Project:

Development of an Evaluation Framework for the Introduction of Electromobility

Project Report: Power System Impacts of Electric Vehicles in Germany

Combined report on three deliverables:

2.2: Report regarding interactions with the power grid

7.1: Report on the updated Dataset and the calibrated and validated Electricity Market Model including different scenarios

7.2: Study regarding interactions between e-mobility and power market

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Summary

Within the project DEFINE, we analyze the integration of future fleets of electric vehicles (EV) into the German power system for various scenarios of 2020 and 2030, drawing on different assumptions on the charging mode. We use a numerical dispatch model with a unit-commitment formulation which minimizes overall dispatch costs over a full year. EV-related input parameters are provided by the Öko-Institut in WP 4. We shed some light on the interactions between different EV charging patterns and power plant dispatch, and respective consequences for the CO_2-intensity of the electricity used to charge EVs.

The overall energy demand of the modeled EV fleets is low compared to the power system at large. EVs account for only 0.1% to 0.2% of total power consumption in 2020 and for around 1.3% to 1.6% in 2030, depending on the charging mode. Hourly charging loads can become very high and differ strongly between charging modes. In the user-driven mode, charging largely occurs during daytime and in the evening with respective consequences for the peak load of the system. In contrast, cost-driven charging is carried out during night-time. These different charging patterns go along with respective changes in power plant dispatch. Cost-driven EV charging strongly increases the utilization of lignite and hard coal plants compared to a scenario without EVs. In the user-driven mode, additional power generation predominantly comes from natural gas and hard coal. The potential of EVs to reduce renewable curtailment is, at the same time, higher in case of cost-driven charging compared to the user-driven mode. Overall, specific CO_2 emissions of electric vehicles are substantially larger than specific emissions of the overall power system in most scenarios as EV-related improvements in renewable integration are over-compensated by increases in the utilization of lignite or hard coal. Only in additional model runs, in which we link the introduction of electromobility to a respective deployment of additional renewable generation capacity, electric vehicles become largely CO_2-neutral. Specific EV emissions are generally slightly larger in the cost-driven charging mode compared to the user-driven one because of increased coal utilization.

Based on these findings we suggest several policy conclusions. First, overall energy requirements of electric vehicles should not be of concern to policy makers, whereas their peak charging power should be. Because of generation adequacy concerns, purely user-driven charging would have to be restricted by a regulator in the future, unless high wholesale prices render user-driven charging unattractive, anyway. Second, policy makers should be aware that cost-driven charging not only increases the utilization of renewable energy, but also of lignite and hard coal plants. If the introduction of electromobility is linked to the use of renewable energy, as repeatedly stated by the German government, it has to be made sure that a corresponding amount of additional renewables is added to the system. Third, cost-driven charging can only lead to emission-optimal outcomes if emission externalities are correctly priced. Otherwise, a cost-driven charging mode may lead to above-average specific emissions, and even to higher emissions compared to user-driven charging. Finally, controlled charging of future electric vehicle fleets interacts with other potential sources of power system flexibility. Accordingly, both the future requirement of such flexibility options and their profitability depend on the size of the future EV fleet, as well as on its charging mode.

Zusammenfassung

Im Rahmen des Projekts DEFINE untersuchen wir die Integration künftiger Elektrofahrzeugflotten in das deutsche Stromsystem für verschiedene Szenarien der Jahre 2020 und 2030 bei unterschiedlichen Ladestrategien. Wir verwenden ein numerisches Kraftwerkseinsatzmodell mit einer Unit-Commitment-Formulierung, bei dem die gesamten Kraftwerkseinsatzkosten über ein komplettes Jahr minimiert werden. Elektrofahrzeugspezifische Inputdaten werden vom Öko-Institut in WP 4 bereitgestellt. Wir beleuchten die Interaktionen zwischen verschiedenen Ladestrategien und dem Kraftwerkseinsatz sowie die Auswirkungen auf die CO_2-Intensität des Ladestroms.

Im Vergleich zur gesamten Stromnachfrage ist der Energiebedarf der modellierten Elektrofahrzeugflotten gering. Er beträgt, je nach Ladestrategie, nur 0,1-0,2% (2020) beziehungsweise 1,3-1,6% (2030) des gesamten Stromverbrauchs. Die stündlichen Ladeleistungen können jedoch sehr groß werden, wobei große Unterschiede zwischen den Ladestrategien bestehen. Bei einer nutzergetriebenen Aufladung werden die Fahrzeuge tagsüber und in den Abendstunden geladen, mit entsprechenden Auswirkungen auf die Spitzenlast des Systems. Eine kostengetriebene Aufladung findet dagegen hauptsächlich in den Nachtstunden statt. Entsprechend ergeben sich Änderungen beim Kraftwerkseinsatz: Kostengetriebenes Laden erhöht die Auslastung von Braun- und Steinkohlekraftwerken erheblich gegenüber einem Vergleichsszenario ohne Elektrofahrzeuge. Nutzergetriebenes Laden erhöht dagegen vor allem die Gas- und Steinkohleverstromung. Gleichzeitig sind die Potenziale zur Verminderung der Abregelung erneuerbarer Energien bei kostengetriebenem Laden am höchsten. Insgesamt sind die spezifischen CO_2-Emissionen des Ladestroms in den meisten Szenarien deutlich höher als im systemweiten Durchschnitt, da der Ladestrom überwiegend von emissionsintensiven Kraftwerken stammt. Nur in zusätzlichen Szenarien, in denen wir die Einführung der Elektromobilität mit einem entsprechenden zusätzlichen Ausbau erneuerbarer Energien verknüpfen, sind Elektrofahrzeuge weitgehend CO_2-neutral. Grundsätzlich sind die spezifischen CO_2-Emissionen des Ladestroms bei kostengetriebener Aufladung am höchsten, weil hier die höchste Kohleverstromung erfolgt.

Auf Grundlage der Modellergebnisse ziehen wir einige politisch relevante Schlussfolgerungen. Zum einen ist der gesamte Strombedarf künftiger Elektrofahrzeugflotten auf längere Sicht als unproblematisch einzuordnen, die stündlichen Aufladeleistungen können jedoch kritisch werden. In Hinblick auf die Systemsicherheit müsste ein rein nutzergetriebenes Aufladen regulativ beschränkt werden, falls eine solche Ladestrategie nicht aufgrund steigender Strompreise ohnehin unattraktiv würde. Zum anderen sollten Entscheidungsträger sich bewusst sein, dass Elektrofahrzeuge nicht nur die Integration erneuerbarer Energien verbessern, sondern auch die Auslastung von Braun- und Steinkohlekraftwerken erhöhen. Falls die Einführung der Elektromobilität – wie beispielsweise von der Bundesregierung geäußert – mit der Nutzung erneuerbarer Energien verknüpft wird, muss sichergestellt werden, dass ein entsprechender zusätzlicher Ausbau erneuerbarer Energien erfolgt. Darüber hinaus kann eine kostengetriebene Aufladung nur dann zu emissionsseitig optimalen Ergebnissen führen, wenn Emissionsexternalitäten hinreichend eingepreist sind. Ansonsten kann eine kostengetriebene Ladestrategie zu überdurchschnittlichen spezifischen Emissionen führen. Nicht zuletzt bestehen relevante Interaktionen zwischen Elektrofahrzeugflotten und anderen Flexibilitätsoptionen für das Stromsystem. Der künftige Bedarf an solchen Flexibilitätsoptionen und ihre jeweilige Profitabilität dürfte stark von der Größe und der Ladestrategie der künftigen Elektrofahrzeugflotte abhängen.

1 Introduction

This report describes DIW Berlin's contribution to the project DEFINE with respect to our modeling activities to study possible future interactions of electromobility with the German power system. This report gives a combined account on DIW Berlin's activities in the following working packages:

- 2.2: Report regarding interactions with the power grid
- 7.1: Report on the updated Dataset and the calibrated and validated Electricity Market Model including different scenarios
- 7.2: Study regarding interactions between e-mobility and power market

Building on the inputs of our project partners, in particular parameters related to electric vehicles (EV) which are contributed by Öko-Institut, we carry out model-based analyses of integrating electric vehicles into the German power system for different scenarios of the years 2020 and 2030. We use a power plant dispatch model with a unit-commitment formulation. This approach is particularly suitable for studying the system integration of electric vehicles and their interaction with fluctuating renewables, as it reflects costs and constraints related to the limited flexibility of thermal power generators and thus adequately values the potential flexibility benefits of a smart system integration of electric vehicles. We are particularly interested in the impacts of electric vehicles on the dispatch of power plants, the integration of fluctuating renewable energy, generation capacity requirements, and CO_2 emissions under different assumptions on the mode of vehicle charging.

Previous research has analyzed various aspects of integrating electric vehicles to the power system, be it purely battery-electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV) and/or range extender electric vehicles (REEV). Kempton and Tomić (2005a) first introduce the vehicle-to-grid (V2G) concept and estimate V2G-related revenues in various segments of the U.S. power market. In the wake of this seminal article, a broad strand of related research has evolved. Hota et al. (2014) review numerous model analyses on the power system impacts of electric vehicles and group these into different categories, e.g., with respect to the assumed type of grid connection and the applied methodology.

A strand of the literature deals with power system implications of different charging strategies of EVs. Hadley (2007) studies the dispatch effects of two different charging patterns of PHEV in the Virginia-Carolinas grid as well as in other U.S. regions using a stylized, spreadsheet-based, linear model. Wang et al. (2011) examine the interactions between PHEVs and wind power in the Illinois power system with a unit commitment approach, distinguishing different levels of coordination in charging. They show that smart coordinated charging leads to a reduction in total system cost and smoother conventional power generation profiles. Kiviluoma and Meibohm (2011) model the power costs that Finnish owners of electric vehicles would face by 2035 under different charging and discharging patterns. In case of optimized charging, power prices turn out to be rather low as low-cost generation capacities can be used. “Smart” electric vehicles may lead to system benefits of more than 227 € per vehicle and year compared to “dumb” EVs. Loisel et al. (2014) analyze the power system impacts of different charging and discharging strategies of battery-electric vehicles for Germany by 2030. Distinguishing grid-to-vehicle (G2V) and vehicle-to-grid (V2G), they also highlight the benefits of optimized charging. At the same time, they find that V2G is not a viable option due to excessive battery degradation costs.

Another strand of the literature focuses on the interactions of electric vehicles with the system integration of fluctuating renewable power and related emission impacts. Lund and Kempton (2008) analyze the integration of variable renewable power sources into both the power system and the transport sector with an energy system model. They find that EVs with high charging power can substantially reduce renewable curtailment and CO_2 emissions. Göransson et al. (2010) carry out a comparable case study for Denmark, concluding that PHEV can decrease net CO_2 emissions of the power system if they are charged in a system-optimized mode. In a more stylized simulation for Denmark, Ekman (2011) highlights the potential of EVs to take up excess wind power. Guille and Gross (2010) do not apply a power system model, but focus their analysis on PHEV's potential for smoothing variable wind generation. Sioshansi and Miller (2011) apply a unit commitment model to analyze the emission impacts of PHEV with regard to CO_2, SO_2, and NO_x in the Texas power system. Imposing an emission constraint on PHEV charging activities, they show that specific emissions may be reduced below the ones of respective conventional cars without increasing recharging costs substantially. In a 2020 model analysis for Ireland, Foley et al. (2013) show that that off-peak charging is the most favorable option with respect to cost and CO_2 emissions. Schill (2011) develops a Cournot model to analyze the impacts of PHEV fleets on dispatch, welfare and emissions in an imperfectly competitive power market environment and finds that both welfare and emission impacts depend on the agents responsible for charging the vehicles, and on the availability of V2G.

With the analyses carried out in the course of the project DEFINE, we aim to contribute to the cited literature in several ways. First, the unit commitment approach used here is more suitable to capture potential flexibility-related power system benefits of electric vehicles compared to linear dispatch models (e.g., Hadley 2007, Lund and Kempton 2008, Göransson et al. 2010, Schill 2011, Loisel et al. 2014). Next, the hourly patterns of electric vehicle power demand and charging availabilities used here are considerably more sophisticated than in some of the aforementioned studies (e.g., Ekman 2011, Foley et al. 2013). In contrast to, for example, Loisel et al. (2014), we moreover consider not only BEV, but also PHEV/REEV. What is more, we do not rely on a stylized selection of hours in particular seasons or load situations (e.g., Wang et al. 2011), but apply the model to all subsequent hours of a full year. We further present a topical case study for Germany for the years 2020 and 2030 with up-to-date input parameters, particularly with regard to a stronger deployment of renewables than assumed in earlier studies, and with a full consideration of the German nuclear phase-out. Finally, we study the effects of electric vehicles not only for a baseline power plant fleet, as carried out in most other studies, but also for cases with adjusted generation capacities of wind and/or PV. This allows assessing the potential benefits of linking the introduction of electromobility to a corresponding expansion of renewable power generation.

The remainder is structured as follows. Section 2 introduces the methodology. Section 3 describes the scenarios used for applying the model to Germany for 2020 and 2030, as well as other relevant input parameters. Results with regard to vehicle charging, power plant dispatch and CO_2 emissions are presented in section 4. The impacts of model limitations on results are critically discussed in section 5. In the final section, we summarize and conclude.

2 Methodology

We use a numerical optimization model that simultaneously optimizes power plant dispatch and charging of electric vehicles. The model determines the cost-minimal dispatch of power plants, taking into account the thermal power plant portfolio, fluctuating renewables, pumped hydro storage, as well as grid-connected electric vehicles. The model has an hourly resolution and is solved for a full year. It includes realistic inter-temporal constraints on thermal power plants, for example minimum load restrictions, minimum down-time, and start-up costs. As a consequence, the model includes binary variables on the status of thermal plants, and can thus be characterized as a mixed integer linear program (MILP). In addition, there are special generation constraints for thermal plants that are operated in a combined heat and power mode, depending on temperature and time of day.

The model draws on a range of exogenous input parameters, including thermal and renewable generation capacities, fluctuating availability factors of wind and solar power, generation costs and other techno-economic parameters, and the demand for electricity both in the overall power sector and related to electric vehicle charging. As for the latter, we draw on future patterns of hourly power consumption and charging availabilities derived in working package 4 by Öko-Institut (Kasten and Hacker, 2014). Hourly demand is assumed not to be price-elastic. Endogenous model variables include the dispatch of all generators, electric vehicle charging patterns, and CO_2 emissions of the power system.

Importantly, we only consider power flows from the grid to the electric vehicle fleet in this study (G2V). We abstract from the possibility that electric vehicles might feed power back to the grid in some periods (V2G), as previous analyses have shown that the potential revenues of such vehicle-to-grid (V2G) applications are unlikely to cover related battery degradation costs (compare Loisel et al. 2014).[2]

In contrast to the linear models used by, for example, Hadley (2007), Lund and Kempton (2008), Göransson et al. (2010), Schill (2011), Ekman (2011), and Loisel et al. (2014), the unit commitment formulation applied here allows assessing the effects of different charging modes of electric vehicles on the power system in a more comprehensive way. In the context of the DEFINE project, DIW Berlin's existing unit-commitment dispatch model has been augmented with additional sets, parameters, variables and equations related to the introduction of electromobility (Table 1).

[2] Kempton and Tomić (2005b), Andersson et al. (2010), Lopes et al. (2011), and Sioshansi and Denholm (2010) argue that V2G may be viable for providing spinning reserves and other ancillary services. However, we abstract from control reserves in this analysis.

Table 1: Sets, parameters, and variables related to electric vehicles

Sets	Description	Unit
EV	Set of 28 EV profiles	
Parameters		
$EVChargePower_{t,EV}$	Hourly power rating of the charge connection (zero when car is in use or parked without grid connection)	kW
$EVConsumption_{t,EV}$	Hourly EV power consumption	kWh
$EVBatteryCapacity_{EV}$	EV Battery Capacity	kWh
$EVEfficiency_{EV}$	EV charging efficiency	%
$PHEV_{EV}$	Defines whether an EV is a PHEV/REEV (1 if yes, 0 otherwise)	
$EVQuantity_{EV}$	Number of EVs per load profile	
$EVFastChargeGoal$	Restricts the relative battery charge level that should be reached as fast as possible (1 for user-driven charging, 0 otherwise)	
Variables		
$evchargelevel_{t,EV}$	Cumulative EV battery charge level	MWh
$evcharge_{t,EV}$	Cumulative EV charging power	MW
$phevfueling_{t,EV}$	Cumulative PHEV conventional fuel use	MWh
$evfullcharge_{t,EV}$	Binary variable (1 if full charge power is required, i.e., when the charge level is below $EVFastChargeGoal$, 0 otherwise)	

$$evchargelevel_{t,EV} = evchargelevel_{t-1,EV} + evcharge_{t,EV} * EVEfficiency_{EV} - EVConsumption_{t,EV} * EVQuantity_{EV} + phevfueling_{t,EV} \quad \forall t, EV \quad \text{(EV1)}$$

$$phevfueling_{t,EV} = 0 \; if \; PHEV_{EV} = 0 \quad \forall t, EV \quad \text{(EV2)}$$

$$evcharge_{t,EV} \leq EVChargePower_{t,EV} * EVQuantity_{EV} \quad \forall t, EV \quad \text{(EV3)}$$

$$evchargelevel_{t} \leq EVBatteryCapacity_{EV} * EVQuantity_{EV} \quad \forall t, EV \quad \text{(EV4)}$$

$$evcharge_{t,EV} \geq 0 \quad \forall t, EV \quad \text{(EV5)}$$

$$evchargelevel_{t,EV} \geq 0 \quad \forall t, EV \quad \text{(EV6)}$$

$$phevfueling_{t,EV} \geq 0 \quad \forall t, EV \quad \text{(EV7)}$$

Equation (EV1) is the cumulative EV energy balance. The battery charge level $evchargelevel_{t,EV}$ is determined as the level of the previous period plus the balance of charging and consumption in the actual period. The charge level of PHEV/REEV is also influenced by conventional fuel use $phevfueling_{t,EV}$. Importantly, only electric vehicles of the PHEV/REEV type may use conventional fuels, whereas $phevfueling_{t,EV}$ is set to zero for battery-electric vehicles (EV2). Equations (EV3) and (EV4) constitute upper bounds on the cumulative power of vehicle charging and the cumulative charge level of vehicle batteries. Note that the parameter $EVChargePower_{t,EV}$ has positive values only in periods in which the EV is connected to the grid. Non-negativity of the variables representing cumulative charging, charge level, and conventional fuel use is ensured by equations (EV5-EV7).

$$EVFastChargeGoal * EVBatteryCapacity_{EV} * EVQuantity_{EV} - evchargelevel_{t,EV} \leq (EVBatteryCapacity_{EV} * EVQuantity_{EV} + 1) * evfullcharge_{t,EV} \qquad \forall t, EV \quad \text{(EV8)}$$

$$evfullcharge_{t,EV} * EVChargePower_{t,EV} * EVQuantity_{EV} \leq evcharge_{t,EV} \qquad \forall t, EV \quad \text{(EV9)}$$

Equations (EV8) and (EV9) are only defined in the user-driven charging mode, i.e., if $EVFastChargeGoal$ is exogenously set to 1. Equation (EV8) makes sure that the vehicle will be charged as fast as possible after it is connected to the grid. This is operationalized by determining the difference between the desired and the current battery charge level. If the battery level is below the target, fast charging is enforced, i.e., the binary variable $evfullcharge_{t,EV}$ is set to 1. Equation (EV9) then enforces charging to be carried out with full power. Note that this model formulation is very flexible. It allows not only representing the two extreme modes of charging, i.e., fully user-driven or fully cost-driven charging; by assigning real numbers between 0 and 1 to $EVFastChargeGoal$, any desired target level of fast battery charging may be specified. For example, if $EVFastChargeGoal$ is set to 0.5, vehicle batteries have to be charged with full power until a charge level of 50% is reached. After that, the remaining battery capacity may be charged in a cost-driven way. We do not fully exploit this model formulation in the present analysis, as only the two extreme charging modes are to be compared in the project DEFINE.

Equations (EV1-EV9) are added to the existing unit commitment model of DIW Berlin. In addition, the model's energy balance is modified such that it considers the additional charging electricity for electric vehicles $\sum_{EV} evcharge_{t,EV}$ in each hour. Likewise, the objective function (minimization of dispatch costs) is modified such that it includes a penalty term for conventional fuel use of PHEV/REEV. This is required in order to make sure that PHEV/REEV use electricity rather than conventional fuels whenever possible.

3 Scenarios and input parameters

We apply the dispatch model to various scenarios. First, we distinguish different developments with regard to electric vehicle deployment: a reference case without electric vehicles, a Business-as-usual (BAU) scenario and an Electromobility+ (EM+) scenario for the years 2020 and 2030.[3] The BAU scenario assumes a moderate increase of EVs, while EM+ reflects an increased deployment of electric vehicles (for further details, see Kasten and Hacker, 2014). These scenarios are solved for all hours of the respective year. In addition, we carry out six additional model runs for the EM+ scenario of the year 2030 with additional renewable capacities (RE+). These capacities are adjusted such that they supply exactly the yearly power demand required by EVs. We assume that the additional power either comes completely from onshore wind, or completely from PV, or fifty-fifty from onshore wind and

[3] Previously, the general conditions of the BAU and EM+ scenarios had been coordinated among the DEFINE project partners.

PV. Comparing the RE^+ scenarios to both the respective EM^+ cases and the RE^+ cases without electric vehicles allows for interesting insights in the sensitivity of dispatch and emission results to the assumed power plant portfolio.

Within the scenarios BAU, EM^+, and RE^+, we further distinguish two extreme charging modes. EVs may either be charged in a completely user-driven mode or in a completely cost-driven mode. User-driven charging reflects a setting in which all electric vehicles are fully recharged with the maximum available power as soon as these are connected to the grid. This mode could also be interpreted as a kind of “plug-in and forget” charging strategy by the vehicle owners. In contrast, the cost-driven charging mode reflects a perfectly coordinated way of charging that minimizes power system costs. It could also be interpreted as system-optimized charging or market-driven charging under the assumption of a perfectly competitive power market. Such a charging strategy could be enabled by smart charging devices and may be carried out by power companies, specialized service providers, or vehicle owners themselves. In the real world, some intermediate mode of charging between these extremes may materialize. Table 2 gives an overview of all model runs. An “x” indicates the configurations for which model runs are carried out.

Table 2: Scenario matrix

EV scenario	Charging mode	Generation capacities			2010	2020	2030
No EVs		Baseline			x	x	x
		RE^+	100%	Wind			x
			50%	Wind/PV			x
			100%	PV			x
			100%	Wind			x
			50%	Wind/PV			x
			100%	PV			x
BAU	User-driven	Baseline				x	x
	Cost-driven					x	x
EM^+	User-driven	Baseline				x	x
	Cost-driven					x	x
	User-driven	**RE^+**	100%	Wind			x
			50%	Wind/PV			x
			100%	PV			x
	Cost-driven		100%	Wind			x
			50%	Wind/PV			x
			100%	PV			x

As for exogenous input parameters, we draw on several sources. First, we use DIW Berlin’s power plant data-base, which includes a block-sharp representation of all thermal generators in Germany. Blocks with a capacity smaller than 100 MW are summed up to 100 MW blocks in order to reduce numerical complexity. Assumptions on the future development of German power plant fleet are derived from the so-called Grid Development Plan (NEP).[4] This plan is drafted on a yearly basis by German transmission system operators for a time horizon of 10 and 20 years. After a series of revisions and public consultations, the NEP serves as the basis for German federal network planning legislation. In this study, we largely draw on the 2013 version of the Grid Development Plan (50Hertz et al. 2013) regarding thermal and renewable generation capacities, fuel and carbon prices (Table 3), and specific carbon emissions.[5]

Table 3: Fuel and carbon prices

	Unit	2010	2020	2030
Oil	EUR_{2010}/t	446	543	663
Natural gas	EUR_{2010}/MWh_{th}	21	25	26
Hard coal	EUR_{2010}/t coal equ.	85	80	86
Lignite	EUR_{2010}/t MWh_{th}	2	2	2
CO_2 certificates	EUR_{2010}/t	13	24	41

As the NEP 2013 only provides generation capacities for the years 2011, 2023, and 2033, we linearly interpolate between these years to derive capacities for 2020 and 2030. As for nuclear power, we use the projected phase-out schedule according to German legislation. Overall, thermal generation capacities slightly decrease until 2030, whereas installed renewable capacities increase substantially (Figure 1). CCGT and OCGT refer to combined or open cycle gas turbines, respectively. We also include an expensive, but unlimited backstop peak generation technology in order to ensure solvability of the model even in cases of extreme vehicle charging patterns.

[4] *Netzentwicklungsplan* (NEP) in German.
[5] More precisely, we draw on the medium projections called "B 2023" and "B 2033", which are deemed to be the most likely scenarios. We also draw on the 2012 and 2014 versions of the NEP in some instances, e.g., regarding 2010 generation capacities as well as 2012 offshore wind capacities (50Hertz et al. 2012, 50Hertz et al. 2014).

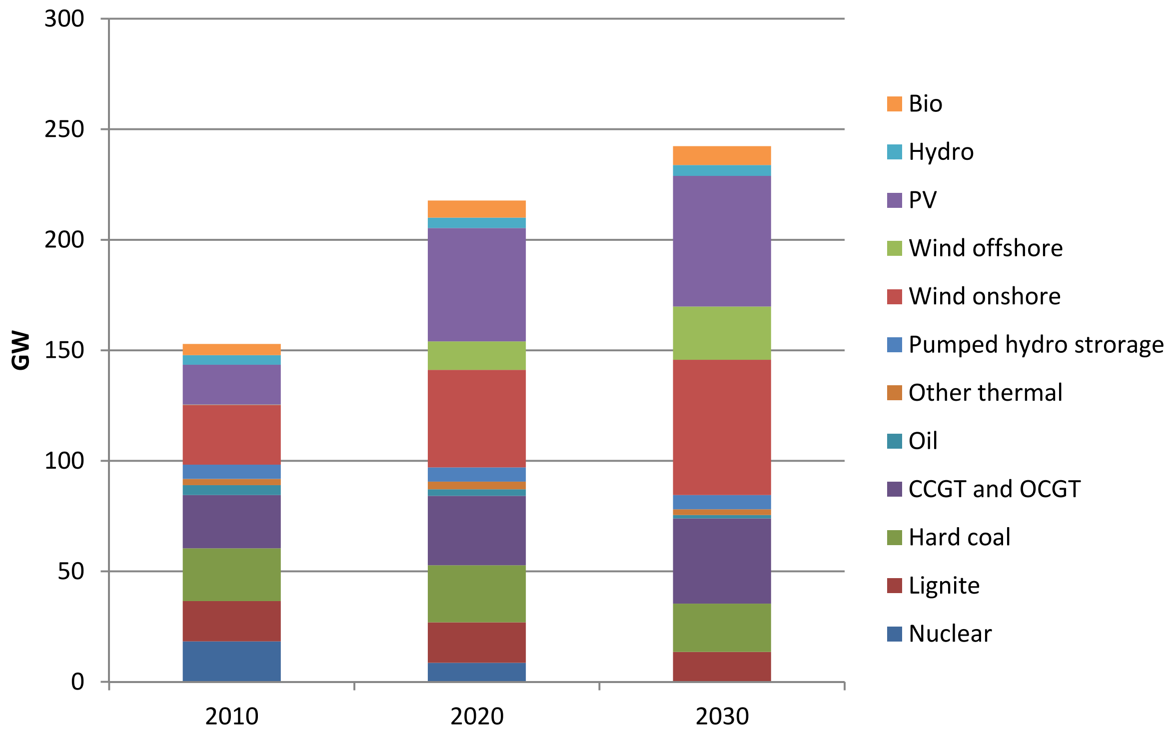

Figure 1: Installed net generation capacities

Hourly availability factors of onshore wind and PV are derived from publicly available feed-in data of the year 2010 provided by German TSOs. We project hourly maximum generation levels of these technologies for the years 2020 and 2030 by linearly scaling up to the generation capacities of the respective year. As for offshore wind, feed-in data is available for selected projects in the North Sea only. We derive hourly availability factors from publicly available 2012 feed-in data provided by TenneT.

Hourly power demand is assumed not to change compared to 2010 levels. We assume a total yearly net consumption of 560.8 TWh, including grid losses, with a maximum hourly peak load of 91.9 GW. As regards other techno-economic parameters such as efficiency of thermal generators, start-up costs, and minimum off-times, we draw on DIW Berlin's power plant database, Egerer et al. (2014), and own research.

All exogenous model parameters related to electric vehicles are provided by Öko-Institut in working package 4 (Kasten and Hacker, 2014).[6] The projected fleets of electric vehicles of the years 2020 and 2030 in the two scenarios BAU and EM+ are translated into aggregate hourly power consumption and maximum charging levels of 28 vehicle categories, of which 16 relate to pure battery-electric vehicles (BEV) and 12 to plug-in hybrid electric vehicles (PHEV) or range extender electric vehicles (REEV). Vehicles differ with respect to both their battery capacity and their typical charging power. All vehicles may be charged with a net power of 10.45 kW in some hours of the year, as these are assumed

[6] There is one exception: the parameter $EVFastChargeCoal$ is set exogenously by us, depending on the scenario run.

to be connected to (semi-)public “medium power charging stations” occasionally. Table 4 provides an overview of EV-related parameters. The cumulative battery capacity in the 2030 is in the same order of magnitude as the power storage capacity of existing German pumped hydro storage facilities. The table also includes an indicative yearly average value of hourly recharging capacities which reflects different assumptions on hourly connectivity to charging stations and different charging power ratings.

Table 4: Exogenous parameters related to electric vehicles

	2020		2030	
	BAU	**EM+**	**BAU**	**EM+**
	Number of vehicles (million)			
BEV	0.1	0.1	2.9	3.7
PHEV/REEV	0.3	0.4	0.9	1.0
Overall	0.4	0.5	3.7	4.8
	Cumulative battery capacity (GWh)			
BEV	2.4	2.8	21.7	25.2
PHEV/REEV	3.0	3.9	27.6	35.9
Overall	5.4	6.7	49.2	61.1
	Cumulative average hourly charging capacity (GW)			
BEV	0.3	0.3	2.9	3.1
PHEV/REEV	0.7	0.8	8.7	10.3
Overall	1.0	1.1	11.6	13.3

Just like wholesale power demand, power consumption by electric vehicles is assumed to be perfectly price-inelastic. As regards plug-in hybrid electric vehicles, we ensure a preference for electric driving mode by including a penalty on conventional fuel use in the objective function.

4 Results

In the following, we compare the model outcomes with respect to EV charging patterns, dispatch of thermal and renewable generators, renewable curtailment, and CO_2 emissions.

4.1 Charging of electric vehicles

The yearly power consumption of electric vehicles in the different scenarios is generally small compared to overall power demand (Table 5). In 2020, the EV fleet consumes 0.7 TWh in the BAU scenarios and around 0.9 TWh in the EM^+ scenarios. These values correspond to only around 0.1% of total power consumption, or 0.2%, respectively. In terms of overall energy consumption, the impact of EVs may thus be considered negligible by 2020. In 2030, EV-related power consumption gets more significant with up to 7.1 TWh in BAU and nearly 9.0 TWh in EM^+, which corresponds to around 1.3% of total power consumption, or 1.6%, respectively. In the user-driven charging modes power consumption is generally slightly lower compared to cost-driven charging because the electric shares of PHEV and REEV are slightly lower. These shares are around 55% in the 2020 scenarios, and between 60% (user-driven) and 64% (cost-driven) in the 2030 scenarios.

Table 5: Power consumption of electric vehicles

EV scenario	Charging mode	Generation capacities		EV consumption (TWh) 2020	EV consumption (TWh) 2030	Share of total load (%) 2020	Share of total load (%) 2030
BAU	User-driven	Baseline		0.70	6.92	0.12	1.22
	Cost-driven			0.70	7.10	0.12	1.25
EM+	User-driven	Baseline		0.88	8.59	0.16	1.51
	Cost-driven			0.88	8.95	0.16	1.57
	User-driven	**RE+**	100% Wind		8.54		1.50
			50% Wind/PV		8.55		1.50
			100% PV		8.59		1.51
	Cost-driven		100% Wind		8.95		1.57
			50% Wind/PV		8.95		1.57
			100% PV		8.95		1.57

While overall power consumption of the assumed EV fleets is rather small compared to overall power demand, hourly charging loads can become very high. Hourly charging levels vary significantly over time, thus requiring large amounts of generation capacity to be available at some times in order to allow for charging many EVs simultaneously. This is especially visible in the case of user-driven charging, where charging takes place independently of power system conditions. Here, EVs are charged as fast as possible given the restrictions of the grid connection.[7] Figure 2 exemplarily shows the average charging power over 24 hours for the 2030 EM+ scenario (with baseline generation capacity assumptions). User-driven charging results, on average, in three distinct daily load peaks. These occur directly after typical driving activities. Almost no charging takes place at night, as EVs are fully charged several hours after the last drive. In contrast, the cost-driven charging mode allows to charge EVs during hours of high PV availability, and to shift charging activities into the night, when other electricity demand is low. Overall, the average charging profile is much flatter in the cost-driven mode compared to the user-driven one.

[7] We do not consider possible restrictions related to bottlenecks in both the transmission and the distribution grids.

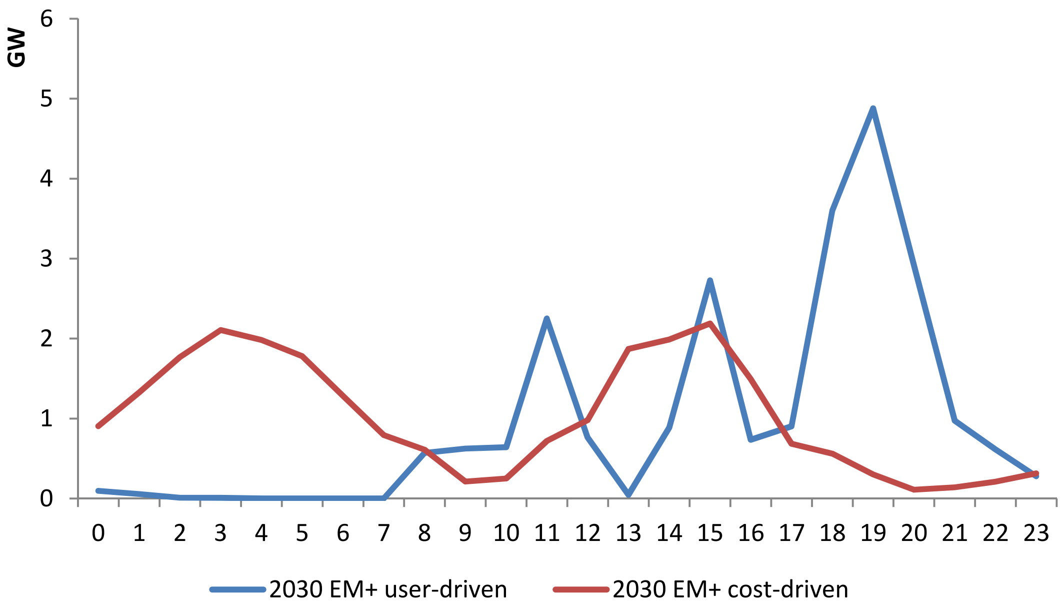

Figure 2: Average EV charging power over 24 hours

From a power system perspective, peak loads may be more relevant than average charging levels. Figure 3 depicts maximum hourly charging levels of each hour of the day over the whole modeled year. The overall pattern is related to the one shown in Figure 2, but the distribution of the peaks is different. In the user-driven case the maximum charging power occurs during the morning hours and in the evening, when people drive to work or home from work. In both cases, charging occurs during hours in which wholesale power demand is already high. This pattern is avoided in the cost-driven case, as especially the maximum peak load never exceeds 7.5 GW during evening hours (5-9 PM). Around noon and at night-time, higher maximum EV charge loads can be observed, again reflecting high availabilities of solar PV, or low wholesale power demand, respectively.[8] In the 2030 scenarios, the backstop peak technology is required in order to solve the model. That is, the generation capacities depicted in Figure 1 do not suffice to serve overall power demand during peak charging hours. The NEP generation capacities are exceeded by around 220 MW in the peak hour of the user-driven 2030 BAU scenario, and by around 360 MW in the respective EM$^+$ scenario. In other words, user-driven charging would raise severe concerns with respect to generation adequacy and may ultimately jeopardize the stability of the power system.

[8] In contrast, Weiller (2011) calculates different charging profiles of PHEVs, drawing on U.S. travel surveys, and finds that the charging power is generally well below 1 kW per vehicle.

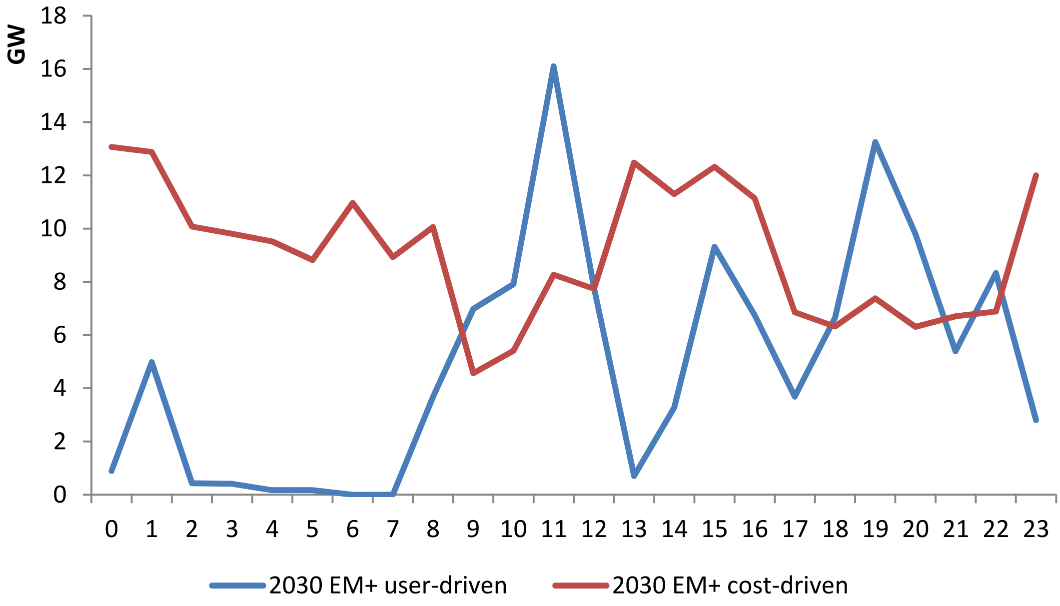

Figure 3: Maximum EV charging power over 24 hours

Figure 4 shows sorted load duration curves of EV charging for the 2030 EM^{+} scenarios (with baseline generation capacity assumptions). The peak charging power in the user-driven mode is about 16 GW, compared to only 13 GW in the cost-driven mode. Importantly, these peak loads occur at different times. The user-driven load peaks occur on weekday evening hours and Saturday morning, while cost-driven load peaks occur at nighttime when overall electricity demand is low. More generally speaking, user-driven charging results in frequent load peaks during daytime hours and – what is worse from a system perspective – during evening hours, in which wholesale power demand is also high. In contrast, cost-driven charging hardly increases power consumption during hours in which wholesale demand is already high.

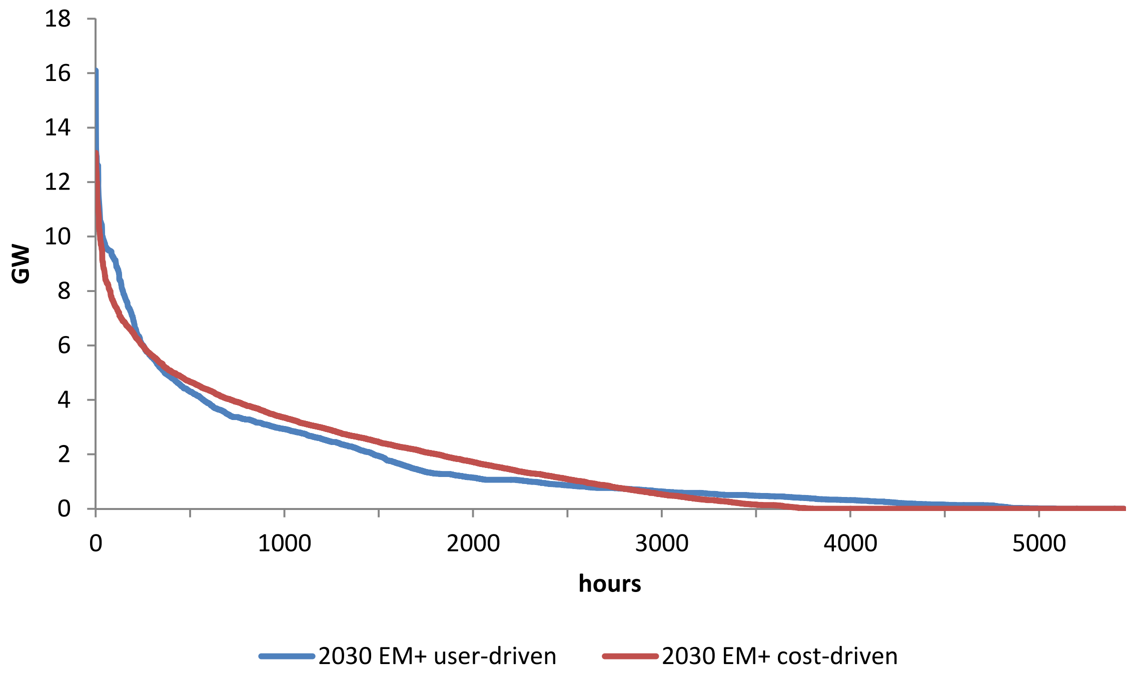

Figure 4: Load duration curves of EV charging

4.2 Power plant dispatch

The differences in hourly EV charging patterns discussed above are reflected in a changed dispatch of the power plant fleet.[9] While EV-related power requirements in the user-driven case mainly have to be provided during daytime, cost-driven charging allows, for example, utilizing idle generation capacities in off-peak hours. Comparing dispatch in the 2020 EM$^+$ scenario to the one in the case without any electric vehicles in the same year, we find that the introduction of electric vehicles under cost-driven charging mostly increases the utilization of lignite plants, which have the lowest marginal costs of all thermal technologies (Figure 5). Generation from mid-load hard coal plants also goes up. These changes in dispatch are enabled by the charging mode, which allows shifting charging to off-peak hours in which lignite and hard-coal plants are under-utilized. Under user-driven charging, power generation from lignite cannot be increased that much, as charging occurs in periods in which these plants are largely producing at full capacity, anyway. Instead, generation from hard coal increases even more than in the cost-driven case. In addition, user-driven charging increases the utilization of – comparatively expensive – gas-fired plants, as these are the cheapest idle capacities in many recharging periods, e.g., during weekday evenings. The utilization of pumped hydro storage decreases slightly under cost-driven charging, as optimized charging of electric vehicles decreases arbitrage opportunities of storage facilities. In contrast, storage use increases slightly under user-driven charging because of increased arbitrage opportunities between peak and off-peak hours.

[9] Regarding power plant dispatch, we only present results for the 2020 and 2030 EM$^+$ and 2030 RE$^+$ scenarios. The respective dispatch results in the BAU scenarios are very similar, but less pronounced than the ones of the EM$^+$ and RE$^+$ runs.

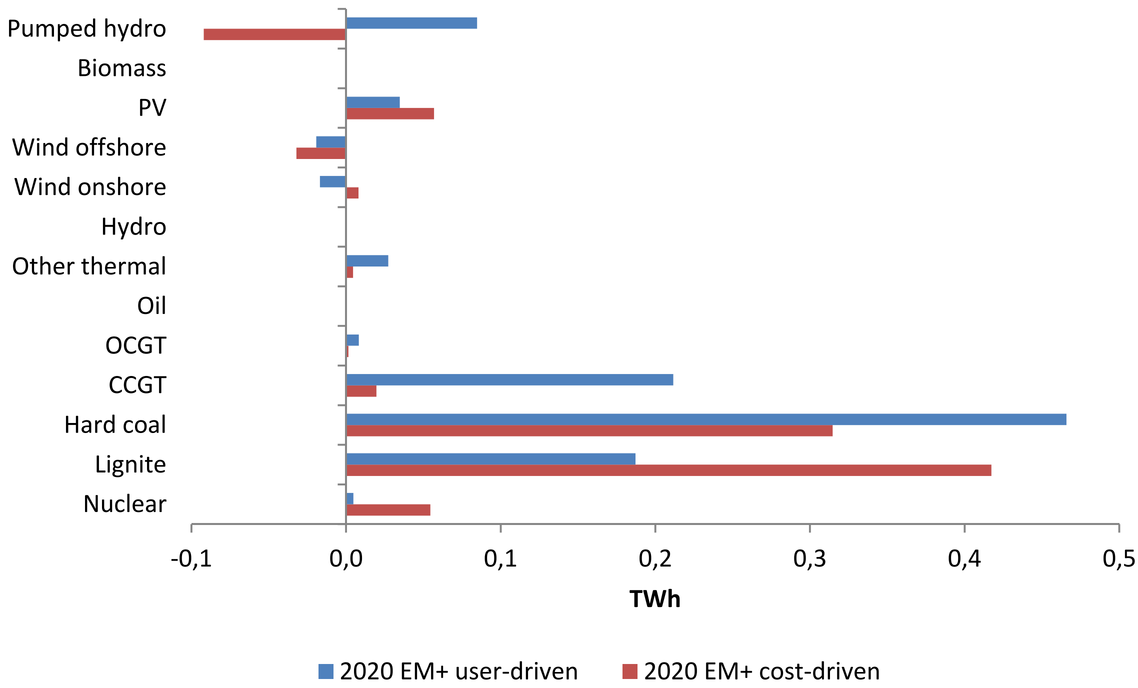

Figure 5: 2020 EM+: dispatch changes relative to scenario without EV

Figure 6 shows respective changes in dispatch outcomes for the 2030 EM+ scenario. Compared to the 2020 results presented above, the introduction of electric vehicles has a much more pronounced effect in 2030, as the overall number of electric vehicles is much higher. While the direction of dispatch changes is largely the same as in 2020, there is a slight shift from lignite to gas: under cost-driven charging, the relative increase in the utilization of lignite plants is less pronounced compared to 2020, whereas the utilization of combined cycle gas turbines (CCGT) is higher. Under cost-driven charging, this effect – which can be explained by an exogenous decrease of lignite plants and a corresponding increase of gas-fired generation capacities (compare Figure 1) – is even more pronounced, such that most of the additional power generation comes from CCGT plants. Worth mentioning, the additional flexibility brought to the system by cost-driven charging also enables additional integration of energy from renewable sources, i.e., onshore and offshore wind as well as PV. Correspondingly, pumped storage, which is another potential source of flexibility, is used less in the cost-driven case.

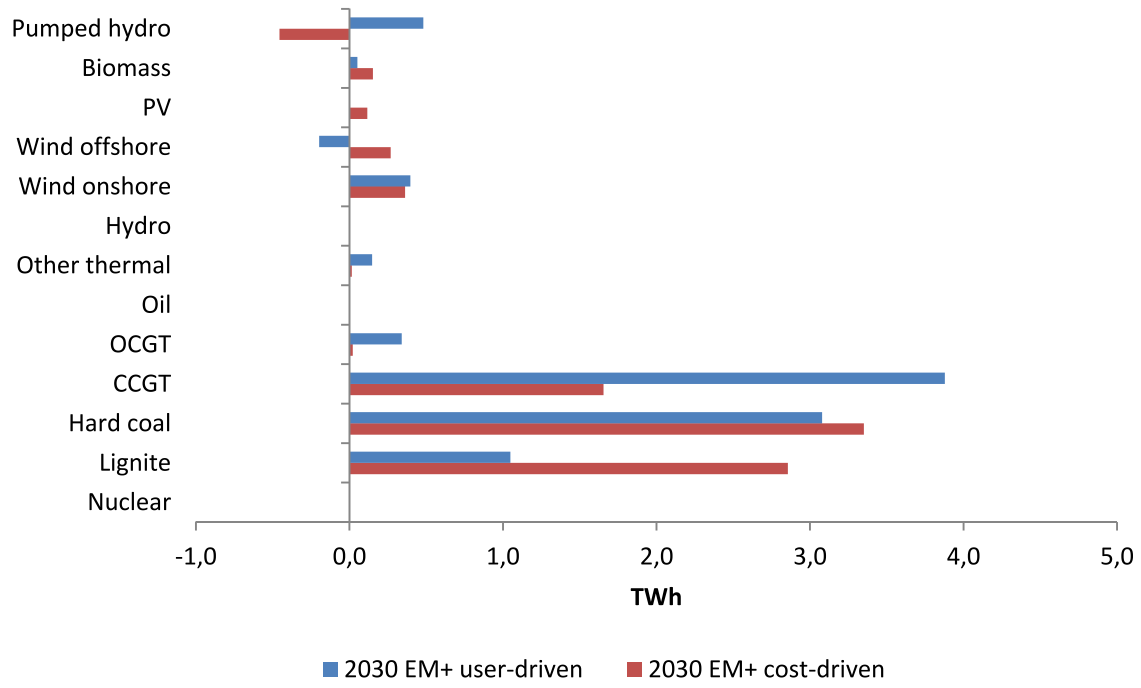

Figure 6: 2030 EM+: dispatch changes relative to scenario without EV

In the cases presented so far, we have assumed that the power plant fleets of the years 2020 or 2030 do not change between the cases with and without electric vehicles. While this assumption proves to be unproblematic with respect to overall generation capacities – at least in the cost-driven charging mode – we are interested in how results change if the power plant fleet is adjusted to the introduction of electromobility. While there are many thinkable changes to the generation portfolio[10], we are particularly interested in cases in which the introduction of electric vehicles is linked to a corresponding increase in renewable energy generation. In fact, German policy makers have directly linked the introduction of electric vehicles to the utilization of renewable power (Bundesregierung 2011). Yet results presented so far have shown that the additional energy used to charge EVs is mainly provided by conventional power plants, and particularly by emission-intensive lignite plants in the cost-driven charging mode.

We thus conduct additional "Renewable Energy+" (RE+) model runs based on the 2030 EM+ scenario. We add onshore wind and/or photovoltaics capacities to such an extent that their potential yearly feed-in exactly matches the amount of energy required to charge EVs. We distinguish three cases in which this power is generated either fully from onshore wind or PV, or 50% from onshore wind and 50% from PV (Table 6).[11] Note that the required PV capacities are much larger compared to onshore wind because of PV's lower average availability. In the cost-driven charging mode, capacities are

[10] For example, additional open cycle gas turbines may be beneficial under user-driven charging, while additional baseload plants may constitute a least-cost option under cost-driven charging. Note that we do not determine cost-minimal generation capacity expansion endogenously, as we use a dispatch model in which generation capacities enter as exogenous parameters.

[11] Onshore wind and PV obviously incur different capital costs. We do not aim to determine a cost-minimizing portfolio; rather, we are interested in the effects of different technology choices on dispatch outcomes.

slightly higher than in the user-driven mode, as the overall power consumption of PHEV and REEV is higher.

Table 6: Additional generation capacities in RE+ scenarios (in MW)

Charging mode	100% Wind	100% PV	50% Wind/PV	
			Wind	PV
User-driven	6,176	13,235	3,088	6,617
Cost-driven	6,438	13,795	3,219	6,897

We first compare the outcomes of the RE+ cases to the 2030 scenario without EVs and without additional renewables. This may be interpreted as a setting in which the deployment of renewables is strictly linked to an additional deployment of renewables, which would not have occurred without the introduction of electromobility. Figure 7 shows the dispatch changes induced by electric vehicles and additional renewables under user-driven charging for the three cases 100% Wind, 50% Wind/PV each, and 100% PV. Not surprisingly, the additional energy is predominantly provided by the exogenously added renewable capacities. In addition, lignite plants are used less, while gas-fired plants and pumped hydro station are increasingly utilized. This can be explained by increasing flexibility requirements in the power system induced by both additional (inflexible) EV charging and fluctuating renewables.

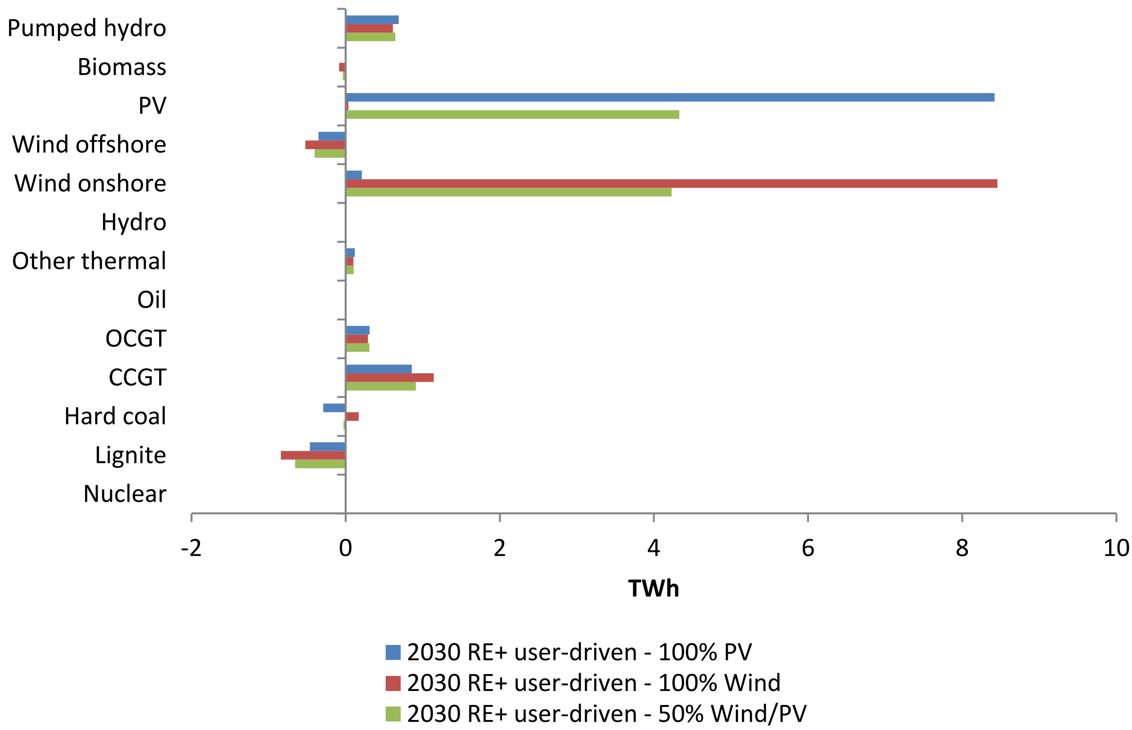

Figure 7: 2030 RE+ user-driven: dispatch changes relative to scenario without EV

In contrast, dispatch of thermal generators changes substantially under cost-driven charging (Figure 8). Power generation from lignite increases, whereas gas-fired plants and pumped hydro facilities are used less. This is because the system-optimized EV fleet brings enough flexibility to the power system to replace pumped hydro and gas-fired plants and increase generation from comparatively inflexible lignite plants at the same time. Moreover, the utilization of renewables is also slightly increased compared to the user-drive charging mode.

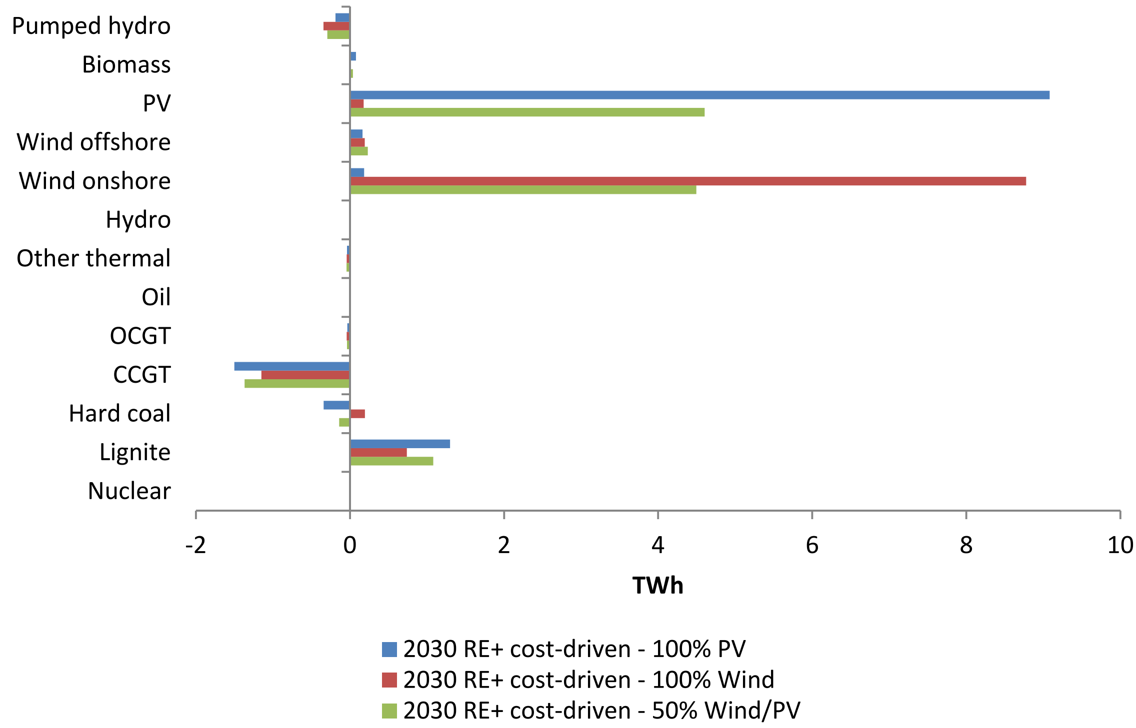

Figure 8: 2030 RE+ cost-driven: dispatch changes relative to scenario without EV

We now compare RE+ results to the respective 2030 EM+ results in order to separate the effects of introducing EV from introducing additional renewable capacities. Comparing the cases with user-driven charging (Figure 9),[12] renewable power generation increases substantially due to the additional capacities. At the same time, power generation from gas-fired plants, hard coal and lignite strongly decreases correspondingly. In other words, additional renewable capacities substitute conventional power generation. Not surprisingly, lignite is substituted to a minor extent than hard coal and CCGT, as lignite is the least-cost thermal generation technology. A comparison of RE+ with EM+ under cost-driven charging leads to similar results (Figure 10). Yet the substitution effect is slightly stronger as cost-driven charging allows increasing the integration of fluctuating renewables, in particularly PV.

[12] Note that the bars of each color add up to nearly zero, as power consumption in EM+ and RE+ is nearly equal, except for slight changes in the consumption of PHEV/REEV.

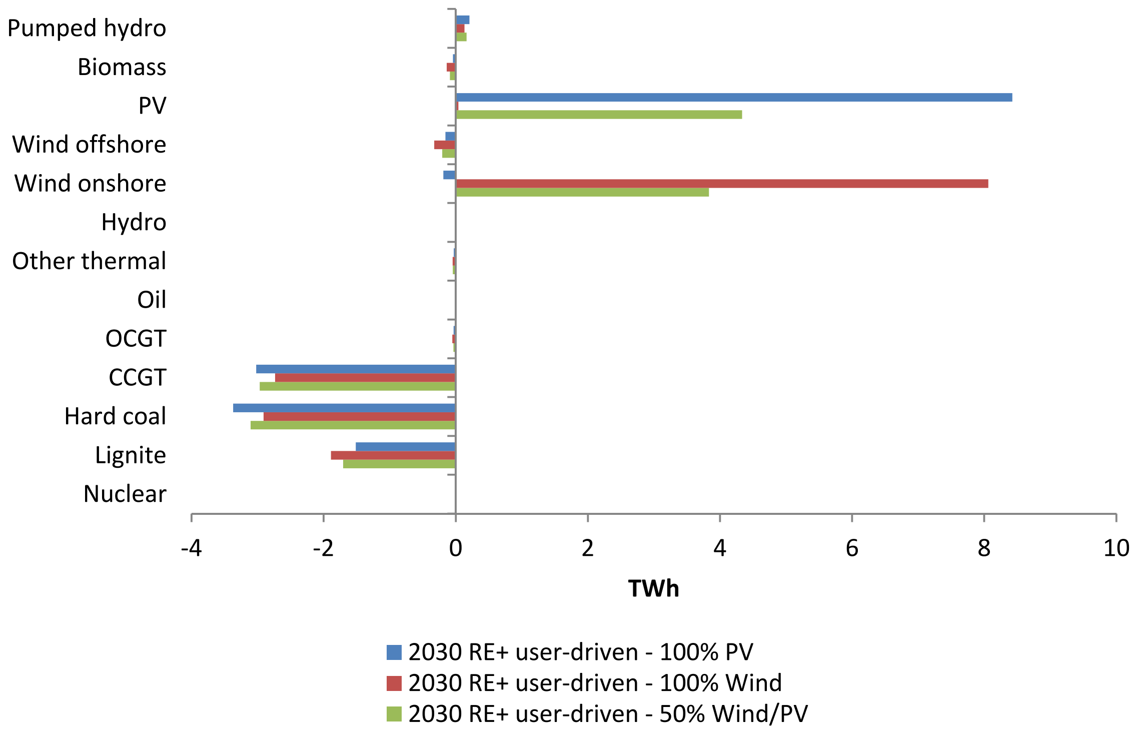

Figure 9: 2030 RE+ user-driven: dispatch changes relative to 2030 EM+ user-driven

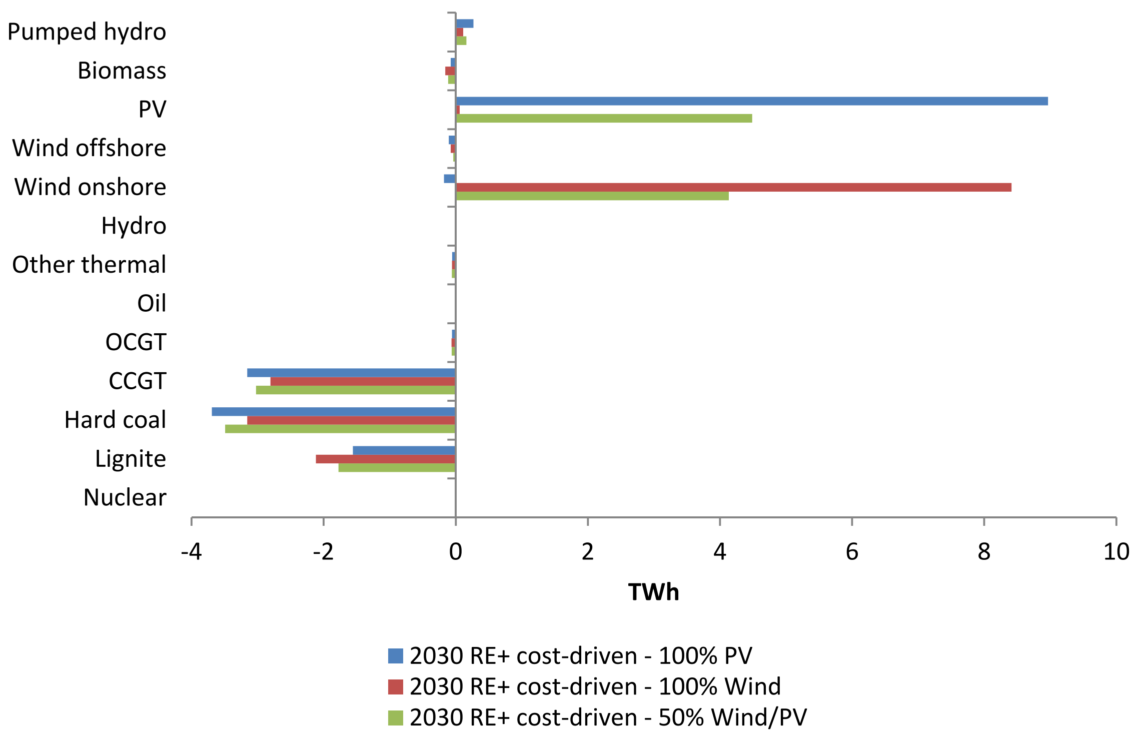

Figure 10: 2030 RE+ cost-driven: dispatch changes relative to 2030 EM+ cost-driven

Finally, we compare all cases with respect to the integration of fluctuating renewables. It has often been argued that future electric vehicle fleets may foster the system integration of fluctuating renewable energies (compare Hota et al. 2014). Our model results show that the potential of EVs to reduce renewable curtailment is rather low under user-driven charging, but sizeable in case of cost-driven charging (Figure 11).[13] In 2020, very little curtailment takes place, and the effect of EVs on curtailment is accordingly negligible. In the 2030 EM^{+} scenario, about 1.3 TWh of renewable energy cannot be used in the case without EVs, corresponding to 0.65% of the yearly power generation potential of onshore wind, offshore wind and PV. User-driven EV charging decreases this value to about 1.1 TWh (0.55%), while only 0.6 TWh of renewables have to be curtailed under cost-driven charging (0.29%). Curtailment is generally higher in the RE^{+} scenarios. Among the three different portfolios of additional renewable generators, the one with 100% PV has the lowest curtailment levels (1.9 TWh or 0.89% in the case without electric vehicles), while curtailment is highest in the one with 100% onshore wind (2.3 TWh or 1.07%). Cost-driven charging again results in much lower levels of renewable curtailment compared to user-driven charging.

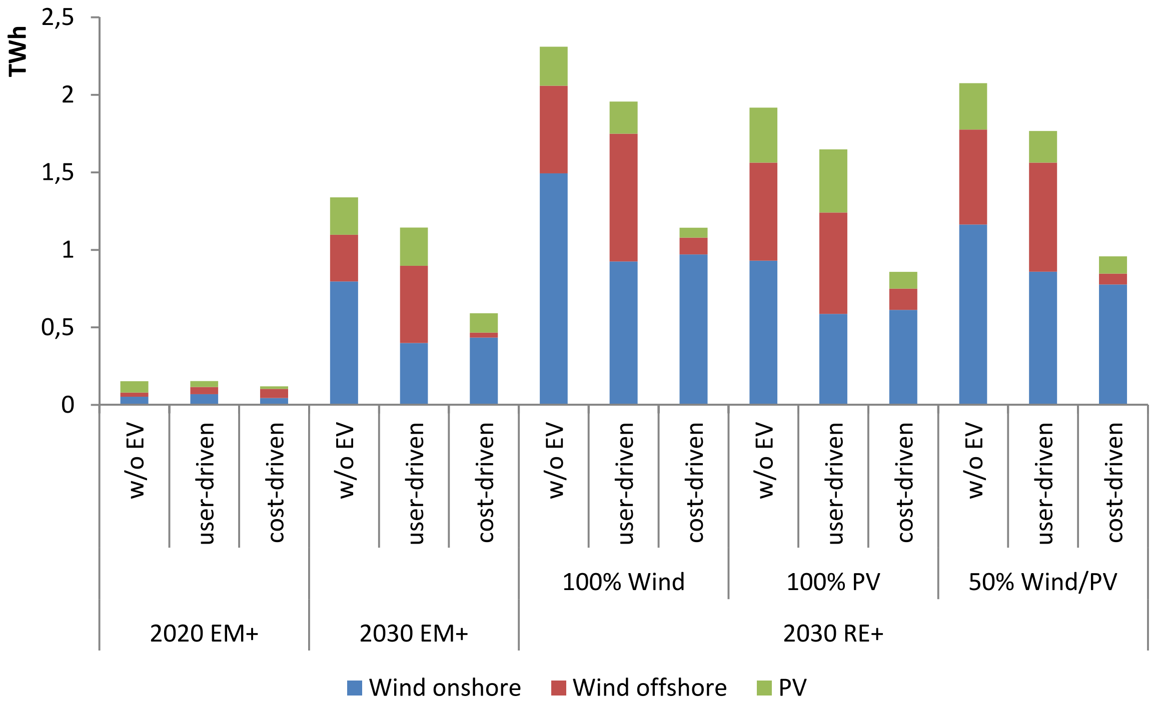

Figure 11: Renewable curtailment in the EM^{+} and RE^{+} scenarios

13 In addition, electric vehicles may indirectly foster the system integration of renewable power generators by providing reserves and other ancillary services energies, which are increasingly required in case of growing shares of fluctuating renewables.

4.3 CO_2 emissions

The changes in dispatch, which are discussed in detail in section 4.2, are reflected by changes in CO_2 emissions.[14] As shown above, the introduction of electric mobility may increase the utilization of both base-load capacities such as lignite and fluctuating renewables. While the first tends to increase CO_2 emissions, the latter has an opposite effect. Both effects overlap. The net effect on emissions is shown in Figure 12, which features specific emissions of both overall power consumption and EV's charging electricity. The latter are calculated as the difference of overall CO_2 emissions between the respective case and the scenario without electric vehicles, related to the overall power consumption of EVs.

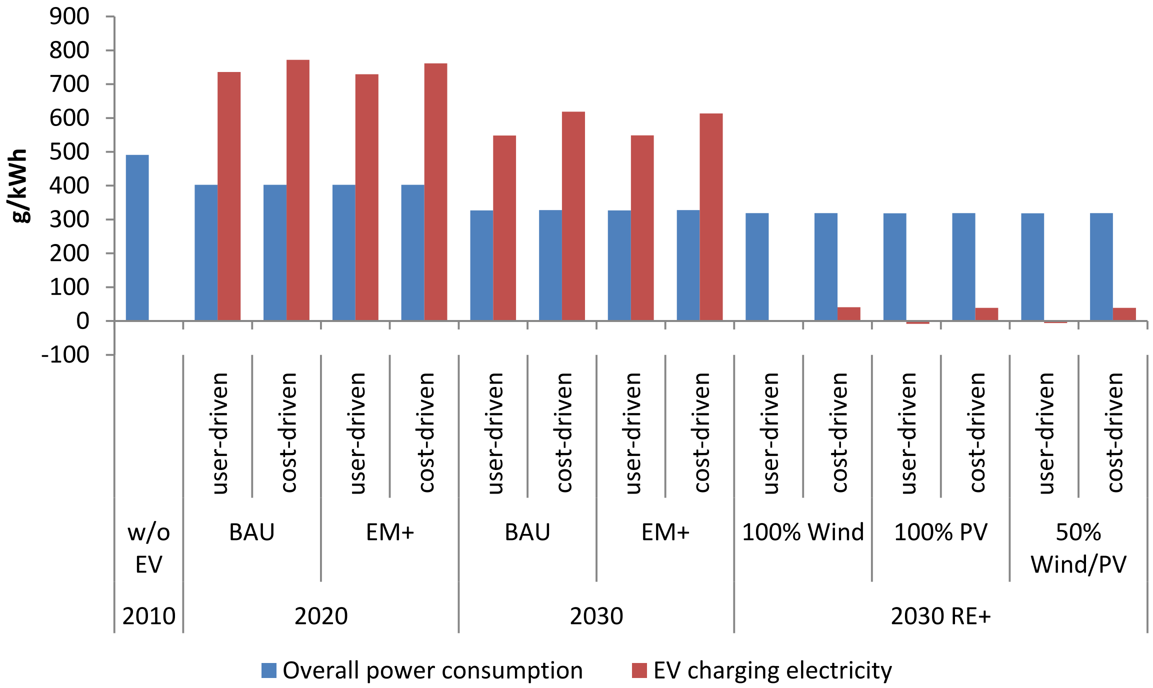

Figure 12: Specific CO_2 emissions

Due to ongoing deployment of renewable generators, specific CO_2 emissions of the overall power consumption change from around 490 g/kWh in 2010 to around 400 g/kWh in 2020, less than 330 g/kWh in the 2030 BAU and EM^+ scenarios, and around 320 g/kWh in the 2030 RE^+ scenarios. In the BAU and EM^+ scenarios of both 2020 and 2030, specific emissions of the EV charging electricity are substantially larger than average specific emissions, as a sizeable fraction of the charging electricity is generated from emission-intensive energy sources like lignite and hard-coal.[15] In terms of CO_2 emissions, the slight improvements in renewable integration related to EVs are by far outweighed by

[14] It should be noted that the dispatch model not only considers CO_2 emissions related to the actual generation of power, but also to the start-up of thermal power plants.

[15] This finding relativizes a qualitative argument brought forward by Schill (2010), according to which future improvements in CO_2 emissions of the overall power system should have a positive influence on the emission balance of EVs.

the increases in power generation from conventional plants. Only in the 2030 RE$^+$ scenarios, in which the introduction of electric vehicles goes along with additional renewable generation capacities, specific emissions of the charging electricity are well below the system-wide average, and even turn negative in some cases. The latter can be interpreted such that the combined introduction of EVs and additional renewables not only results in emission-neutral electromobility, but the additional demand of EVs also triggers a slightly better integration of renewables in the power system at large. Note that we compare the RE$^+$ scenarios to the same reference scenario as the 2030 EM$^+$ runs, i.e., a 2030 scenario without EVs *and* without additional renewable generation capacities. The system-wide emission effect of additional renewables is thus fully attributed to electric vehicles, even if EVs are not fully charged with renewable power during the actual hours of charging.

Among the two different charging strategies, the cost-driven mode always leads to higher emissions compared to the user-driven mode, as the first allows for switching some charging activities into hours in which lignite plants are under-utilized, whereas the latter forces charging to happen mostly in hours in which lignite and hard-coal plants are already fully utilized. Interestingly, this outcome contrast the findings of Göransson et al. (2010), which show for a Danish case study that user-driven charging may increase system-wide CO_2 emissions, whereas cost-driven charging may result in an absolute decrease of emissions. These differences can be explained by different power plant fleets in the two case studies: The Danish system has low capacities of emission-intensive generators and very high shares of wind, with accordingly high levels of curtailment. In contrast, our German application features much higher capacities of emission-intensive generators as well as lower shares of wind power. Accordingly, the increase in power system flexibility related to cost-driven EV charging is predominantly used for reducing renewable curtailment in the Danish case and for increasing the utilization of lignite and hard-coal plants in Germany. For the German case, this may change in the future if emission-intensive plants leave the system and renewable curtailment gains importance.

5 Discussion of limitations

We briefly discuss some of the model limitations and their likely impacts on results. First, the future development of exogenous model parameters is generally uncertain. This refers, in particular, to the development of the German power plant fleet and electricity demand, as well as cost parameters. Because of such uncertainty, we have decided to largely draw on the assumptions of a well-established scenario (50Hertz et al. 2013). In this way, meaningful comparisons to other studies which lean on the same scenario are possible. On the downside, the power plant fleet is necessarily not optimized for the integration of electric vehicles. This shortcoming, however, should not have a large impact on results, as overall power consumption of electric vehicles is very small compared to power demand at large. In general, the effect of different assumptions on, for example, the power plant fleet, CO_2 prices, or diverging charging availabilities of EVs, could be assessed by carrying out sensitivity analyses. As regards our projections of future power generation from fluctuating renewables, drawing on feed-in data of other years than 2010 may lead to slightly different results with regard to renewable curtailment. What is more, calculating availability factors from historic feed-in time series neglects potential smoothing effects related to future changes in generator design or changes in the geographical distribution. This may result in exaggerated assessments of both fluctuation and surplus generation, as discussed by Schill (2014).

Next, our dispatch model assumes perfectly uncongested transmission and distribution networks. This assumption appears to be reasonable with respect to the transmission grid, as the NEP foresees substantial network expansion. Yet on the distribution level, a massive deployment of electric vehicles may lead to local congestion. Such local effects can hardly be considered in a power system model as the one used here. It is reasonable to assume that congestion in distribution grids may put additional constraints on the charging patterns of electric vehicles. While this effect should in general be relevant for both the user-driven and the cost-driven charging mode, distribution grid bottlenecks may be particularly significant for the user-driven mode, as charging is carried out largely in peak-load periods in which the distribution grid is already heavily used, anyway. In case of binding distribution network restrictions, both extreme modes of charging may not be fully realizable, and the power system impacts of electric vehicles are likely to be somewhere in between the two extreme cases modeled here.

In addition, we abstract from interactions with neighboring countries. In the context of existing interconnection and European plans for increased market integration in the future, this assumption appears to be rather strong. Yet considering power exchange with neighboring countries would require a much larger model with detailed representations of these countries' power plant fleets. This would require making detailed assumption on the development of neighboring countries' power systems as well as on their deployment of electric vehicles. Moreover, solving such a large European unit-commitment model for a full year (and various scenarios, as carried out here), would be very challenging. By treating the German power system as an island, we may generally overestimate the flexibility impacts of electric vehicles such as additional integration of lignite and renewables, as well as peak capacity problems in the user-driven mode, as exchange with neighboring countries would entail additional flexibility which may mitigate both peak and off-peak load situations.

We only consider power flows from the grid to the electric vehicle fleet (G2V) and do not consider potential flows in the other direction (V2G). This assumption may be justified for the wholesale market, as wholesale price differences likely do not suffice to make V2G economically viable with respect to battery degradation costs (Schill 2011, Loisel et al. 2014). The provision of reserves and other ancillary services by V2G, however, appears to be more promising (Andersson et al. 2010, Sioshansi and Denholm 2010, Lopes et al. 2011). Moreover, considering reserves may result in higher levels of conventional generation, which may in turn increase renewable curtailment. This could have important implications for the relative emission effects of user-driven and cost-driven charging (compare the end of section 4.3). An according analysis would require extending the model to also incorporate the provision of reserves of different qualities – most importantly, secondary control reserves and minute reserve – by electric vehicles. This interesting task is left for future research.

Finally, it should be noted that we attribute all power system changes that occur between the cases with and without electromobility to electric vehicles. This is particularly important with regard to specific CO_2 emissions. While we are convinced that this approach is correct as such, it raises questions of accountability. To be more precise, the emission balance of electric vehicles is directly related to the structure and the flexibility of the power system, which is largely exogenous to the introduction of EVs, both regarding the power system's current state and its future development.

6 Summary and conclusions

We analyze the integration of future fleets of electric vehicles into the German power system for various scenarios of 2020 and 2030, drawing on different assumptions on the charging mode. We use a numerical dispatch model with a unit-commitment formulation which minimizes overall dispatch costs over a full year. This approach is particularly suitable for studying the system integration of electric vehicles as it reflects the limited flexibility of thermal power generators and thus adequately values the potential flexibility benefits of a smart system integration of electric vehicles. We build on DIW Berlin's existing dispatch model, which has been augmented with additional sets, parameters, variables and equations related to electric vehicles. As for exogenous input parameters, we largely draw on public and/or semi-governmental data, as well as on EV parameters provided by the Öko-Institut in WP 4 (Kasten and Hacker 2014). We shed some light on the interactions between different EV charging patterns and power plant dispatch, with respective consequences for the CO_2 intensity of the charging electricity.

First, the overall energy demand of the modeled EV fleets is low compared to the power system at large. In 2020, the EV fleet accounts for only 0.1% to 0.2% of total power consumption, depending on the charging mode. By 2030, these share increase to around 1.3% (user-driven) and 1.6% (cost-driven), respectively. Yet the hourly charging loads can become very high, with according effects on the power system. Hourly charging levels vary significantly over time and differ strongly between the user-driven and the cost-driven modes. User-driven charging largely results in vehicle charging during daytime and in the evening. This may lead to substantial increases of the system peak load, which raises serious concerns about system security. In the user-driven scenarios of the year 2030 there are several hours both in BAU and EM^+ during which the available generation capacity is fully exhausted. In contrast, cost-driven charging is carried out during night-time, and thus leads to a much smaller increase of the system peak load. The average charging profile of the cost-driven mode is much flatter compared to the user-driven one.

These different charging patterns go along with respective changes in the dispatch of the power plant fleet. In the 2020 EM^+ scenarios, cost-driven EV charging strongly increases the utilization of lignite and hard coal plants compared to a scenario without EVs. In the user-driven mode, in which charging often has to occur in periods when lignite plants are producing at full capacity, additional power generation predominantly comes from hard coal plants, followed by CCGT and lignite. In the 2030 EM^+ scenarios, we find comparable results, but a relative increase in the utilization of CCGT plants, given the underlying assumptions on the development of the power plant fleet.

In additional model runs, we link the introduction of electromobility to an additional deployment of renewable power generators (RE^+). Under user-driven charging, this leads, obviously, to increased power generation from renewables, but also to a slightly decreased utilization of lignite plants and increased power generation from natural gas, compared to a scenario without EVs and without additional renewable capacities. Under cost-driven charging, this effect reverses due to the additional demand-side flexibility of the EV fleet.

As regards renewable integration, model results show that the potential of EVs to reduce renewable curtailment is much higher in case of cost-driven charging compared to the user-driven mode. In the

2030 EM+ scenario, cost-driven charging decreases the share of renewable curtailment from 0.65% in the case without EVs to 0.29%. In the RE+ scenarios, the one with 100% PV has the lowest curtailment levels whereas the one with 100% onshore wind has the highest ones. Accordingly, PV feed-in patterns may match the charging patterns of electric vehicles slightly better than onshore wind.

The CO_2 emission balance of electric vehicles in the different scenarios depends on the underlying power plant fleet as well as on the mode of charging. EVs may increase the utilization of both emission-intensive capacities such as lignite or hard coal, and fluctuating renewables. While the first tends to increase CO_2 emissions, the latter has an opposite effect. In the BAU and EM+ scenarios of 2020 and 2030, the first effect dominates the emission balance, in particular in the cost-driven charging mode. Specific emissions of the charging electricity are thus substantially larger than specific emissions of the overall power system, irrespective of the charging mode. In contrast, introducing additional renewable capacities pushes specific emissions of the charging electricity well below the system-wide average, and they even become negative in some cases. Importantly, these effects strongly depend on the power plant structure and on the extent of renewable curtailment in the system.

Based on these findings we suggest a range of policy-relevant conclusions. First, the overall energy requirements of electric vehicles should not be of concern to policy makers for the time being, whereas their peak charging power should be. With respect to charging peaks and system security, the cost-driven charging mode is clearly preferably to the user-driven mode. Because of generation adequacy concerns, purely user-driven charging would have to be restricted by a regulator in the future, at the latest if the vehicle fleet gets as large as in the 2030 scenarios – unless high wholesale prices render user-driven charging unattractive, anyway.

Second, policy makers should be aware that cost-driven, i.e., optimized, charging not only increases the utilization of renewable energy, but also of hard coal and lignite plants. If the introduction of electromobility is linked to the use of renewable energy, as repeatedly stated by the German government, it has to be made sure that a corresponding amount of additional renewables is added to the system. With respect to CO_2 emissions, an additional expansion of renewables is particularly important as long as substantial – and increasingly under-utilized – capacities of emission-intensive generation technologies are still present in the system. Importantly, from a system perspective it does not matter if these additional renewable capacities are actually fully utilized by electric vehicles exactly during the respective hours of EV charging; rather, the net balance of the combined introduction of electromobility *and* renewables compared to a baseline without EVS *and without* additional renewables is relevant.

We suggest a third – and related – conclusion on CO_2 emissions of electric vehicles. Cost-driven charging, which resembles market-driven or profit-optimizing charging in a perfectly competitive market, can only lead to emission-optimal outcomes if emission externalities are correctly priced. Otherwise, cost-driven charging may lead to above-average specific emissions, and even to higher emissions compared to user-driven charging. Accordingly, policy makers should make sure that CO_2 emissions are adequately priced. Otherwise, some kind of emission-oriented charging strategy would have to be applied, which is possible in theory (compare, for example, Sioshansi and Miller, 2011), but very unlikely to be implemented in practice.

Finally, controlled charging of future electric vehicle fleets interacts with other potential sources of flexibility in the system. For example, our analysis indicates that the utilization of pumped hydro storage substantially decreases if the EV fleet charging mode is switched from the user-driven to the cost-driven mode. The same may apply to other storage technologies as well as demand-side management. Accordingly, both the requirement of such flexibility options and their profitability depends on the size of the future EV fleet, as well as on its charging mode.

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