normal distributions for the VKTs within the different segments. Unfortunately, the large MoP data set does not provide information on the segment of the vehicles. We therefore resided to use a second data set of German travel behaviour (MiD, 2008) which provides this information. Under the assumption of segment-wise log-normal distributions, we obtained the two parameters μ and σ for each segment. The results are summarised in table 4 and the resulting annual VKT distributions are shown in figure 4.

	small	medium	large
scale μ	3.08	3.30	3.46
shape σ	0.83	0.81	0.72

Table 4: Parameters for log-normal fit of VKT for different segments.

These parameters and distributions will be used for the following TCO computations.

3.4. Lifetimes for Vehicles

A lifetime distribution for the vehicles to remain in stock is needed for the stock model introduced above. We use data for the complete German vehicle fleet and the age dependent scrapping probability over the last ten years (KBA, 2011) . 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. This was performed for all years available and then averaged over all years. We excluded the years 2010 and 2011 since the one-time initiative of the federal government in 2009 ("Umweltprämie") drastically altered the scrapping. The resulting probability for leaving the stock at a certain age, i.e. the scrapping probability, is shown in the left panel of figure 5 together with a fit by Weibull function.

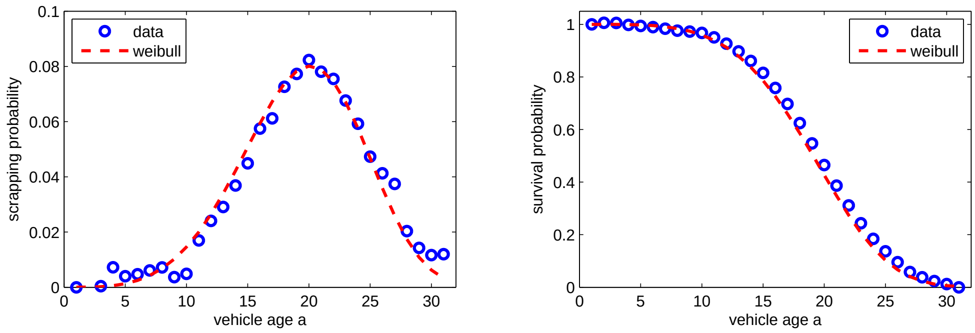

Figure 5: Scrapping and survival probability of German vehicle fleet. *Left panel*: Scrapping probability of German vehicle fleet obtained from changes in age-dependent stock since 2001, with 2010 and 2011 excluded, together with a least squares Weibull fit. *Right panel*: Survival probability of German vehicle fleet obtained from changes in age-dependent stock since 2001, with 2010 and 2011 excluded, together with a least squares Weibull fit.

The right panel of figure 5 shows the resulting survival probability or lifetime distribution $L(t) = 1 - \sum_{s<t} P_{\text{scrapping}}(s)$. The Weibull distribution of lifetimes is accordingly given by

$$L(t) = \mathrm{e}^{-(t/\tau)^{\beta}} \tag{12}$$

where the parameters $\tau = 21.25$ for scale and $\beta = 4.51$ for shape have been obtained from a least square fit. Please note that this is the situation in the German vehicle stock for roughly the last ten years. We are well aware of the fact that vehicles are getting older now than they used. The actual age distribution of the German vehicle fleet does in fact not coincide with the survival probability shown in the right panel of figure 5 but falls off faster. However, the age distribution will naturally get closer to the current survival probability and thus the the Weibull fit mentioned above is the better choice for modelling future vehicle stocks. Thus for the stock model of the German vehicle fleet we will use this Weibull distribution with the parameters given.

4. TCO Projections and Stock Evolution

In the present section we apply the formalism with the parameters introduced above to compute and compare the TCOs of the four vehicle technologies.

Figure 6 shows the the TCO projections for the four vehicle technologies and three size segments at different instances of time. The purchase price for an ICE has been substracted and the TCO have been shown for a single day for easier reading. The panels show how all daily costs are linear in the VKT driven since they enter the TCO linearly via the respective consumption costs. The difference in consumption costs are reflected by different slopes in all panels. Furthermore, we observe that particularly PHEVs and BEVs have higher initial costs,i.e. a finite difference to ICEs at $L = 0$, but lower consumption costs, i.e. smaller slopes. The range of VKTs L for which one technological option is cheapest is simply the range of Ls where the respective curve is below all others. Thus, there is a minimal driving distance required for BEVs and PHEVs to become cost-effective compared to ICEs and HEVs.

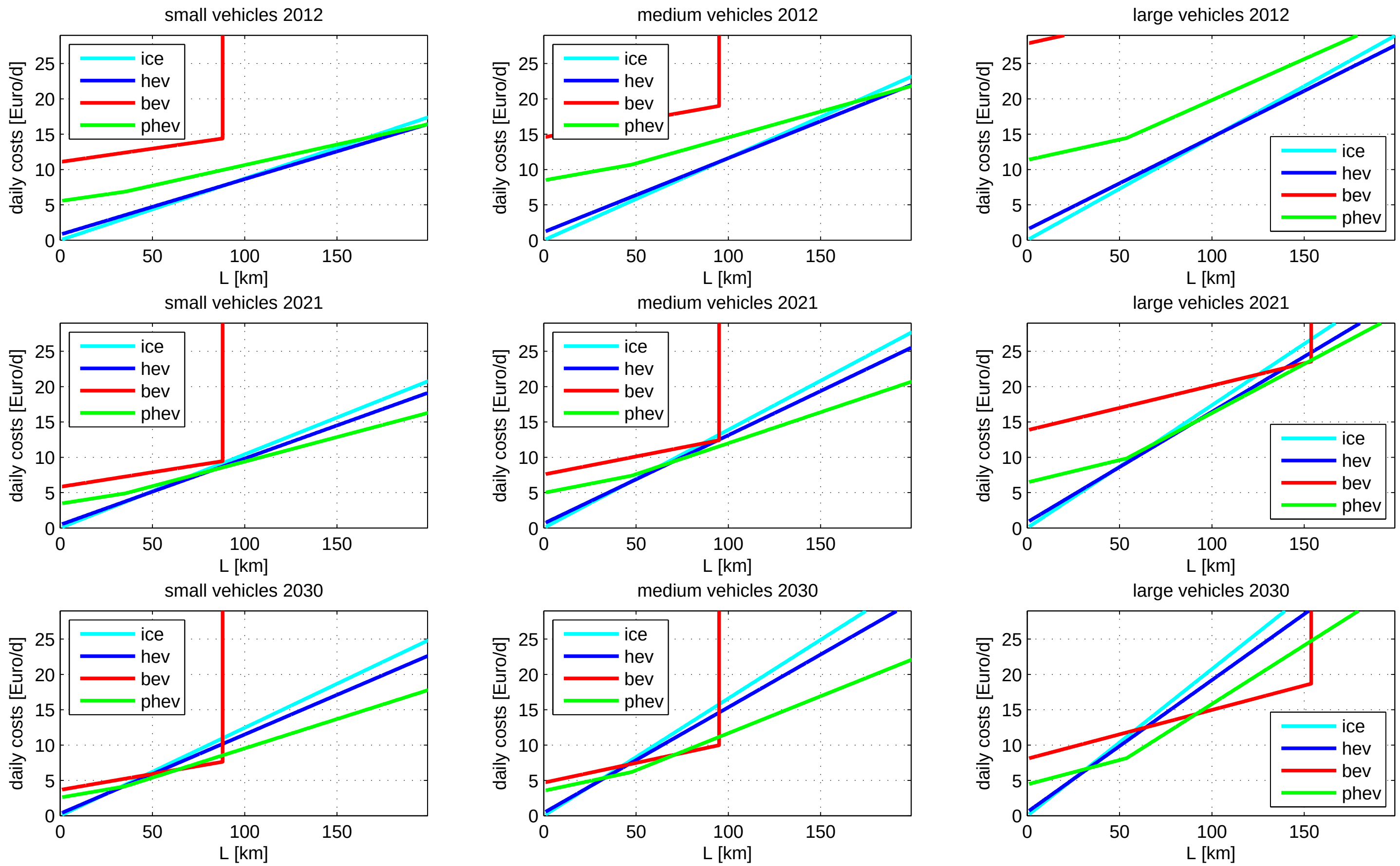

Figure 6: TCO projections by segment and technology as a function of the daily driving distance. *Top panel*: Sales shares for the individual technologies per segment (from left to right: small, medium, large) with ICE (light blue), HEV (dark blue), PHEV (green) and BEV (red). *Lower panel*: The same as in the upper panel, but sales shares are stacked.

Clearly visible in all panels is the finite driving range per day of BEVs which allows them to be considered only for daily trips within that range. This driving range could be extended by fast charging, however, since this option is rather expensive and its proliferation difficult to estimate, we do exclude it for our present discussion. Furthermore, the two specific consumption costs for PHEVs, one for electric and one for range extender driving are clearly visible in the changing slopes for PHEVs. Overall, the low additional invest and low consumption cost make PHEVs highly relevant in all segments and particularly dominating in the large vehicle class, where fuel consumption is rather high. This is partially due to the high assumptions on fuel consumption. Put differently, stronger reduction goals in CO_2 emissions for future vehicles could significantly reduce fuel consumption of conventional vehicles, especially in the large segment and the picture would change. Furthermore, new battery generations such Lithium-Sulfur or Lithium-air may drastically alter the battery capacities and prices for electric vehicles. However, for the sake of comparability, we stick to the assumptions presented above in the following (Helms and Hanusch, 2010; Wietschel et al., 2010; Fraunhofer ISI, 2010).

Based on these TCO projections we compute market shares. Figure 7 shows the market share projections for the four vehicle technologies and three size segments. Again,

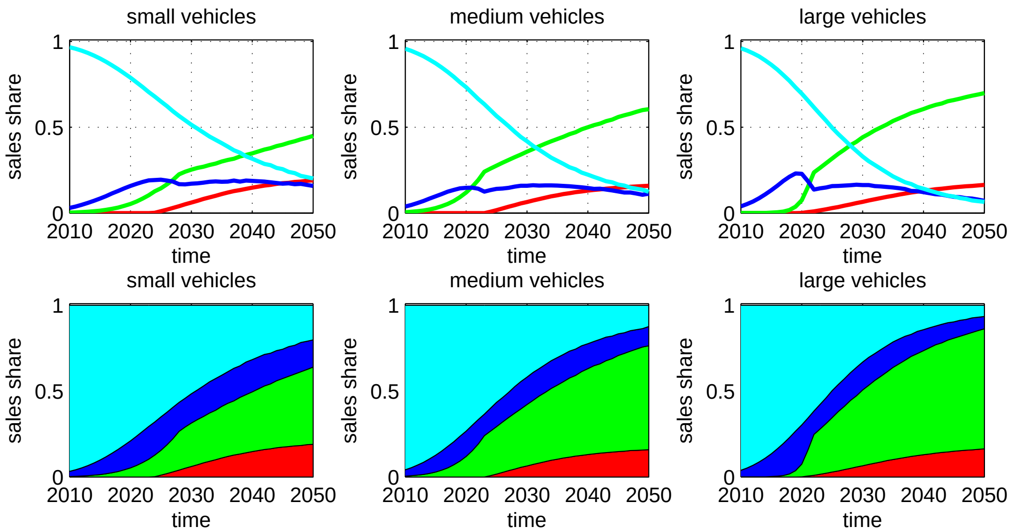

Figure 7: Sales shares projections based on TCO-calculation by segment. *Top panel*: Sales shares for the individual technologies per segment (from left to right: small, medium, large) with ICE (light blue), HEV (dark blue), PHEV (green) and BEV (red). *Lower panel*: The same as in the upper panel, but sales shares are stacked.

we observe that PHEVs are dominating in market shares as well, particularly in the large vehicle segment. This a consequence of the TCO projections and the VKT distributions. In the case of large vehicles, where large VKTs are more common, the dominance of PHEVs is even emphasised by multiplication the VKT distribution. Furthermore, the market shares for PHEVs show a slight kink, indicating the crossover from electric and range extender driving for market shares to a regime where costs have changed such that electric driving only is sufficient for PHEVs to become cheaper in terms of TCO than

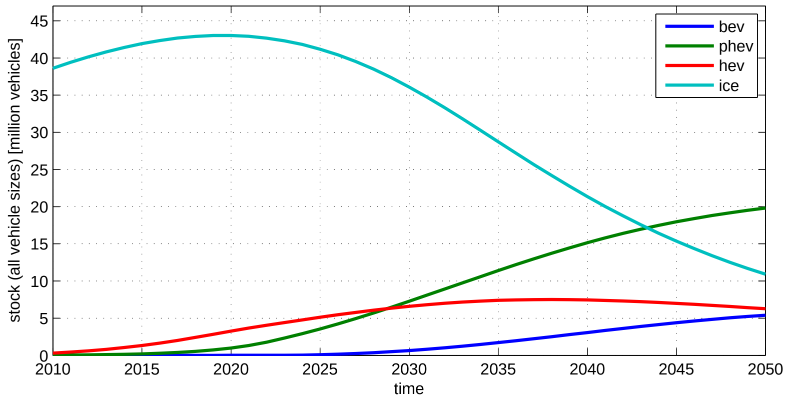

Figure 8: Stock projections based on TCO market shares and summed over segments (see legend for colour code).

conventional vehicles. Please note that these are only theoretical market shares based on our TCO projections. The actual buying decision is more complex. Furthermore we have not taken into account, that only a very limited number of PHEVs is currently offered for all segments and almost no BEVs are available for the large segment in Germany.

Using the stock model of eq. (8) and assuming slowly decreasing absolute sales from 3 million per year in 2011 to 2 million per year in 2050, we obtain projections for the total stock of German vehicles. The results are shown in figure 8 summed over all vehicle segments.

We observe that the dynamics in the stock are much slower. With the absolute number of vehicles growing, the market diffusion of ICEs reaches according to the TCO projections a maximum around 2020. The HEVs are a relevant and cheap option for not too long VKT and reach a small but significant share in stock of approximately 5 million vehicles that declines only very slowly towards the distant future. The PHEV turns out to be the most cost-efficient technology for most users in the long run and acquired very high market shares in sales as well as in stock.

The stacked time evolution of the German vehicle stock according to the TCO projections is shown in figure 9. Due to the cost effectiveness of PHEVs, the goals in terms of stock the German federal Government has set for EVs, appear possible: 1 or more million electric vehicles in 2020 and 5 or more in 2030. However, as already mentioned, TCO are one important aspect of vehicle buying decisions but not the only one. Furthermore, private car-owners do usually not directly calculate the TCO but rather stick to more heuristic estimates. In this sense, the projected stock evolution shown in figure 9 is no actual market prediction. However, it demonstrates that the federal goals are not unrealistic.

5. Implications for Electricity and Power Demand

Clearly, a large number of electric vehicles represent additional electricity consumers and several studies on the expected additional demand both for electricity and power

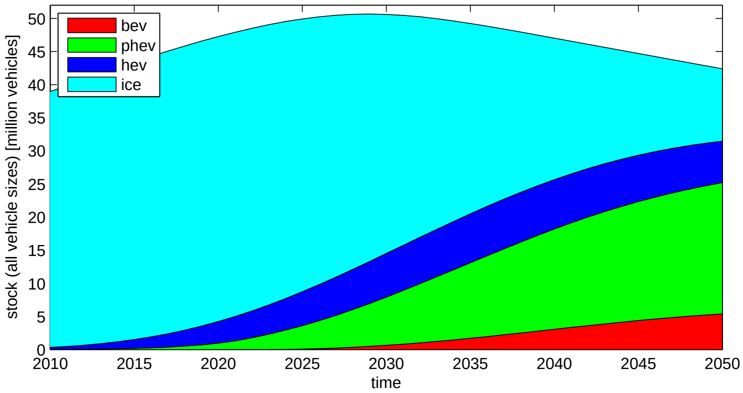

Figure 9: Stacked stock projections based on TCO calculation and summed over segments with ICE (light blue), HEV (dark blue), PHEV (green) and BEV (red).

exist (see, e.g., (Biere et al., 2009) and references therein). In the present section, we combine the results of the stock model and on VKTs to compute the additional annual electricity consumption. Furthermore, we simulate battery states of charge to compute when to expect charging if every car owner would directly charge his or her vehicle after arrival at his or her final destination.

5.1. Additional annual Electricity Demand for Electric Vehicles

The total number of distance driven electrically by PHEVs of size class i is given by all kilometres below the electric driving range driven by PHEVs as optimal vehicles. This has to be multiplied by the electricity consumption per kilometre to obtain the additional electricity demand

$$E_{phev,i}(t) = u_{E,i} \int_0^{L_{E,i}} rP_i(r)\,\chi_{phev,i}(r,t)\mathrm{d}r. \tag{13}$$

A similar relation holds for BEVs. We observe that eq. (13) bears strong similarity to the eq. (7) for the computation of market shares since $\chi_i(L,t)$ selects only that fraction of drivers for which the given technology i is optimal. However, to compute the total electricity consumption of all vehicles in stock, we need to adopt the stock model of eq. (8) to electricity demand. That is, we replace the sales share $p_i(t)$ in eq. (8) by electricity consumption $E_i(t)$ from eq. (13) and obtain the total electricity demand by all electric vehicles in stock with their respective annual VKTs.

Figure 10 shows the additional electricity demand per year of all electric vehicles in stock based on the TCO projections and stock model results of the previous section.

We observe a slow s-shaped increase of electricity demand over time, that seems to follow the stock of electric vehicles quite nicely. However, the situation is more complicated since the resulting electricity is not directly proportional to the number of vehicles in stock. The difference is two-fold. Firstly, the EVs that enter stock early according to our TCO projections drive more VKT per year than vehicles entering the stock later.

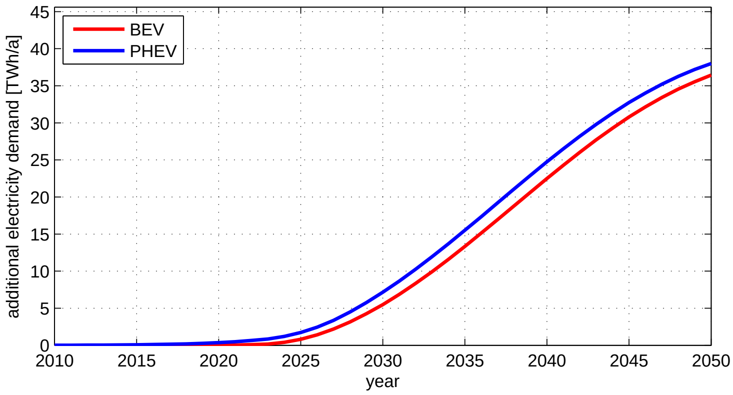

Figure 10: Additional annual electricity demand electric vehicles in stock based on the TCO projections and stock model results. Shown are the electricity demand of BEVs (red) and PHEVs (blue).

Secondly, PHEVs add significantly to the electricity demand, but can drive both electrically and on conventional fuel. Thus, the smoothly growing curve for electricity demand is slightly misleading since the underlying mechanisms are more complex. Needless to say, a computation using average values for the VKT can nevertheless give the right order of magnitude.

It is interesting to note that figure 10 demonstrates that the electricity demand of PHEVs is very important. Their smaller batteries and limited electric driving range, which is equivalent to a limited daily electricity consumption, is more than compensated by their large market shares.

5.2. Time of Charging and Power

Let us now turn to the time that could be expected for charging the computed electricity. The upper panel of figure 11 shows the times when the vehicles from a large scale survey of German driving behaviour (MoP 1994 – 2008, see MoP (2008)) arrival at their final destination for the day of the survey.

Most drivers arrive at their final destination in the afternoon with a peak around 5 to 7 pm. The lower panel of figure 11 shows on a logarithmic scale the distribution of required electricity for recharging if all vehicles of the survey were operated as electric vehicles. That is, we performed the battery state of charge simulation as described in section 2.3 irrespective whether they could be operated as electric vehicles or whether they were economically attractive as electric vehicles. We observe that the theoretical distribution of required energy recharging is approximately Gaussian on the logarithmic scale, as expected from the log-normal distribution of daily driving ranges that has been demonstrated and discussed in section 3.3.

The arrival times alone are not sufficient for the time to decide when additional power demand is to be expected. To this end, we need to combine the individual arrival times with the individual electricity demand. We assume that all drivers start recharging as soon as they arrive at their final destination and remain connected to the power grid until they potential battery is completely recharged (using a standard German 3.7 kW power

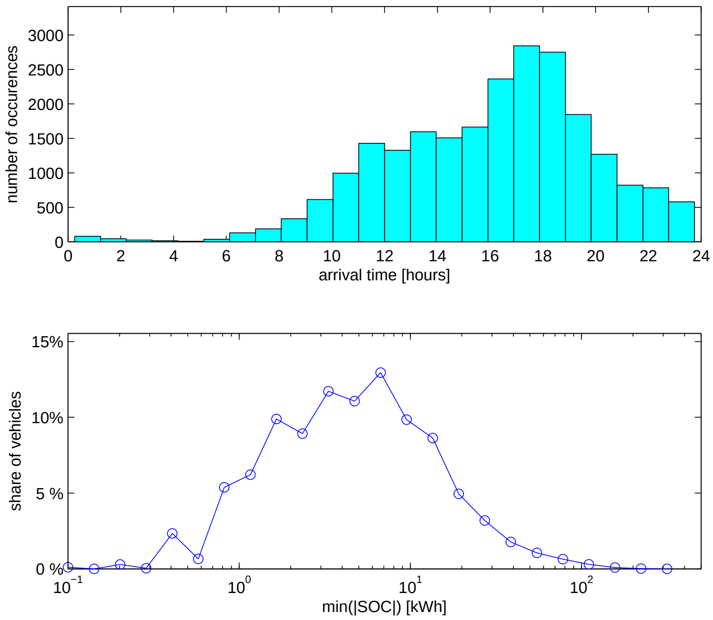

Figure 11: Arrival times and Electricity need for recharging. *Upper Panel*: Distribution of arrival times with absolute values of occurrence from a large scale survey of German mobility behaviour. *Lower Panel*: The distribution of required electricity for recharging.

supply). The result of this computation is shown in figure 12 with a time resolution of 15 minutes.

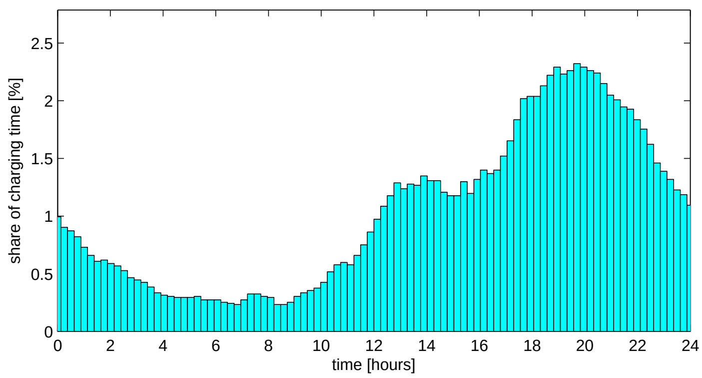

Figure 12: Share of charging times over the day in 15 minute steps. Shown is the fraction of total charging required in per cent that would be done if all users started charging directly after arrival at their final destination for the day under consideration.

If car owners started to charge their vehicles directly after arrival, as assumed for the computation, a maximum in power demand would lie around 8 pm. Please note the special y-axis in figure 12: What is shown is the distribution of the total time for charging over the whole day in units of 15 minutes. The average is roughly 1%. Multiplication with 96 for the 96 quarter hours of a whole day yields roughly 100% of charging needed. Put differently: Figure 12 shows what fraction of the total energy required would be charged in which quarter of an hour (if all users started charging directly after arrival at their destination). To obtain the power in physical units one needs to combine this fraction with the total electricity demand of a given number of vehicles. For example, based on the TCO projections, figure 10 showed that for 2030 the approx. 1 million BEVs and 7.5 million PHEVs (see figure 8) would need 5+7=12 TWh per year (cf. figure 10). Of this energy, 2.5% would be charged within 15 minutes around 8 pm (if all users started charging directly after their final arrival) would result in (12 TWh/365 d) $\cdot$ 2.5%/0.25 h $\approx$ 3.3 GW. This additional evening peak represents a significant power demand to the typical 70 GW or so evening power demand in Germany (Biere et al., 2009). To avoid such a peak, measures of demand side management would be required. The distribution of charging times shows, that it should be possible for most users to shift charging to the late night or early morning and still have a fully recharged battery ready for driving in the morning.

6. Summary and Conclusion

To summarize, we computed TCO projections for conventional and electric vehicles based on changing future fuel, electricity and battery prices. Since TCO is an important cornerstone of buying decisions, we derived future market shares and corresponding stocks of electric vehicles for Germany. Our results show that PHEVs are cost optimal for many drivers since they combine low variable costs, unlimited total range and not too high additional initial investment compared to ICEs. Despite their smaller batteries and limited electric driving range, PHEVs also contribute largely to the electricity consumption that could be expected from the growing number of electric vehicles in stock. We presented calculations with a time frame until 2050, but the assumptions made can well be justified until approximately 2030. With the possible introduction of new battery technologies and limited availability of fossil fuels, the technical parameters, e.g. the driving range of electric vehicles, and prices can change significantly. The results presented here beyond 2030 are more to follow the rather slow diffusion into stock and provide an outlook what could happen if existing trends were extrapolated. Finally, the power demand from a large number of electric vehicles if they started charging directly after arrival at their final destination, would result in a significant power peak around 8 pm and means to shift this demand to the later night seem necessary.

Acknowledgement

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