ESTIMATING ELECTRIC CAR'S EMISSIONS IN GERMANY: AN ANALYSIS THROUGH A PIVOTAL MARGINAL METHOD AND COMPARISON WITH OTHER METHODS

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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 as an appealing option in order to reduce CO_2 emissions. This expectation however needs to be tested against a realistic calculation of the CO_2 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 quantifying emissions usually rely on assigning the average emission of the generation system to EVs, or the emissions of the technology deployed during peak load hours. These approaches are frequently referred to in the political debate, but they may be misleading, as will be illustrated in more detail, for a proper assessment of the factual climate impact of EV's. On the other hand, energy economists have also developed more elaborated techniques, fully fledged microsimulation models that offer riche capabilities but are highly resource intensive and require a large amount of data.

The purpose of this paper is to propose an alternative methodology to estimate emissions, based on pivotal marginal approach, to compare it with the most relevant existing approaches and draw conclusions relevant for the ongoing policy debate in Germany and Europe. The pivotal approach provides, in our view,

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parsimonious yet reasonably precise estimates in a context where policy decisions are often driven by oversimplified claims and calculations. Our simulation are calculated within EMOB, a comprehensive simulation model that estimates the penetration of three EV technologies (Plug-in Hybrid, Range Extender, Battery Electric Vehicle) together with six other 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, in our view, diminish the validity of CO_2 emission calculations 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 CO_2 calculation. Section 4 presents the data used in computation and the obtained results. Section 5 explores how much coordination of battery reloading can alter CO_2 emissions. Section 6 draws the conclusion.

1. Existing methods for emission computation and literature findings

1.1. Methodologies to compute CO_2 emissions

We first present the different methods available for CO_2 emissions calculation and investigate how they are used in current research. The dominating computation method for CO_2 emissions relies on average emissions and marginal (to be understood as peak marginal) emissions.

Average emissions can be expressed as

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

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:

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

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

Peak Marginal emissions are simply 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

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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 are often readily available. For instance, the German Federal Bureau for the Environment[1] 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 provides a rough, and probably misguiding, estimate of emissions.

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 the 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 support considering that a large part of the additional electricity request from EVs adds on non-peak demand.

Apart from "average mix" and "marginal (peak)" some other methods are considered in the literature.

Historical marginal emissions are based on 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:

$$\frac{\left(\Sigma_{k\in K} e_{k,t} \cdot Q_{k,t}\right) - \left(\Sigma_{k\in K} e_{k,t} \cdot Q_{k,t-1}\right)}{\left(\Sigma_{k\in K} Q_{k,t}\right) - \left(\Sigma_{k\in K} Q_{k,t-1}\right)} \qquad \text{Eq. 3}$$

where $e_{k,t}$ refers to the emissions (g/kWh) of plant operating with technology k at time t $(t=1,\dots,T)$, and $Q_{k,t}$ refers to the production with technology k at time t periods (for simplification we omit the notation denoting each single plant). These marginal emissions can be computed for $T-1$ periods. The main advantage of this

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method is that it is fully consistent with existing 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

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

where i refers to backward years that are taken into account in the calculation, while I_k refers to the additional capacity of technology k integrated into the supply system in a given year, and τ_k replicates 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 plants programmed for each technology in the relevant time horizon, thereby suggesting a **forward built marginal** approach. The implementation of this approach may provoke 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.

Another method for computing emissions is based on **Microsimulation Model**s. They offer a detailed description of how the energy system responds at the plant (or group of plants) level, to changes in the demand. For example, Pehnt, Helms *et al.* (2011) combine separate sub-models simulating short-term fluctuations in the

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German electricity market and long-term capacity planning in the European market, and integrate grid constraints in the distribution network. Provided the dynamic of micro simulation models 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 (US Department of Energy), PERSEUS (used among others by Pehnt, Helms *et al.*, 2011), or EnergyPLAN (used by Lund and Kempton, 2008), can yield valuable insights into the evolution of CO_2 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 which gives room to the definition of more parsimonious methods. The question of the predictive validity of such modes is also still an object of discussion (Synapse, 2004, p. 6).

Eventually, a comprehensive view of the different available techniques is provided in Tab. 1, which also provides some values of emissions for Germany using these different methods.

Tab. 1 - Emissions computed through different methods and results for Germany

Methodology	**Example (Countries in Brackets)**	**Emissions in gCO_2/kWh (Selection for Germany)**
Average emissions:		
	Baum, Dobberstein *et al.* (2011), p. 17 (D)	533 g/kWh (2010) 330 g/kWh (2020)
	Horst, Frey *et al*. (2009) (D)	625 g/kWh (2009)[(a)]
	UBA (2011) (D)	565 g/kWh (2010)
Short term (operating) marginal:		
• peak marginal emissions	Machat and Werner (2007)[(b)] (D) Carlsson and Johansson-Stenman (2003) (S) De Boncourt (2011) (F) Kammen (2009) (US)	560 g/kWh (2007)
• "historical" marginal emissions	Hawkes (2010) (UK)	
Long term (built) marginal:		
• Forward built	Pehnt, Höpfner *et al.* (2007) (D)	770 kWh to 840 kWh[(c)]
• Historical long term marginal emissions	Market Transformation Programme (2009) (UK)	
Pivotal emissions	Inexistent to our best knowledge	
Micro simulation		
	Göransson, Karlsson *et al*. (2009) (DK)	
	Pehnt, Helms *et al.* (2011), (D)	590 kWh-710 kWh (2030)[(d)]

(a) Estimate includes lifecycle greenhouse gas emissions.
(b) These authors do not formulate the statement that peak marginal method is the adequate one, but they provide information based on which this data can be estimated.
(c) Corresponding to the range of emissions of planned coal plants.
(d) Without the integration of additional renewable energies.

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1.2. The effects of EV's on emissions: literature findings

Based on these different methods, and considering the growing relevance of Electromobility on the policy agenda, a significant number of researches investigate the effect of electric vehicles on CO_2 emissions and provide an answer to the policy question of whether (and to what extent) EVs decrease emissions. 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 CO_2 abatement through EV deployment.

The majority of publications on the topic belong to the first stream of research. Tab. 2 introduces some among these recent contributions. The general message that emerges from these studies is that CO_2 emissions can be reduced through EV diffusion. We find, however, that there are some limitations in these results that specifically relate to the following points:

1. For the estimation of non-tailpipe emissions most of the results make use of the *average* CO_2 content of the electricity generation (see column "CO_2 intensity") or peak marginal, while some studies undertake a detailed and disaggregated simulation of the electric sector.
2. The majority of the studies concentrate on Plug-in Hybrid Electric Vehicles (PHEV), whereas much fewer results are available for pure Battery Electric Vehicles (BEV) and, more importantly, for the mix of vehicle technologies (BEV, PHEV and possibly Range Extenders) that constitutes the possible future of electro mobility.
3. Most of the existing results do not take into consideration the time pattern of the reloading operations (column "Time pattern" in Tab. 2). 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.
4. 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 (CO_2 saving per vehicle) results, it certainly casts doubts on any quantification of the aggregate savings of all newly registered EVs.

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Tab. 2 - Emissions savings due to EV's across various studies

Study	Diffusion	CO_2 intensity	Policy responsive	Time pattern	Key finding
Brady and O'Mahony (2011)	EV: Exogenous 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: Exogenous 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	Reloading coordination policies	Yes (different coordination policies)	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 an high cost (> 800€/t. for BEV)
EPRI and NRDC (2007)	PHEV	Marginal Natural Gas			
Smith (2010)	PHEV: Exogenous assumption		No	No	Up to 50 % reduction in CO2/km compared with other technologies.
Kyle and Kim (2011)	EV (and Hydrogen). Exogenous	Based on CGE simulation	Responsive to carbon pricing policy	No	Reductions of emissions due to emission pricing are larger in scenarios with large share of EV.

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Additional to these contributions on CO_2 emission computations, some authors have gone one step beyond in their analysis and have investigated the cost efficiency of EV diffusion as a means to reduce CO_2 emissions.

Kammen *et al.* (2009) estimate the cost of CO_2 reduction as the CO_2 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.CO_2eq*", leading to the conclusion that "*PHEV are not currently a cost effective means of mitigating GHG's*" (Kammen, 2009). De Boncourt (2011) bases the cost of CO_2 abatement in France on a 2 billion Euro policy package for 2 million vehicles. The cost of this policy is then divided by the corresponding reduction in emissions in order to obtain the unit cost of CO_2 reduction. Based on the assumption that cars circulate on average 150,000 km the author calculates a cost of 50€/t CO_2.

While these figures cast doubt on the cost effectiveness of EV as a tool to reduce CO_2 emissions, they 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 CO_2 content of non-tailpipe emissions and the responsiveness of car purchasers to policy instruments.

2. The EMOB modeling approach to vehicle diffusion and CO_2 emissions

In this section, we propose to contribute to the on-going debate by taking into account a number of additional features of EV diffusion. First, we estimate CO_2 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. 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.

2.1. EMOB in short

EMOB is a simulation model designed to forecast and evaluate policies toward the diffusion of electric vehicles in Germany. EMOB has been developed in the Goldsim simulation package. Results presented in this paper refer to EMOB release 0.1.3.6 developed in Goldsim 10.5.

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EMOB includes five main modules: policy, energy sector, car industry, car market, cost benefit analysis together with economic impact analysis. We provide hereafter some more information on energy sector, car industry and car market that are central to the present analysis. Readers interested by a more detailed description of the model can refer to the project-related policy report (Gosh et al., 2011).

The energy module allows for a quantitative evaluation of the effects of short- and medium-scale policy measures as well as the representation of long-term interaction between electric cars and the energy sector. It is based on exogenous forecasts of the German generation portfolio and uses Monte Carlo simulation based on observations of German photovoltaic and wind feed-in to represent fluctuating renewable energy supplies.

The car industry module generates the features of the different car alternatives present on the market. It incorporates the effects of technological progress (for instance the increase in energy density of batteries) and regulatory drivers, in particular Regulation EU/443 on CO_2 emissions: facing this regulation, car producers have to change the optimal fuel efficiency of the vehicle. This latest element is found to be highly influential of the general diffusion pattern and cost benefit analysis results.

EMOB's core component is a market simulation module that is based on a Discrete Choice Model that forecasts the diffusion of different automotive technologies on the German market. It represents vehicle choice with a high level of resolution. Namely: it incorporates 9 competing technologies (Gasoline, Diesel, Hybrid, Biofuels, LPG-CNG, BEV, Range Extender, Plug-in Hybrid, Fuel Cell). This choice process is run in parallel for 6 submarkets (privately owned household cars, rental cars, car purchased by resellers, cars provided by companies to their employees as a fringe benefit, corporate fleet, and public procurement), which are characterized by differing purchase mechanisms. In this section, we concentrate on the household vehicles that constitute the single largest submarket.

Vehicle segments of the market are taken 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 Federal Bureau of Motorization[2] in use in Germany. It includes 11 categories: Minis, small cars, Compacts, Middle range, Higher middle range, Luxury, Sports Utilities Vehicles, Sport cars, Minivan, People-carriers and Light Freight Vehicles. The choice of the vehicle segment is endogenous; this means that faced with changing car attributes people can choose to change segment rather than technology. 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 discrete choice model elaborates on a meta-analysis of Stated Preferences surveys and constructs a Synthetic Utility Function based on willingness-to-pay (WTP) and elasticities

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defined through a meta-analysis of the literature. A separate paper is exclusively dedicated to this topic (Massiani, 2012).

The model also contains a "diffusion" module, which 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 CO_2 emissions in the reference and policy scenarios, which can then be performed as presented in the next section.

2.2. The pivotal approach to CO_2 calculation

In the computation of CO_2 reduction due to electromobility two aspects are usually considered. First, what is the CO_2 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 concentrate on the issue of emissions related to electricity consumption as we identify this as an area of potential relevant methodological progress.

Before turning to 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 (Nationale Plattform Elektromobilität, 2011, p. 4). By contrast, car use emissions are not regulated, and neither 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 key reason is that this substitution comes at some social cost, as it typically excludes some other (CO_2 emitting) social needs to be served by the energy sector. This implies that omitting the CO_2 emissions related to EV diffusion would distort the assessment of the total costs or benefits of electromobility from a welfare point of view. Rather one has to take into account CO_2 emissions even when they are not strictly speaking additional[3].

In order to compute these emissions, the approach we propose can be labeled **Pivotal Marginal (**or alternatively "**hourly marginal**"**)**. It intrinsically

[3] The question of how to take into account this social cost is a tricky one. Possible solutions range from modeling the impact of this additional demand on energy prices or using some information on the preferences embodied in the policy maker's utility function.

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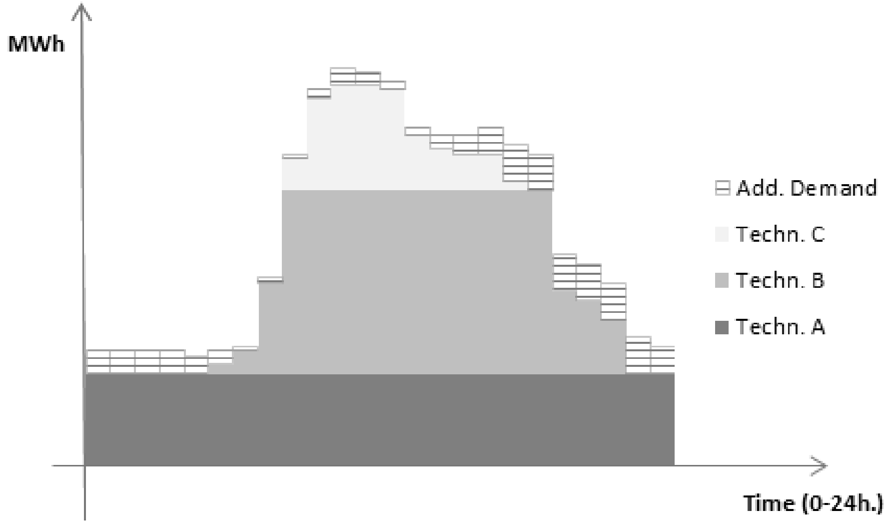
acknowledges the fact that additional electricity request due to EV deployment has a peculiar time pattern that needs to be accounted for in the calculation. Focusing on hourly distribution of this additional demand, one can consider that the technology used to respond to a change in the demand is not identical across hours depicts 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. In the long run, 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 choices. 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 future energy supply curve.

Fig. 1 - Simplified representation of pivotal technologies and additional demand



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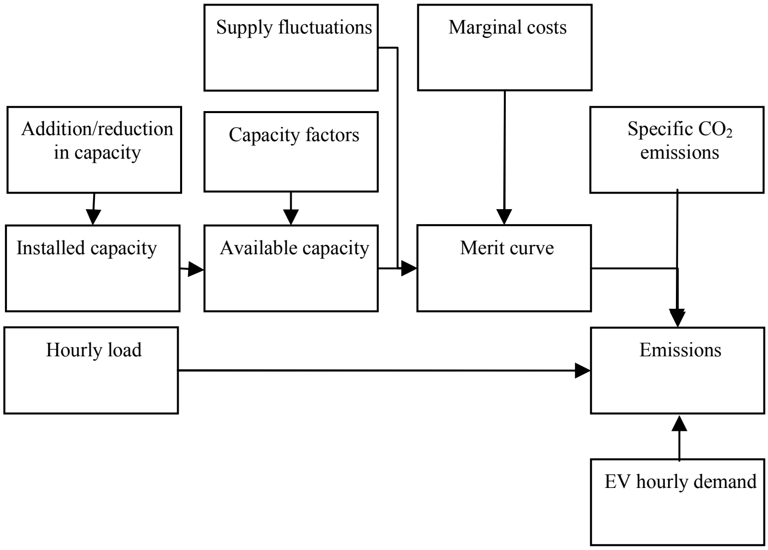
The methodology expands easily to take into account different types of daily loads, e.g. weekdays compared to Saturdays and Sundays, and different seasons (the load curve can be defined for as many seasons as necessary). Additionally, this demand can easily integrate "excess supply" of renewables that 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.

2.3. Computation in EMOB

We describe now more in detail the calculation process. The general flow of data for calculation is depicted in the Tab. 3.

Fig. 2 - Computation flow



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Tab. 3 - Input data used for future emission calculations

Data type	Source	Remark
Hourly load	UCTE (2009)	Hourly load; we replicate the daily load pattern in future years, adjusting the volume to the electricity consumption.
Installed capacity incl. additions and withdrawals; annual electricity production	Prognos-EWI-GWS (2010)	Reference scenario, 2008 to 2050, consistent with nuclear policy prospect of the German federal government. Nuclear abandoned 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).
Future marginal costs	Nitsch (2007) Kruck (2008, p. 75)	Costs for renewable and fossil energies until 2050. Costs for pump storage.
Specific CO_2 emissions	Machat and Werner (2007)	2002 data: – natural gas (560g/kWh) – coal (938g/kWh) – lignite (1228g/kWh) – 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	German transmission operators (50hertz 2011; amprion 2011; EnBW Transportnetze 2011; TenneT 2011)	Aggregated, publicly available feed-in data of the four German grid operators.
EV hourly demand	Infas and DRL (2010)	Mobilität in Deutschland survey from 2008 provides information on the distribution of km travelled (and corresponding battery depletion) and on the distribution of time when vehicles return home.

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The calculation is made based on 12 prototypical weeks per year, one per month, with hourly resolution, that provides, in our view, with 168 hours/weeks x 12 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: switching capability and (future) marginal cost. With respect to switching capability, we consider nuclear, lignite and run-off river hydropower 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 and provides estimates of the annual average dispatch[4] (Prognos-EWI-GWS, 2010). This factor takes into account both unavailability of installations for maintenance purposes and switching off of plants for operating reasons. Additionally the model integrates fluctuations of renewable energy sources their capacity as will be illustrated more in detail below.

The forecasts of the underlying Prognos-EWI-GWS scenario assume a net export of electricity produced in Germany until 2020. This relation reverses until 2030, when approximately 8 percent of electricity is imported (Prognos-EWI-GWS 2010, p. A1-10). This share declines again until 2040. The authors disaggregate power imports into renewable energies and other primary energies, with renewable energies accounting for about a third of the imports. However, in the projections the composition of fossil generation technologies remains unclear. Given the German utilities' role as net electricity exporters until 2020 and the relatively low share of imports thereafter, power exchanges with surrounding countries are not taken into account by EMOB. Any import of *substantial* amounts of so-called "grey" energy could distort the emissions profile significantly upward (e.g. by lignite plants in Eastern Europe) or downward (e.g. by nuclear power from France), though, and could dilute or alter the results for the German case. Such a simplification is a limitation, it is however common in energy system simulations[5].

Fig. 3 illustrates a merit order curve for 2020, as it is used in the model.

[4] The so-called "Jahresvolllaststunden" in German terminology.

[5] For example, Pehnt, Helms *et al.* (2011, p. 225) mention the potential emission effect of imports, but do not explain how the effect is quantified.

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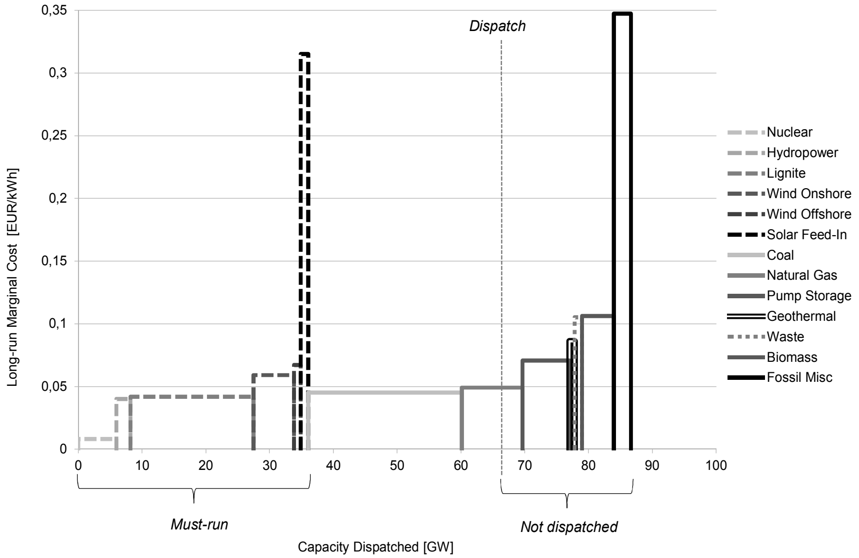
Fig. 3 - Example of a dispatch curve (6pm on a weekday in the year 2020)



The graph distinguishes between must-run technologies that are dispatched irrespective of their long-run marginal costs (to the left), and the line-up of all other technologies according to their long-run marginal costs[6]. Any technology beyond the dotted, vertical dispatch line, indicating the level of instantaneous demand, is not dispatched.

For a realistic representation of the resources with stochastic variation: solar and wind, which exhibit substantial meteorological fluctuations, we take possible variations of the output into consideration.

In the case of wind power, this is accomplished by the statistical analysis of hourly wind feed-in data of the four German grid operating companies in the year 2010. To integrate these variations in our calculations we calibrate four probability density functions based on hourly observations for each season. To calculate the seasonal distributions, the Palisade software "@Risk" has been used. For each quarter, a statistical analysis determines via a Chi-Square best-fit algorithm the

[6] Long-run marginal can be defined as "the levelised cost of meeting an increase in demand over an extended period of time. It is calculated by determining the difference in the NPV of two optimal generation development (installation) programs over an extended period (say 30 years)". (IES, 2004. The Long Run Marginal Cost of Electricity Generation in New South Wales – A Report to the Independent Pricing and Regulatory Tribunal.)

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distribution that corresponds most closely to the observed pattern[7]. In addition, the model differentiates between on-shore and off-shore wind power intake.

The second fluctuating energy source in the generation mix is solar power. As in the case of wind power, data from the four German grid operators is aggregated according to seasonal patterns. The methodology of translating the feed-in quantities is different from the wind pattern, though. Solar radiation occurs in a daily cycle with slight variations, starting in the morning and ending in the afternoon or evening. For the simulation, the daily solar intake is modelled as the average hourly value for each season with a deviation that is drawn from the Normal Distribution with parameters based on the observed values. Hence, for each day the sunlight is assumed to fluctuate around the hourly mean values with an intensity that corresponds to the Normal Distribution's divergences.

At each hour of our 12 prototypical weeks, we compute the electricity demand and the supply of each technology according to the 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.

To determine the time pattern of EV reloading, EMOB simulates the behaviour of electric car owners for a sample week of each month from 2011 to 2050. For this purpose, data from the survey "Mobility in Germany" (2008) is extracted[8].

The 2008 dataset of Mobility in Germany provides information about how many cars are actually used during each day of a week. In addition, it provides exact information on distance, start and end of each trip, its purpose (commuting to work, shopping, leisure activities), and whether it is a "loop" or "leg" in the terminology of transport economists, *i.e.* a round trip for instance to work and back at home or a trip with multiple stops, including e.g. shopping activities, and the time spent in the car. The information can be used to construct an exact representation of how the total German vehicle stock is used.

In the EMOB reference scenario, electric vehicle owners charge in the evening when they return home. If travel distances of pure battery electric vehicles exceed their limited battery range, they are assumed to charge at quick charging stations on the road. Range extenders and plug-in hybrids are assumed to use their full electric range before switching to the additional gas intake. Emissions for PHEV and RE (and corresponding kilometres) are accounted for only for the distance driven on electric traction. Based on these assumptions it is possible to estimate the aggregate hourly electricity requirement of electric vehicles.

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[7] For autumn and Winter, the Gamma distribution yields the best fit, while for Spring and Summer the Lognorm distribution achieves the highest Chi-Square. We make random extraction from each seasonal density function for every hour of the week, taking into account the observed correlation of wind across successive hours.

[8] Under the simplifying assumption that car owners do not change their travel behaviour based on the type of car technology they choose.

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3. Results and comparison with other computing methods

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

3.1. Results

We first present results about the emissions and compare with other methods of calculation. Successively, we present results about the source of energy used to reload EV's. Based on the Pivotal Marginal method, we obtain a time varying non-tailpipe emission of electric cars. Starting from 87 g./km in 2012 it decreases to 60 g./km in 2030.

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% of EV consumption 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 10% of the supply. After 2030, pump storage will capture a small share of the EV demand.

3.2. Comparison with other computing methods

We can compare these estimates with others, obtained by alternative (less convincing, to our view) methods. Tab. 4 show the results of the comparison. All estimates are made within EMOB 0.1.3.6, so the difference in results can be assigned to the difference across methods while input data are kept identical.

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 CO_2 emissions.

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, they are expected to remain at 560 g/kWh.

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 would have to rely on more aggregate, official figures of foreseen

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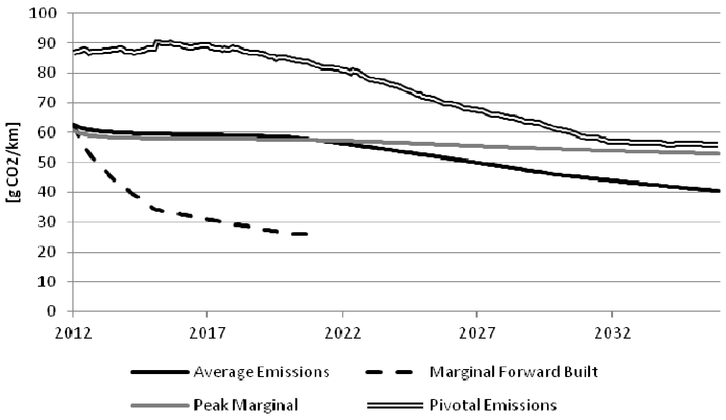
capacity expansion. According to the BMU, the extension of renewable energy capacity will continue and it will successively replace a large fraction of the existing fossil-based and nuclear plants.

Tab. 4 - Comparisons of CO_2 emissions by EVs based on four different methods (g CO_2/km, annual average, in parenthesis g/kWh)

	2020	**2030**
Pivotal Marginal	84,0 g/km (817 g/kWh)	60,2 g/km (620 g/kWh)
Peak Marginal[9]	57,6 g/km (560 g/kWh)	54,3 g/km (560 g/kWh)
Average	58,1 g/km (565 g/kWh)	45,4 g/km (468 g/kWh)
Marginal Forward Built	26,2 g/km (255 g/kWh)	n.a.

Fig. 4 - Comparison among different computation methods



Interestingly, Fig. 4 shows that the Pivotal Marginal calculation always provides larger emissions than alternative methods – except around 2030 where it converges toward peak marginal.

Clearly, **Average Emissions** (scoring around 60 g CO_2/km until 2020, with a subsequent decline to around 40 g CO_2/km in 2035) consistently underestimates the non-tailpipe emissions of EVs, compared with the suggested pivotal approach. The reason for this is that the average emissions are actually less CO_2 intensive than pivotal marginal, which are often fuel based.

[9] While Peak Marginal emissions of natural gas plants are assumed to remain constant, the efficiency of electric car powertrains increases endogenously over time in EMOB.

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The **Peak Marginal** approach underestimates EV emissions until 2025. This relates to the fact that, in the close future, non peak technologies often have higher emissions than peak. The emissions computed on the basis of **Forward Built Marginal** approach 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. Eventually, we can provide comparisons of pivotal approach with micro simulation. We observe for instance a minor deviation of around 5% between the emissions estimates in 2030 computed by our model and the one provided by Pehnt, Helms *et al.* (2011). It cannot be measured, though, what part of this difference results from difference in assumptions and what part results from a higher elaboration of the microsimulation model. It is however fair to note that if microsimulation model was to be taken as a benchmark, the pivotal approach brings the result fairly close to this benchmark. From this comparison, it emerges that the pivotal approach is capable of taking into account significant features of the energy distribution that are absent from other simple methods. It thus appears, in our view, as a valuable tool to aid public decision making. It also counteracts the risk of having spurious numbers taking too much room in the public debate. While it is certainly simplified compared with more elaborated microsimulation methods, it still provides robust results and is far less demanding in terms of data and computational resources.

4. Emissions in coordinated EV charging scenarios

Our results so far do not take into account the possibility of so-called coordination. This option is however usually perceived (NPE, 2011) as an opportunity to reap the whole benefits of electromobility. We consider several options how to increase the share of renewable energies to fuel EV's through coordination.

The reference scenario of EMOB assumes that car owners charge their vehicles when they return home. However, one of the benefits of the storage capability of electric batteries is that they could reload batteries when excess supply from renewables is available. Additional benefits of coordination relate to local grid constraints (Perujo and Ciuffo, 2010)[10]. Electric vehicles could hence play a role in balancing the system towards greater efficiency and environmentally sound

[10] Coordination in the charging patterns of electric vehicle owners may become necessary when the low and medium voltage grid is no longer capable of supporting a joint charging behaviour within a geographic area (see e.g. for the case of the Province of Milan, Italy). Technical restrictions may induce individual parts of the equipment, like transformers in the low and medium voltage grid, to fail. Coordinated charging switches parts of the load to later points in time, such that critical technical thresholds of the local network are not exceeded.

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resource use. As a consequence, the average non-tailpipe emissions of EV's would decrease.

In this section, we consider several options to increase the share of renewable energies to fuel EV's in a coordinated way.

We consider four different charging schemes:

1) **Uncoordinated charging at home**: car owners reload when they return home. This is the EMOB reference scenario;

2) **Coordinated charging after coming home and next morning 6am**: reloading operations may be shifted between the time car owners return home and next morning 6am;

3) **Uncoordinated charging at home and at work**: car owners reload when they arrive at work or as soon as they return home;

4) **Coordinated charging** at work and at home: reloading operations may be shifted between the time car owners arrive at work before they return home, as well as after coming home and next morning 6am.

Alternative 2 allows for load shifts at night, when overall demand is low and excess wind energy may be available. Our calculation assumes perfect short-term foresight of meteorological conditions[11], so a certain amount of charging may be shifted, as long as all EV's are fully loaded before 6 am[12].

Alternatives 3 and 4 suppose that car owners are also able to charge their vehicles during day-time, when they are at home, or at their workplace until they leave, in an uncoordinated and coordinated way, respectively. An increased load during day-time may absorb excess generation by photovoltaic cells and hence decrease the overall emission balance of electric cars.

Coordinated charging could also comprise Vehicle-to-Grid (V2G) power flows, where batteries can supply electricity to compensate for lack of renewable energy intake (see e.g. Andersen, Mathews *et al.*, 2009; for discussions of the Danish case; Galus, Zima *et al.*, 2010, and Kley, Lerch *et al.*, 2011, for business models related to controlled recharging). However, the additional charging and discharging cycles induced by V2G may face stiff car holder opposition, because the batteries' life times may be substantially diminished, while revenues remain limited (Delucchi and Lipman, 2010; Peterson, Apt *et al.*, 2010; Bashash, Moura *et al.*, 2011). For this reason, we refrain from including V2G in our calculation and guess it could be misleading for policy analysis[13].

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[11] It is likely that computational tools for weather forecasts, in particular wind speed, continue to further improve, see also the discussion in ISET (2007). Prognosesicherheit Ausgleichseffekte, University of Kassel. Working Paper 2007-067.

[12] More precisely, car owners are guaranteed to have their batteries reloaded at 6 am as much as if they were not coordinated. It can occur that some car owners do not have their batteries fully reloaded at 6 am, but this occurs only if they return home late at night.

[13] Additionally, depending on grid configuration and generation mix, coordinated charging may be beneficial to ease bottlenecks on the low voltage network, but may actually *increase* overall emissions due to a shift from peak load gas power plant to base load coal power stations, a situation that has been analyzed in details for the case of PHEV in Ohio,

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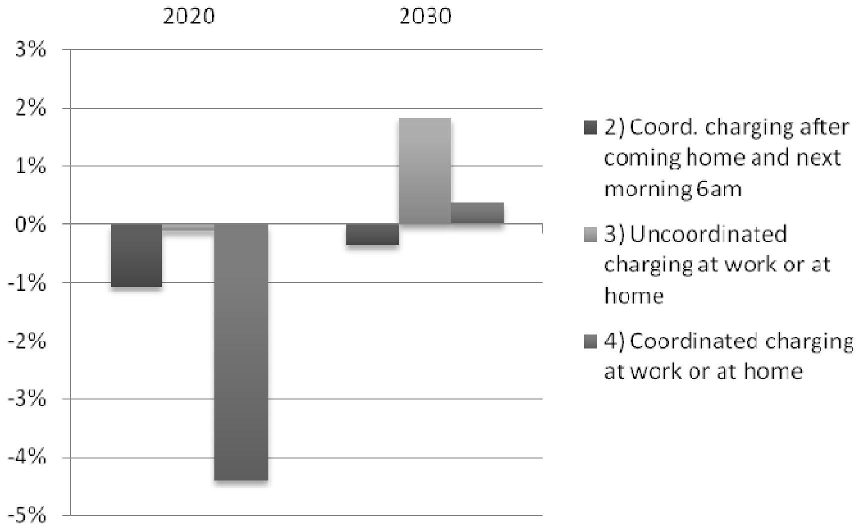
Fig. 5 shows the impact of each charging alternative on average non-tailpipe emissions of EV's, compared to the reference scenario.

Fig. 5 - Changes in pivotal emissions, compared to the reference scenario



The analysis reveals that coordinated charging at night (Alternative 2) only marginally reduces non-tailpipe emissions. Alternatives 3 and 4, which allow for charging at work and during daytime at home, bear some savings around 2020, but lead to slightly higher emissions in 2030, because coal power plants still represent 20 percent of the pivotal capacities and will be mainly used during daytime. Coordinated charging may have a positive impact on the local network, though, which is not represented in the graph (see also Göransson, Karlson *et al.*, 2010, on this topic).

5. Discussion and conclusion

From a methodological point of view, the pivotal approach appears a relevant one in that it provides a parsimonious alternative to the average and marginal calculation that populate the policy and part of the scientific debate about electric vehicles. While we are aware that the pivotal approach provides simplified representation compared with detailed microsimulation methods we see an interest

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Sioshansi R., Fagiani R. *et al.* (2010). Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. *Energy Policy*, 38(11): 6703-6712.

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for the scientific community in considering pivotal approach in that it adds significant understanding of the energy system, especially considering the time pattern of reloading. Interestingly, it provides results that are strikingly close to microsimulation methods, but are reasonably less resource consuming at least by one (if not two) order of magnitude.

Apart from the comparison of methodologies, our analysis provides insights about a number of issues relevant for the policy debate. First, we estimate EV emissions based on an endogenous simulation of EV market uptake.Second, our analysis provides information about 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. 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 results shows that this technology, given its position on the merit order curve, only rarely 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 or solar "excess supply" to charge EVs. Given the complementarity between gas and renewable generation, the increasingly flexible supply structure will only on rare occasions allow for a renewable surplus beyond the regular demand.

Eventually, this limited reliance on renewable persists even considering possible coordination schemes. In the simple situation where reloading operations can be shifted during night (with the constraint of maximal reload at 6 am in the morning), average CO_2 emissions of EV's decrease by less than 1 percent.

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 advantage of electromobility as a buffer for excess renewable energy may therefore be overstated, even under investment scenarios that are already strongly promoting renewables.

Eventually the picture that emerges from our analysis is polyedric. On the one side, looking at merely technological aspects, an EV car is generating less CO_2 than an ICE, although certainly not so few emissions 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 CO_2 emitting uses of energy. It is however legitimate and necessary to bear in mind that these emissions are a cost to society as they substitute other energy uses.

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