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Working Paper

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greenhouse gas emissions:
methods, results and policy
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ISSN: 1827/3580
No. 21/WP/2012

Electric cars as a means to reduce greenhouse gas emissions: methods, results and policy implications in Germany

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Abstract

Electric vehicles are usually perceived by policy makers and the general public as an attractive means to reduce greenhouse gas emissions. In this paper we provide a rigorous assessment of the emissions resulting from the diffusion of electric vehicles. We make use of EMOB, a comprehensive model that provides a forecast and evaluation of alternative fuel vehicles diffusion in Germany in the next decades. As far as computation of emissions is concerned, our method differs from existing one by a “pivotal marginal” or “hourly marginal” emission computation that takes into account the predicted long-term time pattern of EV reloading. We obtain non-tailpipe emissions of around 75 g/km in 2020. Additionally, our findings cast serious doubts on the general claim that electric cars could be fed in with renewable energy in general, and with fluctuating excess supply of renewables (wind, solar) in particular.

Keywords: electric vehicles, CO₂ emissions, generation portfolio, non tail-pipe emission:

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Version of 24 July 2011. An updated version of this paper has been accepted for publication with title “Estimating electric car's emissions in Germany: an analysis through a pivotal marginal method and comparison with other methods” in Economics and Policy of Energy and the Environment and is due for publication in 2012. The updated version comprises updates of the investment scenario for energy generation in Germany.

1. Introduction

Electric vehicles (EV) are seen by policy makers and the general public as a means to reduce the environmental impact of mobility. In particular, the potential of this technology echoes the climate change debate and it appears appealing as an option to reduce CO₂ emissions. This expectation however needs to be tested against a realistic calculation of the CO₂ impact of electric vehicles. The electric powertrain, by definition, induces Zero tailpipe emissions. However, the impact of non-tailpipe emissions deserves careful attention: The energy that is used by EV's is supplied by power plants, which – in most electricity systems – consist of a mixture between emission-free sources of energy, e.g. wind or solar power, and fossil-based plants that release greenhouse gases while in operation. Calculations of these non-tailpipe emissions pose a methodological challenge, because the physics of a meshed, multi-nodal electrical network, following the so-called Kirchhoff's law, do not allow for actively directing an electron's path from a source to a specified destination.

Suggestions for overcoming this methodological obstacle include assigning the average pollution of the generation structure to EVs, or the emissions of the technology deployed during peak load hours. These approaches are frequently mentioned in the political debate, but may be misleading, as will be illustrated in more detail, for a proper assessment of the factual climate impact of EV's.

In this paper, we discuss the most relevant approaches to estimate non-tailpipe emissions and suggest a methodology based on pivotal marginal emissions. The results are calculated with EMOB, a comprehensive simulation framework that estimates the penetration of three EV technologies (Plug-in Hybrid, Range Extender, Battery Electric Vehicle) together with six non-electric technologies (Diesel, Gasoline, Hybrid, Biofuel, Hydrogen, LPG-CNG) on the German automotive market.

This paper is organized as follows. Section 2 presents the findings of preexisting research on this topic; it also indicates the limitations that, to our view, occult the validity of CO₂ abatement calculation when they are based on average generation mix and/or on (peak) marginal emissions. Section 3 introduces our modeling approach, dealing both with the general description of our simulation tool EMOB and with our proposed approach for CO₂ calculation. Section 4 presents the data used in computation and the obtained results

2. State of the art: the effect of ev development on co2 emissions

Consistent with the growing relevance of electromobility on the policy agenda, a significant number of academic papers and studies from think tanks and state-sponsored institutes on the effect of electric vehicles on CO₂ emissions has been published in the most recent years. The research

can broadly be classified in two categories: first, research that merely quantifies the effects on emissions of EV diffusion; second, research that adds cost considerations to this, and thus estimates the unit cost of CO2 abatement through EV deployment.

The majority of publications on the topic belongs to the first stream of research. Table 1 introduces some among these recent contributions. The general message that emerges from these studies is that CO2 emissions can be reduced through EV diffusion. We find, however, that there are some limitations in these results. First, the majority of the studies concentrates on Plug-in Hybrid Electric Vehicles (PHEV), whereas much fewer results are available for pure Battery Electric Vehicles (BEV). Second, most of the studies use an exogenous assumption for EV diffusion (see column “diffusion”), i.e. the market uptake does not depend on consumer choice modeling. While this could, to a certain extent, be neglected when looking at unit (CO2 saving per vehicle) results, it certainly casts doubts on any quantification of the aggregate savings of all newly registered EVs. Third, for the estimation of non-tailpipe emissions most of the results make use of the average CO2 content of the electricity generation (see column “CO2 intensity”). We consider this assumption as heavily influential on the results and we see it as discussable. Other studies relate the CO2 content to the emissions of the peak marginal technology, i.e. the power plant that delivers the energy to the ultimate unit of additional demand. A solution that, as will be illustrated in section 3, seems as well questionable to us. Eventually, a last set of studies makes use of a detailed and disaggregated simulation of the electric sector to determine CO2 emissions. This latest possibility, provided the underlying simulation method is well-documented and offers sufficient scientific credentials, appears suitable; it comes however at a high price in terms of data requirements and is heavily resource consuming, which gives room to the definition of more parsimonious methods.

Additionally, in most of the studies emissions are found to be non-responsive to policy (column “policy responsive”). This can be a hindrance for the general need to assess the effect of given policies on emissions. Moreover, one can observe that most of the existing results rely on a load of the energy sector that has no specific time pattern (column “Time pattern”). This appears to us as a limitation as well, considering the expectation that EV reloading may have a specific time pattern and some policies may specifically be targeted to alter this time pattern.

Additional to these contributions, some authors have gone one step beyond in their analysis by investigating the cost efficiency of EV diffusion as a means to reduce CO2 emissions.

Kammen 2009 estimates the cost of CO2 reduction as the CO2 abatement divided by the monetary incentive that would (in our wording) make alternative vehicles cost equivalent to conventional vehicles. Their main finding is that “(without affordable batteries) GHG emission reductions from PHEV’s cost well over 100\$/t.CO2eq”, leading to the conclusion that “PHEV are not currently a cost effective means of mitigating GHG’s”. de Boncourt 2011 bases the cost of CO2 abatement in France on a 2 billion € policy package for 2 million vehicles. The cost of this policy is then divided by the resulting reduction in emissions in order to obtain the unit cost of CO2 reduction. Based on the assumption that cars circulate on average 150,000 km the author calculates a cost of 50€/t CO2.

Table 1 EV emissions across various studies.

Study	Diffusion	CO₂ intensity	Policy responsive	Time pattern	Key finding
Brady and O'Mahony 2011	EV. Exogeneous diffusion assumption -90% penetration by 2035.	Average CO ₂ mix.	No	No	Even with large penetration CO ₂ gains are modest compared with the size of national CO ₂ emissions.
Doucette and McCulloch 2011	BEV. Exogeneous diffusion assumption	Average CO ₂ mix.	No	No	In countries with high CO ₂ energy production sector, shift to BEV may increase emissions.
Göransson, Karlsson et al. 2009	PHEV so as to represent 3, 12 or 20 % of electric consumption	Based on simulation		Yes. With different coordination policy.	Coordination can drastically change emissions from PHEV.
Thiel, Perujo et al. 2010	PHEV, EV, BEV	Average mix	No	No	CO ₂ abatement can be effective but at a high cost (> 800€/t. for BEV)
EPRI and NRDC 2007	PHEV	Marginal Natural Gas.			
Smith 2010	PHEV. Exogeneous assumption		No	No	Up to 50 % reduction in CO ₂ /km compared with other technologies.
Kyle and Kim 2011	EV (and Hydrogen). Exogeneous	Based on CGE simulation	Responsive to carbon pricing policy.	No	Reduction of emissions due to emission pricing are larger in scenarios with large share of EV.

These figures cast doubt on the cost effectiveness of EV as a tool to reduce CO₂ emissions, but cannot in themselves be found conclusive. One reason among others is that these ratios have a limited representation of micro-economic, behavioural assumptions: the response of the purchasers is not functionally linked to the incentive. For instance, no empirical findings are presented to support the hypothesis that cost equivalence between EV and ICE makes a fraction of people switch from one to the other. Consequently, it appears that there is ample room for contributing to the current debate on EV policy by producing results that use reasonable assumptions on both the CO₂ content of non-tailpipe emissions and the responsiveness of car purchasers to policy instruments.

Elaborating on existing studies, we propose to contribute to the on-going debate by taking a number of additional features of the EV diffusion into account. First, we estimate the (cost of) CO₂ reduction based on a wide set of available car engine technologies. We take into account BEV and PHEV together with Range Extender, covering the spectrum of electric and hybrid powertrains that are or will shortly be available in the market. Second, we base our approach on an explicit micro-founded representation of how different stakeholders behave. This renders the representation of the diffusion intrinsically policy responsive. The costs and effects of EV policies are hence connected, and the two terms of the ratio (CO₂ abatement/cost of policy) are made consistent together rather than remaining two exogenous assumptions. Eventually, different to previous works in this field, we base our approach on a “pivotal” or “hourly marginal” emission calculation that, in our view, overcomes many of the limitations of the more frequent “average” or (peak) marginal approaches.

We now turn to a more detailed presentation of the model we use for EV diffusion forecast, and to our calculation of emissions.

3. The EMOB modeling approach to vehicle diffusion and co₂ emissions

In this section, we first present the main features of our modeling approach. Second, we provide an overview of the existing calculations of non-tailpipe CO₂ emissions and suggest a method to compute the emissions based on a pivotal marginal approach.

3.1 EMOB in short

EMOB is a simulation model designed to forecast and evaluate policies toward the diffusion of electric vehicles.

Its core component is a market simulation module that is based on a Discrete Choice Modeling to forecast the evolution of different automotive technologies on the German market. It represents the choice among 9 competing technologies (Gasoline, Diesel, Hybrid, Biofuels, LPG-CNG, BEV, Range Extender, Plug-in Hybrid, Fuel Cell). The car market is divided into different submarkets (privately owned household cars, rental cars, car purchased by resellers, Dienstwagen i.e., cars provided by companies to their employees as a fringe benefit, corporate fleet including company cars, and public procurement), which are characterised by differing purchase mechanisms. In this section, we concentrate on the household vehicles that constitutes the single largest submarket.

In addition to the differentiated characterization of consumer groups, the model takes the different vehicle segments of the market into account, corresponding to different vehicle sizes, with a level of decomposition that is fairly larger than in other existing models, and is based on the categorization of the Kraftfahrtbundesamt (KBA) in use in the German administration. It includes 11 categories (Minis, Kleinwagen (small cars), Kompaktwagen, Mittelklasse, Obere Mittelklasse, Oberklasse, Geländewagen (Sports Utilities Vehicles),

Sportwagen, Minivan, Großraumvan (people-carrier), and Utilities (light freight vehicles)). The model is “dynamic”, i.e., the market shares of respective technologies and segments are a function of the time-dependent value of car attributes.

The model elaborates on a meta-analysis of Stated Preference surveys and constructs a synthetic utility function based on willingness-to-pay (WTP) and elasticities found in the literature. The model also contains a “diffusion” module, that uses the Discrete Choice model as input data (to be understood as “potential market shares”) and computes adjusted market shares based on a Bass-like diffusion model (Bass 1969). The model can be run for a reference scenario that represents the most likely scenario. It can also be run for a variety of policy scenarios that activate a series of policy measures (purchase incentive, fuel taxation, etc). The model provides the data for computation of CO₂ emissions in the reference and policy scenarios, which can then be performed as discussed in the next section.

3.2 Computation of CO₂ emissions

In the computation of CO₂ reduction due to electromobility two aspects should be considered. First, what is the CO₂ content of the energy used by electric cars. Second, how comprehensive the analysis should be of “secondary” emissions, that relate for instance to upstream fuel production or to car and battery production. While both of these aspects are relevant, in this paper we investigate more in depth the issue of electricity generation as we identify this as an area of potential relevant methodological progress.

Before turning towards different approaches for the estimation of non-tailpipe emission, it should be emphasized that the notion of additional emissions is in itself problematic. Within the current framework of EU climate policy and regulation, the energy sector is part of the European Emission Trading System (EU ETS). This means that its emissions are intrinsically capped. By contrast, car use emissions are not regulated, and neither is intended to be in a foreseeable future. Hence, electromobility shifts energy demand from a non-capped sector to a capped sector. This intrinsically annihilates the emissions of the vehicle, as underlined by Hacker, Harthan et al. 2009 and Horst, Frey et al. 2009 . While this perspective is consistent and grasps, to our view, the ultimate underlying mechanisms of emissions regulations, we argue that there are still some valid reasons in quantifying EV-related emissions. A weak objection is that EV diffusion will direct some output of the energy sector to EV in substitution to other use, so the question of EV emissions is still relevant. A more fundamental argument is that this substitution comes at some social cost, as it typically excludes some other (CO₂ emitting) social needs to be served by the energy sector. This implies that omitting the CO₂ emissions related to EV diffusion would distort the assessment of the total costs or benefits of electromobility from a welfare point of view. Rather, relying on the preferences embodied in the policy maker’s utility function, one can use the marginal cost of EV-related CO₂ emissions as a measure of the other CO₂ emitting uses foregone.

3.3 Methodologies to compute additional CO₂ emissions

As introduced in section 2, the dominating computation method for CO₂ emissions relies on average emissions and marginal (to be understood as peak marginal) emissions.

Average emissions can be expressed as

$$\frac{\sum_{k=1}^K e_{k,y} \cdot Q_{k,y}}{\sum_{k=1}^K Q_{k,y}} \quad \text{Eq. 1}$$

With k , energy generation technology, y year considered, $e_{k,y}$ emission factor of a given technology in a given year, and $Q_{k,y}$ quantity of energy produced with a given technology in a given year.

In some cases, these ratios are computed net of “must-run” facilities, such as in:

$$\frac{\sum_{k \in K_1} e_{k,y} \cdot Q_{k,y}}{\sum_{k \in K_1} Q_{k,y}} \quad \text{Eq. 2}$$

where K_1 is a subset of technologies that excludes must-run generation.

Peak Marginal emissions are just the emissions of the technology that is activated to meet demand in peak hours,

These two methods can deliver fundamentally different results. Bettle, Pout et al. 2006 (as quoted by Doucette and McCulloch 2011) point out that using average CO_2 emissions rather than Marginal Emissions Factors can underestimate emissions by up to 50 %. However, most of the users of average emission do not comment on the reasons for preferring this method over others. The approach bears a major practical advantage, though: Data on average emissions is often easily available. For instance, the German Umweltbundesamt provides historical records of specific CO_2 emissions per Megawatt hour of the German generation mix (see UBA 2011). A legitimate conjecture is that the average mix is only suitable as a first approximation.

By contrast, supporters of the peak marginal approach provide reasons for their method arguing, for instance, that “PHEV represent a new electricity demand and consume electricity produced by the marginal plant. In the short run it is incorrect to calculate the environmental impacts of PHEV’s using average electricity emissions” (Kammen 2009, see as well Carlsson and Johansson-Stenman 2003). While this statement is, *prima facie*, acceptable as long as it makes explicit that it deals with short-term fluctuations of demand, it becomes discussible when the additional electricity demand stemming from electromobility is a recurrent and fairly predictable one. Individual car owners may follow different charging routines – similar to households using electricity in slight timely variations – but on the aggregate level the load profile will be highly predictable, especially because of the slow uptake, which allows grid operators and utilities to observe charging behaviours and anticipate the required additional demand. Moreover, one can doubt on how peak marginal approach takes realistically into account the peculiar time pattern (relating to the distribution of demand across hours, across working/non working days, and across seasons) of additional electricity consumption of EVs. Implicitly, it makes use of the “peak” additional plant, an assumption that becomes difficult to sustain considering that large part of the additional electricity request from EV that may add on non-peak demand.

Table 2 – method used for emission calculations of EV

Methodology	Example (Countries in Brackets)
Short term marginal (operating marginal)	Carlsson and Johansson-Stenman 2003 (S) Pöyry 2010 (BE, D, DK)
peak marginal emissions	de Boncourt 2011, (F) Kammen 2009 (US)
“historical” marginal emissions	Hawkes 2010 (UK)
Long term (built) marginal	
Forward built	Pehnt, Höpfner et al. 2007, assuming 770 g/kwh to 840g/kwh, corresponding to emission estimates of planned coal plants (D)
based on historical long term marginal emissions	Market Transformation Programme 2009 (UK)
Pivotal emissions	Inexisting to our best knowledge
Simulation based on simulated technology mix.	Göransson, Karlsson et al. 2009
Average emissions	Baum, Dobberstein et al. 2011, p. 17, assuming 533 g/kwh in 2010 and 330 g/kwh in 2020 (D) Horst, Frey et al. 2009, assuming 625 gCO ₂ /kWh (D) UBA 2011, estimating 565 g/kWh in 2010 (D)

A more comprehensive view of the different available techniques is provided in Table 2, which also provides some values of emissions for Germany making use of these methods. Apart from “average mix” and “marginal (peak)”

some other methods that are considered in the literature will be presented briefly.

Historical marginal emissions are based on the real world data reflecting how, in power sector operations, emissions change with electricity output (Hawkes 2010). Based on time series, indicating with a fairly high time resolution (typically 15 to 60 min) the dispatch status of single plants and their respective emissions, one can obtain a vector of observed marginal emissions per kwh:

$$\frac{(\sum_{k \in K} e_{t,k,t}) - (\sum_{k \in K} e_{t,k,t-1})}{(\sum_{k \in K} Q_{k,t}) - (\sum_{k \in K} Q_{k,t-1})} \quad \text{Eq. 3}$$

where $e_{k,t}$ refers to the emissions of plant operating with technology k at time t , and $Q_{k,t}$ refers to the production with technology k for a number of t periods (for simplification we omit the notation for each single plant). The main advantage of this method is that it is fully consistent with current operating practices. This advantage however turns to a limitation when one wants to apply the method to emissions in other countries and, most importantly in future years, when operating conditions of the energy system may have significantly changed.

Long term marginal emissions – sometimes referred to as “built marginal” – overcome parts of these limitations in considering that the energy system can respond to a change in the demand pattern by adjusting the installed power plants. This method often encounters some skepticism due to the “marginal” (meaning “low magnitude”) nature of the demand. Bradley and Frank 2009, for instance, claim that even in scenarios assuming a very large diffusion of PHEV, they “*could be serviced using the present generation and transmission capacity of the US electrical grid*”. Such a statement does however not invalidate the idea that this additional demand may alter the optimum (profit maximizing) mix of energy plants. Thus it is conceptually correct to analyze the impact of a recurrent demand using the built marginal approach. The difficulty is then to identify the marginal “built” technology.

One solution is to look at historical data what French literature designate as “marge récemment construite”. For instance: “the built marginal is [...] generation weighted average emission factor of the service power units that have been built most recently”(AECOM 2010). It can be based on

$$\frac{\sum_{k=1}^K \sum_{i=1}^I e_{y-i} \cdot \tau_{k,y-i} K_{k,y-i}}{\sum_{k=1}^K \sum_{i=1}^I \tau_{k,y-i} K_{k,y-i}} \quad \text{Eq. 4}$$

where i refers to backward years that are taken into account in the calculation, while K_k refers to the installed capacity of each technology, and τ_k integrates the fact that only a fraction of installed capacity actually produces energy in a given year (this relates to maintenance operations and to facilities not operating at full capacity). The limitation of the approach is that such an “historical” built marginal may not reflect possible changes in the energy policy of a country.

This limitation can be overcome, though, by taking into account realistic assumptions about the size (and operating rate) of future new plants that are programmed for each technology in the relevant time horizon, thereby giving rise to a **forward built marginal** approach. The implementation of this approach may rise some discussions in contexts where the overall domestic energy consumption is anticipated to shrink in the future years (see e.g. Prognos-EWI-GWS 2010), a phenomenon that relates to demographic decline, increased efficiency, and a shift from energy-consuming industries to services. In this context, one could claim that built marginal reflects substitution rather than expansion mechanisms. It is however fair to say that planned construction provides consistent information on which technology are likely to be expanded in case of additional demand.

Two other methods for computing emissions can be used. Electric sector simulation models, offer a detailed description of how the energy system responds at the plant (or group of plants) level, to changes in the demand. Provided their dynamic is suitably documented and has received sufficient scientific scrutiny, and provided that they can realistically replicate both investment and operating decisions of the energy sector, these models, such as

NEMS or IPM, can yield valuable insights into the evolution of CO₂ emissions in response to additional electricity consumption. As previously stated, the main limitation of this method is however that it is very data intensive and resource consuming.

Eventually, we present one additional method that we consider appropriate for a rigorous computation of additional CO₂ emissions. This method, that can be labeled as **Pivotal Marginal (or alternatively “hourly marginal”)**, intrinsically acknowledges the fact that additional electricity request due to EV deployment has a peculiar time pattern that needs to be accounted for in the calculation. Focusing on hourly distribution of this additional demand, one can consider that the technology used to respond to a change in the demand is not identical across hours.

Figure 1 represents the impact of an additional demand on a pre-existing load profile and replicates how various technologies are operated, based on their merit order, to respond to variations in demand. In the short run, it is legitimate to consider that an additional demand in a given time slot will be met by activating the “pivotal” technology that corresponds to this time slot, meaning the technology that on the merit order curve feeds the marginal demand. Over the long term, the question of which additional plant could be built due to this additional demand is more complex. One can however observe that the merit order curve, and the corresponding definition of the pivotal technology for each level of output, inherently represents the optimal technology for each layer of the demand. Thus the pivotal technology shall not only be seen as informative of operating conditions but as well of investment conditions. For this reason, it is compatible both with short term and long term adjustment mechanisms to assign any additional demand to the technology that is pivotal for that range of demand in the forecasted energy supply curve.

Figure 1 - simplified representation of pivotal technologies and additional demand

The methodology expands easily to take into account different types of daily loads, e.g. weekdays compared to Saturdays and Sundays, and different seasons (the load curve can be defined for as many seasons as necessary). Additionally, this demand can easily integrate “excess supply” of renewables that may be available in certain time periods. This can be accomplished by deducting this “renewables’ excess supply” from the additional EV demand. Moreover, the computation can easily be made stochastic by introducing some distribution of renewables. This can be done for instance by replicating the calculation for a given daily load with different extractions of a distribution.

4. Results

We first provide a detailed description of the computation made and subsequently compare the results with those obtained using other methods of interest.

4.1 Computation

We describe hereafter the calculation process. The relevant information on the data sources used for calculation is included in Table 3 below.

The calculation is made based on four prototypical weeks, one per season, with hourly resolution, that provides, in our view, with 168 hours/weeks x 4 weeks/year, sufficient variety of load conditions on the network. For each hour, we use the energy requirement provided by the load curve, and identify the pivotal technology based on the comparison of energy request and effectively available capacity of the different technologies. In this computation, technologies are ordered based on two considerations: (future) marginal cost, and switching capability: we consider nuclear and lignite plants as must-run: because their start-up costs are prohibitively high, they are typically located on the merit curve in this sequence (Bundeskartellamt 2011). On the contrary, due to prospective technological advances, coal plants will be more flexible than in the present. Given the current German feed-in regulation, the two most prominent renewable energies, solar and wind power, are also considered must-run plants. Other renewable energies, like hydropower, geothermal, biomass and waste, are deployed according to their positions in the marginal cost curve. Each technology accounts for its capacity factor, which takes into account a number of days of unavailability of each plant. Figure 2 illustrates a merit order curve for 2020, as it is used in the model.

Figure 2 – dispatch curve (example 2020, based on averages at 6 pm)

For a realistic representation of the stochastic resources: solar and wind, which exhibit substantial meteorological fluctuations, we take possible variations of the output into consideration. This is accomplished by the statistical analysis of feed-in data of the four German grid operating companies. To integrate these variations in our calculations we calibrate a probability density function based on these data and we make random extraction out of this density function for each hour of the week taking into account the correlation of wind across successive hours. In addition, the model differentiates between

on-shore and off-shore wind power intake. The solar power supply has a more predictable pattern than wind. This is reflected in the model by using daily feed-in quantities in each season that vary over the day according to differing degrees of radiation.

At each hour of our 4 prototypical weeks, we compute the electricity demand and the supply of each technology (with deterministic or stochastic output) with a ranking of technologies based on their merit order. The pivotal technology is the one that equates supply and demand.

The calculation is subsequently expanded to a whole year, and replicated for every horizon year of the model.

Table 3 – input data used for future emission calculations

Data type	Source	Remark
Future installed capacity, electricity production, and plants utilization rate	Prognos-EWI-GWS 2010	Reference scenario, 2008 to 2050, consistent with nuclear policy prospect of the German federal government. Nuclear comes to 0 between 2020 and 2030
Capacity factors	BEE-AEE 2009	Capacity factors for each technology are the percentages of the actual generation compared to their theoretical maximum output; they take routine maintenance outages or equipment failures, droughts, unavailability of wind or sun radiation, and other incidences into account; in Germany, they range from peak 1.5% (photovoltaics) to 92% (lignite)
Marginal costs	Nitsch 2007 Kruck 2008	Cost estimates for renewable and fossil energies until 2050; Cost estimates for pump storage, p. 75
Specific CO ₂ emissions	Machat and Werner 2007	Data on CO ₂ emissions of electricity production based on the following fossil resources: natural gas (560g/kWh), coal (938g/kWh) and lignite (1228g/kWh) for 2002; fuel oil estimates (741g/kWh) can be deducted from appendix 1, p. 11; all specific emissions are assumed to be constant over the time horizon
Variations in wind and solar availability	50hertz 2011; amprion 2011; EnBW Transportnetze 2011; TenneT 2011	Aggregated, publicly available feed-in data of the four German grid operators
Daily load profiles	UCTE 2009	Hourly load; we replicate the daily load pattern in future years, adjusting the volume to the electricity consumption
The time profile of EV reload	Davies and Kurania 2010	Recharging behavior of a pilot project with 40 Plug-in hybrid electric vehicles (PHEVs), recorded with respect to the time of the day, the frequency of plugging-in, and electricity demand to recharge the vehicles

4.2 Results and comparison with other computing method

Based on the Pivotal Marginal method, we obtain a time varying non-tailpipe emission of electric cars, whose values decrease swiftly from 77g/km in 2020 to 55 g/km in 2030.

Figure 3 shows the source of the energy provided by the various technologies for EV charging over the next decades.

Figure 3 – share of various technologies in EV load

The model shows that the predominant generation technology used for EV charging will be coal until the early 2020's. By then, natural gas takes over and remains the main technology, reaching levels of over 90% before 2030. Renewable energies will play a negligible role in the provision of electricity for electromobility. According to the model, onshore and offshore wind will account for less than 1% of the supply. After 2030, pump storage will capture a small share of the EV demand.

In the subsequent paragraphs of this paper we compare these estimates to the ones that would be obtained by other (less convincing, to our view) methods. The approach to measure specific CO₂ emissions of electric vehicles with the pivotal technology is contrasted with three frequently used methodologies presented in section 2. Table 4 and Figure 4 show the results of the comparison.

Table 4 – comparisons of CO₂ emissions by EV based on three different methods (g CO₂/km, annual average)

	2020	2030
Pivotal Marginal	77,2	55,4
Peak Marginal	57,6	54,3
Average	58,1	45,4
Marginal Forward Built	26,2	25,3

Figure 4 – comparison among different computation methods

The **average emissions** of the electricity sector (represented in the figure by the full dark line) are calculated exogenously by using the reference scenario forecast by Prognos-EWI-GWS 2010 on annual electricity production of each generation technology, and multiplying it with the respective CO₂ emissions. Figure 4 shows that until 2030 this methodology consistently underestimates the non-tailpipe emissions of EVs compared with our pivotal approach. The reason for this is that the average emissions actually are less CO₂ intensive than pivotal marginal, that contrarily to expectations, are often fuel based. It is found an average emission of around 60 g CO₂/km until 2020, and a subsequent decline to around 40 g CO₂/km in 2035.

The second approach that can be used for comparison, “**peak marginal**”, is assumed to correspond to gas-fired technology (Sensfuß, Ragwitz et al. 2007; Pöyry 2010). Given the already high efficiency of the technology, corresponding emissions are likely to remain above 50 gCO₂/km. Again, it can be observed that they yield different estimates than the pivotal marginal emissions for the next 15 years by underestimating EV-related non-tailpipe emissions until 2025.

The estimates for the **forward built marginal** emissions are derived from two sources: for the fossil fuels, actual large-scale plant projects until 2020 are published by the association of German electricity producers (BDEW 2011) and cross checked with data on the construction of new power plants released by the German energy agency (EUTECH 2008). Data on predominantly decentralized renewable energy projects is based on estimates of the German Environment Ministry (BMU 2011). However, any projections beyond 2020 data become speculative and have to rely on more aggregate, official figures of planned or envisaged capacity expansion. According to the BMU, the extension of renewable energy capacity will continue and successively replace a large fraction of the existing fossil-based and nuclear plants. In the model, the capacities of each generation technology are exogenously adjusted according to estimates of the annual actual dispatch (Jahresvolllaststunden) provided by Prognos-EWI-GWS 2010. This rate takes into account both unavailability of installations for maintenance purposes and switching off of plants for operating reasons, together with fluctuations of renewable energy sources below their capacity. The emissions computed on the basis of forward built marginal technologies show high emissions at the beginning of the simulation period, induced by the completion of several large-scale lignite and coal-fired plants before 2020, and a substantial uptake of renewable energy installations thereafter. Hence emission estimates merely based on projections of newly built

capacity may underestimate non-tailpipe emissions even more drastically than the average and peak marginal emission approaches.

5. Discussion and conclusion

In this discussion we want to shed light on several energy policy issues relevant for the debate on electromobility.

First, our calculation provides information on which generation technology will be used to deliver electricity to EV's. Our results indicate that fossil fuel-based plants provide most of the energy for charging EVs. The share of EVs' energy requirements that are satisfied with renewables remains very low (below one percent until 2035). The dominance of coal-based plants and, later, the expansion of natural gas plants will account for the bulk of the pivotal dispatch. Despite the substantial increase in onshore and offshore wind energy, the computation shows that this technology, given its position on the merit order curve, only occasionally happens to be the marginal technology. Almost all wind energy is absorbed by future non-EV demand and, if neither solar nor wind is temporarily available, they are substituted by gas. In other words, the future energy sector is organized based on the complementarity between gas and renewables: gas generation is used to compensate for changes in the output of renewables.

In these conditions, our findings also indicate that there is little room for the use of potential "wind excess supply" to charge EVs. Given the substitution effect of gas and renewable generation, the increasingly flexible supply structure will only on rare occasions allow for a renewable surplus beyond the regular demand.

In conclusion, the notion of feeding electric cars with renewables, which is often used as an argument in favor of EV's, seems discussible in the future German energy scenario. The additional advantage of electromobility as a buffer for surplus renewable energy may therefore be overstated, unless wind patterns or plant projections change drastically.

Eventually the picture that emerges from our analysis is polyedric. On the one side, looking at merely technological aspects, an EV car is generating fairly less CO₂ than an ICE, although certainly not so few as to make the "zero emissions" label a correct one. On the other side, one should recall that EV non tailpipe emissions may not be additional emissions, due to the insertion of energy production in the capped Emissions Trading Systems, but are rather substitutions to other CO₂ emitting uses of energy. It is however fair to consider that these emissions are a cost to society as they substitute other energy uses.

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