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Power system impacts of electric vehicles in Germany: Charging with coal or renewables?

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Discussion
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Power System Impacts of Electric Vehicles in Germany: Charging with Coal or Renewables?

Wolf-Peter Schill¹ and Clemens Gerbaulet²

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Abstract: We analyze future scenarios of integrating electric vehicles (EV) into the German power system under different assumptions on the charging mode. We use a numerical dispatch model with a unit commitment formulation which minimizes dispatch costs over a full year. While the overall energy demand of the EV fleets is rather low in all scenarios, the impact on the system's load duration curve differs strongly between charging modes. In a fully user-driven mode, charging largely occurs during daytime and in the evening, when power demand is already high. User-driven charging may thus have to be restricted in the future because of generation adequacy concerns. In contrast, cost-driven charging is carried out during night-time and at times of high PV availability. Using a novel model formulation that allows for intermediate charging modes, we show that even a slight relaxation of fully user-driven charging results in much smoother load profiles as well as lower charging costs. Different charging patterns go along with respective changes in power plant dispatch. By 2030, cost-driven EV charging strongly increases the utilization of hard coal and lignite plants, whereas additional power in the user-driven mode is predominantly generated from natural gas and hard coal. Specific CO₂ emissions of EV are substantially larger than those of the overall power system, and highest under cost-driven charging. Only in additional model runs, in which we link the introduction of EVs to a respective deployment of additional renewable generation capacity, electric vehicles become largely CO₂-neutral.

JEL: Q42; R41; Q54

Keywords: Electric vehicles; power system; dispatch model; renewable energy

1 Introduction

The use of electric vehicles is set to increase substantially in many countries around the world (OECD/IEA 2013). EV may bring about numerous benefits, such as lower emission of various air pollutants and noise, increasing energy efficiency compared to internal combustion engines, and the substitution of oil as the main primary energy source for road transport. Yet a massive uptake of electric vehicles may trigger strong power system interactions. Importantly, the impacts on power plant dispatch, system peak load, charging cost, and carbon emissions may depend substantially on the charging mode of electric vehicles (cf. Hota et al. 2014).

In this paper, we study possible future interactions of electric vehicle fleets with the German power system. The German case provides an interesting example as the government has announced ambitious targets of becoming both the leading manufacturer and the lead market for electric vehicles in the world (Bundesregierung 2011). Moreover, the German power system undergoes a massive transformation from coal and nuclear towards renewable sources, also referred to as *Energiewende*. We carry out model-based analyses for different scenarios of the years 2020 and 2030, building on detailed vehicle utilization patterns and a comprehensive 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 integrating electric vehicles into the power system. We are particularly interested in the impacts of electric vehicles on the dispatch of power plants, the integration of fluctuating renewable energy, changes on the power system load, variable charging costs and CO₂ emissions under different assumptions on the mode of vehicle charging.

Previous research has analyzed various interactions of electric mobility and 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. 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. Kristoffersen et al. (2010) as well as Juul and Meibohm (2011 and

2012) also find that EVs provide flexibility mostly by optimized charging activities and not so much by discharging power back to the grid.

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 CO₂ emissions. Göransson et al. (2010) carry out a comparable case study for Denmark, concluding that PHEV can decrease net CO₂ 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. Similar results are described by Dallinger et al. (2013), where the integration of intermittent renewables is analyzed for case studies for California and Germany in 2030. They show that the correlation of the charging patterns and the renewable infeed significantly influences the integration potential, but residual load smoothing can on both cases be achieved by model driven charging. Guille and Gross (2010) do not apply a power system model, but also 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 CO₂, SO₂, 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 CO₂ emissions. Doucette (2011) notes that EV's CO₂ reduction potential is highly dependent on the existing power plant portfolio and concludes that additional decarbonization efforts might be needed to obtain CO₂ emission reductions. Schill (2011) develops a Cournot model to analyze the impacts of PHEV fleets in an imperfectly competitive power market environment and finds that both welfare and emission impacts depend on the agents being responsible for charging the vehicles, and on the availability of V2G.

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., Lund and Kempton 2008, Göransson et al. 2010, Ekman 2011, 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 as well as a stronger deployment of renewables than assumed in earlier studies, and with a full consideration of the German nuclear phase-out. Further, we do not only distinguish between the two stylized extreme cases of fully cost-driven and fully user-driven charging, but also include additional analyses with intermediate modes of charging, which appear to be more realistic. This is made possible by drawing on a novel formulation of EV charging restrictions. 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 electric mobility to a corresponding expansion of renewable power generation.

The remainder is structured as follows. Section 2 introduces the methodology. Section 3 describes the scenarios and input parameters. Model results 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 by 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 CO₂ 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).³

The basic formulation of the unit commitment model is provided in the Appendix. In the following, we highlight the equations related to electric vehicles. Respective sets, parameters and variables are listed in Table 1. Exogenous parameters are in lower case letters, endogenous continuous variables have an initial upper case letter, and binary variables are completely set in upper case letters.

³ 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
$ev \in EV$	Set of 28 EV profiles	
Parameters		
$batcap_{ev}$	EV Battery Capacity	kWh
$chargemax_{ev,t}$	Hourly power rating of the charge connection (0 when car is in use or parked without grid connection)	kW
$cons_{ev,t}$	Hourly EV power consumption	kWh
η_{ev}	EV charging efficiency	%
$fastchargegoal$	Restricts the relative battery charge level that should be reached as fast as possible (1 for user-driven charging, 0 otherwise)	
$penalty^{Phevfuel}$	Penalty for non-electric PHEV operation mode	€/MWh
$phev_{ev}$	Defines whether an EV is a PHEV/REEV (1 if yes, 0 otherwise)	
$quant_{ev}$	Quantity of EVs per load profile	
Binary variables		
$FULLCHARGE_{ev,t}$	1 if full charging power is required, i.e., when the charge level is below $fastchargegoal$, and 0 otherwise	
Continuous variables		
$Charge_{ev,t}$	Cumulative EV charging power	MW
$Chargelev_{ev,t}$	Cumulative EV battery charge level	MWh
$Phevfuel_{ev,t}$	Cumulative PHEV conventional fuel use	MWh

Equation (EV1) is the cumulative EV energy balance. The battery charge level $Chargelev_{ev,t}$ is determined as the level of the previous period plus the balance of charging and mobility-related consumption in the actual period. The charge level of PHEV/REEV is also influenced by conventional fuel use $Phevfuel_{ev,t}$. Importantly, only electric vehicles of the PHEV/REEV type may use conventional fuels, whereas $Phevfuel_{ev,t}$ is set to zero for purely battery-electric vehicles (EV2). In order to ensure a preference for using electricity in PHEV/REEV, we penalize the use of conventional fuels with $penalty^{Phevfuel}$ in the objective function (equation 1 in the Appendix). 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 $chargemax_{ev,t}$ 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). In addition, the model's energy balance (equation 14 in the Appendix) considers the additional electricity that is required for charging electric vehicles $\sum_{ev} Charge_{ev,t}$ in each hour.

$$Chargelev_{ev,t} = Chargelev_{ev,t-1} + Charge_{ev,t}\eta_{ev} - cons_{ev,t}quant_{ev} + Phevfuel_{ev,t} \quad \forall ev, t \quad (EV1)$$

$$Phevfuel_{ev,t} = 0 \text{ if } phev_{ev} = 0 \quad \forall ev, t \quad (EV2)$$

$$Charge_{ev,t} \leq chargemax_{ev,t}quant_{ev} \quad \forall ev, t \quad (EV3)$$

$$Chargelev_{ev,t} \leq batcap_{ev}quant_{ev} \quad \forall ev, t \quad (EV4)$$

$$Charge_{ev,t} \geq 0 \quad \forall ev, t \quad (EV5)$$

$$Chargelev_{ev,t} \geq 0 \quad \forall ev, t \quad (EV6)$$

$$Phevfuel_{ev,t} \geq 0 \quad \forall ev, t \quad (EV7)$$

Equations (EV8) and (EV9) are only defined in the user-driven charging mode, i.e., if *fastchargegoal* 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 $FULLCHARGE_{ev,t}$ assumes the value 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 any real number between 0 and 1 to *fastchargegoal*, any desired target level of fast battery charging may be specified. For example, if *fastchargegoal* is set to 0.5, vehicle batteries have to be charged with full power until a charging level of 50% is reached. After that, the remaining battery capacity may be charged in a cost-driven way. We focus on the two extreme charging modes in the model analyses, i.e., set *fastchargegoal* to 0 (fully cost-driven) or 1 (fully user-driven), respectively in most scenarios. In addition, we carry out some additional analyses values of 0.25, 0.5 and 0.75 (see section 3).

$$fastchargegoal * batcap_{ev} quant_{ev} - Charge_{ev,t} \leq (batcap_{ev} quant_{ev} + 1) FULLCHARGE_{ev,t} \quad \forall ev, t \quad (EV8)$$

$$FULLCHARGE_{ev,t} chargemax_{ev,t} quant_{ev} \leq Charge_{ev,t} \quad \forall ev, t \quad (EV9)$$

3 Scenarios and input parameters

We apply the dispatch model to various scenarios. First, we distinguish different developments with regard to electric vehicle deployment:⁴ a reference case without electric vehicles, a Business-as-usual (BAU) scenario and an “Electric mobility“ (EM⁺) scenario for the years 2020 and 2030. The BAU scenario assumes an EV stock of 0.4 million in 2020 and 3.7 million in 2030. The EM⁺ scenario assumes a slightly increased deployment of electric vehicles with a stock of 0.5 million EV by 2020 and 4.8 million by 2030. This is made possible by additional policy measures such as a feebate system, adjusted energy taxation and ambitious CO₂ emission targets (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 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 the two extreme charging modes described in section 2. 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 re-

⁴ In doing so, we draw on the scenarios developed by Kasten and Hacker (2014) in the context of the European research project DEFINE. <https://www.ihs.ac.at/projects/define/>.

charged with the maximum available power as soon as these are connected to the grid. This mode could also be interpreted as a “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. To approximate these, the 2030 EM⁺ scenarios are additionally solved with fast charging requirements of 25%, 50%, and 75%, respectively. That is, set *fastchargegoal* is set to 0.25, 0.5 and 0.75. 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	
		100% Wind			x	
		50% Wind/PV			x	
		100% PV			x	
		100% Wind			x	
		50% Wind/PV			x	
		100% PV			x	
BAU	User-driven			x	x	
	Cost-driven	Baseline		x	x	
EM ⁺	User-driven			x	x	
	75% fast charge				x	
	50% fast charge	Baseline			x	
	25% fast charge				x	
	Cost-driven			x	x	
			100% Wind			x
		User-driven	50% Wind/PV			x
		100% PV			x	
		100% Wind			x	
	Cost-driven	50% Wind/PV			x	
		100% PV			x	

As regards 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 de-

rived from the so-called Grid Development Plan (NEP).⁵ 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.⁶

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
CO₂ 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.

⁵ *Netzentwicklungsplan* (NEP) in German.

⁶ 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).

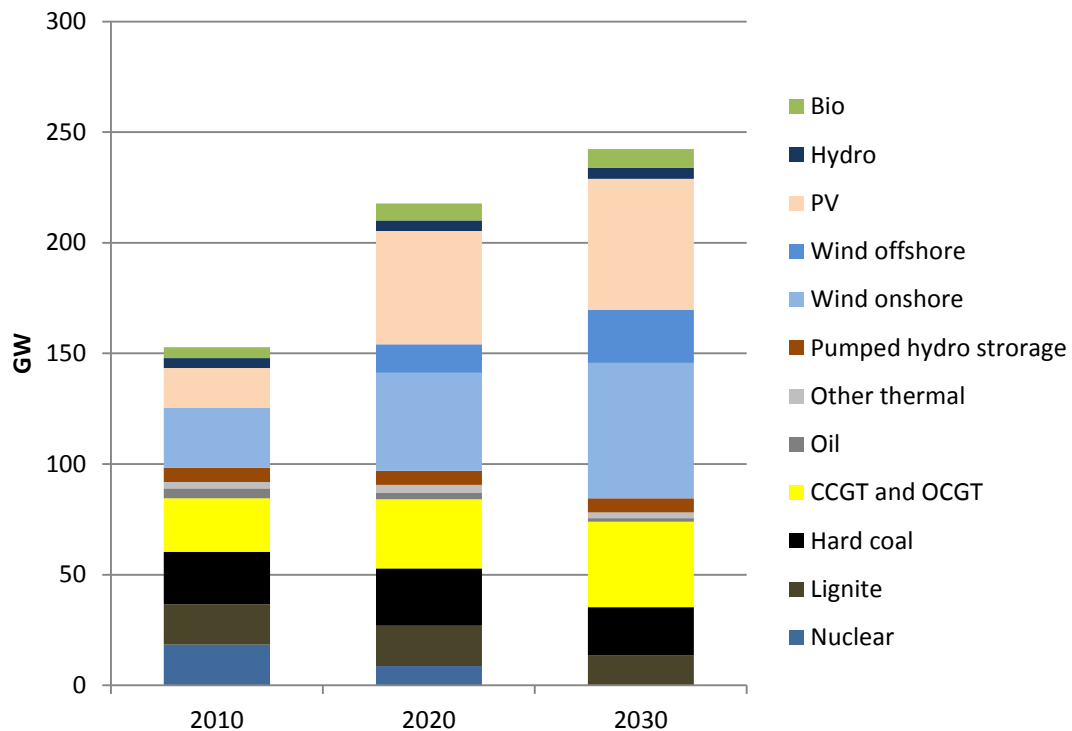


Figure 1: Installed net generation capacities

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 the transmission system operator 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 Kasten and Hacker (2014).⁷ The assumed fleets of electric vehicles of the years 2020 and 2030 in the two scenarios BAU and EM⁺ imply aggregate hourly power consumption and maximum charging profiles 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 to be connected to (semi-)public “medium power charging stations” occasionally. Table 4 provides an overview of EV-related parameters. The

⁷ There is one exception: the parameter *fastchargegoal* is set exogenously by us, depending on the scenario run.

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	0.9	1.0
PHEV/REEV	0.3	0.4	2.9	3.7
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, charging costs, and CO₂ 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 around half a million EVs may thus be considered negligible in Germany. 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 electric utility factors are around 55% in the 2020 scenarios, and between 60% (user-driven) and 64% (cost-driven) in the 2030 scenarios. This is in line with other model-based analyses. Kelly et al. (2012) estimate a utility factor of around 67% based on data from 170,000 vehicle's driving patterns in the U.S. The slightly higher value is

probably caused by the assumption of larger batteries in future PHEV. Weiller (2011) also determines utility factors for U.S. PHEV between 50% and 70%, depending on the battery size and car usage.

Table 5: Power consumption of electric vehicles

EV scenario	Charging mode	Generation capacities	EV consumption (TWh)		Share of total load (%)			
			2020	2030	2020	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	RE⁺	0.88	8.59	0.16	1.51		
	75% fast charge			8.90		1.56		
	50% fast charge				8.95		1.57	
	25% fast charge				8.95		1.57	
	Cost-driven			0.88	8.95	0.16	1.57	
				100% Wind		8.54		1.50
				50% Wind/PV		8.55		1.50
		100% PV		8.59		1.51		
		100% Wind		8.95		1.57		
	Cost-driven			8.95		1.57		
				8.95		1.57		

While overall power consumption of the assumed EV fleets is rather small compared to overall power demand, hourly charging loads vary significantly over time and sometimes become rather high. This is especially visible in the case of user-driven charging, where charging takes place without consideration of current power system conditions. Here, EVs are charged as fast as possible given the restrictions of the grid connection.⁸ 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.

⁸ We do not consider possible restrictions related to bottlenecks in both the transmission and the distribution grids, which may pose barriers to both the fully user-driven and the fully cost-driven charging modes.

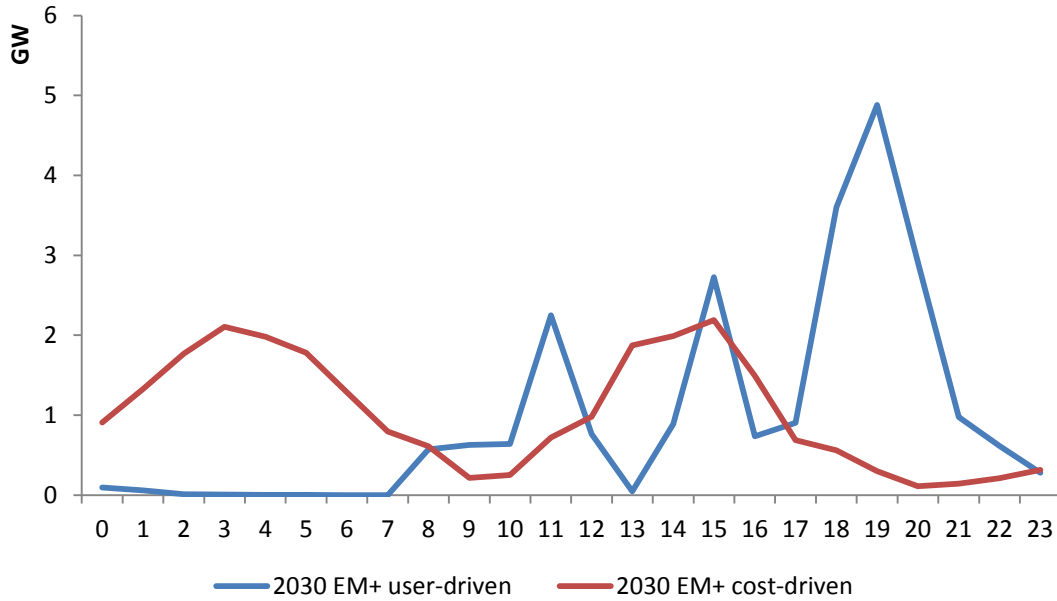


Figure 2: Average EV charging power over 24 hours (2030, EM+)

While Figure 2 only shows average charging power under the two extreme modes, Figure 3 provides additional information for the cases with intermediate charging modes, in which at least 25%, 50%, or 75% of the vehicles' battery capacities have to be recharged as quickly as possible after the vehicles are connected to the grid. Even a slight relaxation of the fully user-driven mode, i.e., reducing *EVFastChargeGoal* from 1 to 0.75, results in a substantially smoothed load profile, while presumably only slightly reducing the users' utility. The maximum average charging load peak in the evening hours accordingly decreases from 4.9 to 3.1 GW. Reducing *fastchargegoal* further to 0.5 entails additional smoothing, with a corresponding reduction of the evening load peak to 2.1 GW.

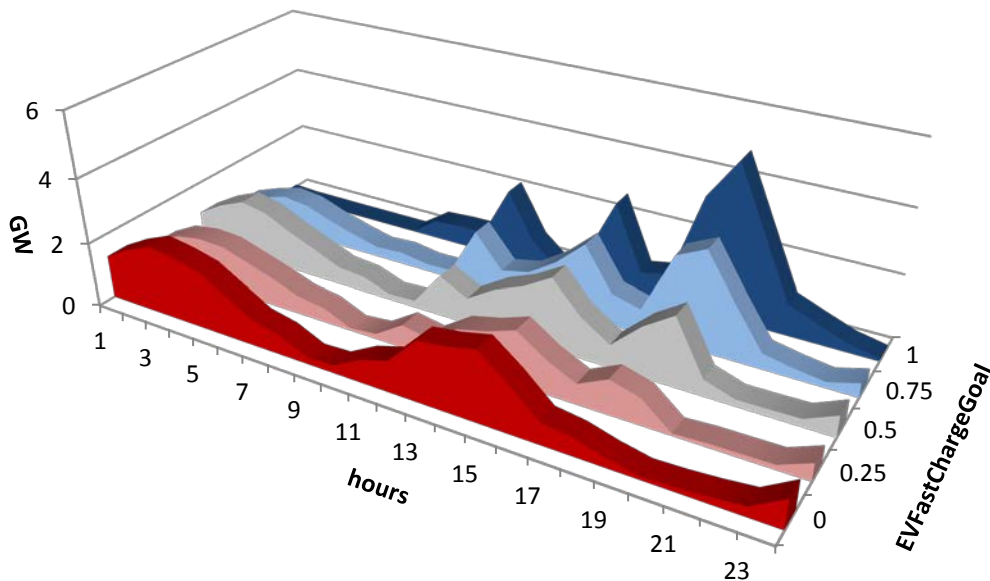


Figure 3: Average EV charging power over 24 hours for intermediate charging modes (2030, EM+)

From a power system perspective, the impact of electric vehicles on the load duration curve, in particular on the system’s peak load, may be more relevant than average charging levels. For the 2030 EM+ scenarios, Figure 4 shows the load duration curve of the case without electric vehicles (right vertical axis) as well as additional loads imposed on the system’s load duration curve induced by EVs under different charging modes (left vertical axis). The latter are derived as follows: first, we establish the load duration curves of all scenarios by sorting hourly loads in descending order. Then, hourly differences between these sorted load duration curves are calculated. That is, the differences shown in Figure 4 refer to load deviations between hours with the *same position* in the load duration curve, but not necessarily between the *same hours*, i.e., the index t will typically differ.

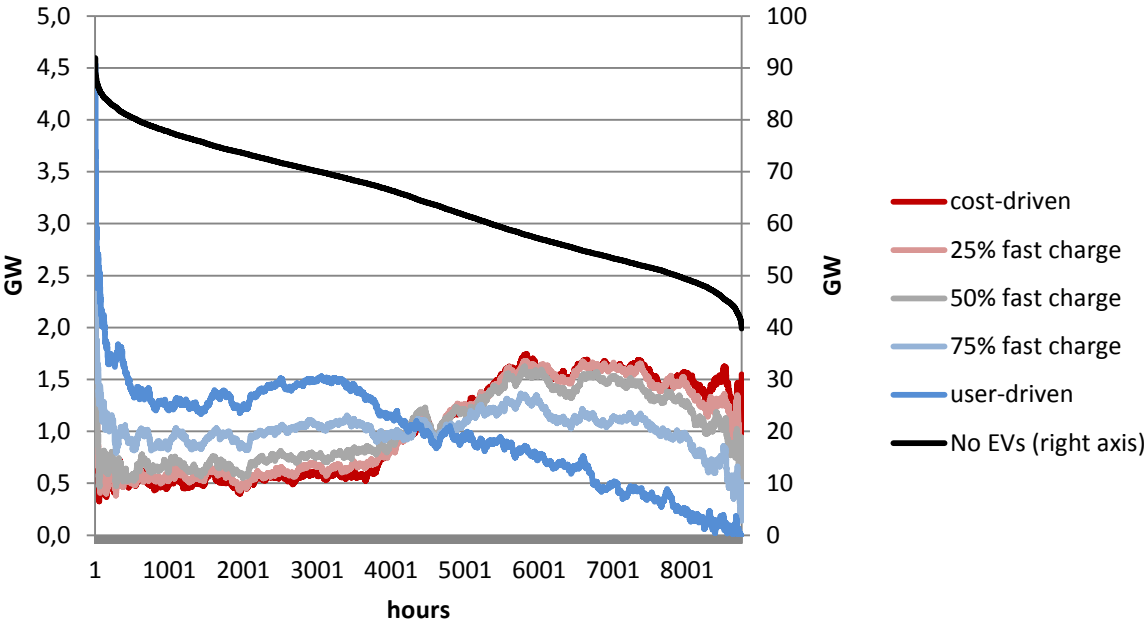


Figure 4: Impacts of EVs on the load duration curve under different charging modes (2030, EM+)

Figure 4 shows that user-driven charging generally makes the load duration curve of the system steeper, as additional power is mainly required on the left-hand side. That is, user-driven charging increases the system load during hours in which demand is already high. On the very left-hand side, the peak load in the fully user-driven mode increases by around 3.6 GW, compared to only 1.5 GW in the purely cost-driven mode. In contrast, cost-driven charging largely occurs on the right-hand-side of the load duration curve, which implies a better utilization of generation capacities plants during off-peak hours. We again find a strong effect of even slightly deviating from the fully user-driven mode: reducing *fastchargegoal* from 1 to 0.75, i.e., requiring only 75% of the battery capacity to be charged instantaneously instead of 100%, results in substantial smoothing of the residual load curve. If this parameter is further reduced to 50%, the load duration curve closely resembles the one of the fully cost-driven charging mode.

It should be noted that the backstop peak technology is required in the 2030 scenarios under fully user-driven charging 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.

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 increases substantially. 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 grows 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 diminishes 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 EM⁺ scenarios of 2020 and 2030 as well as 2030 RE⁺. The respective dispatch results in the BAU scenarios are very similar, but less pronounced than the ones of the EM⁺ and RE⁺ runs.

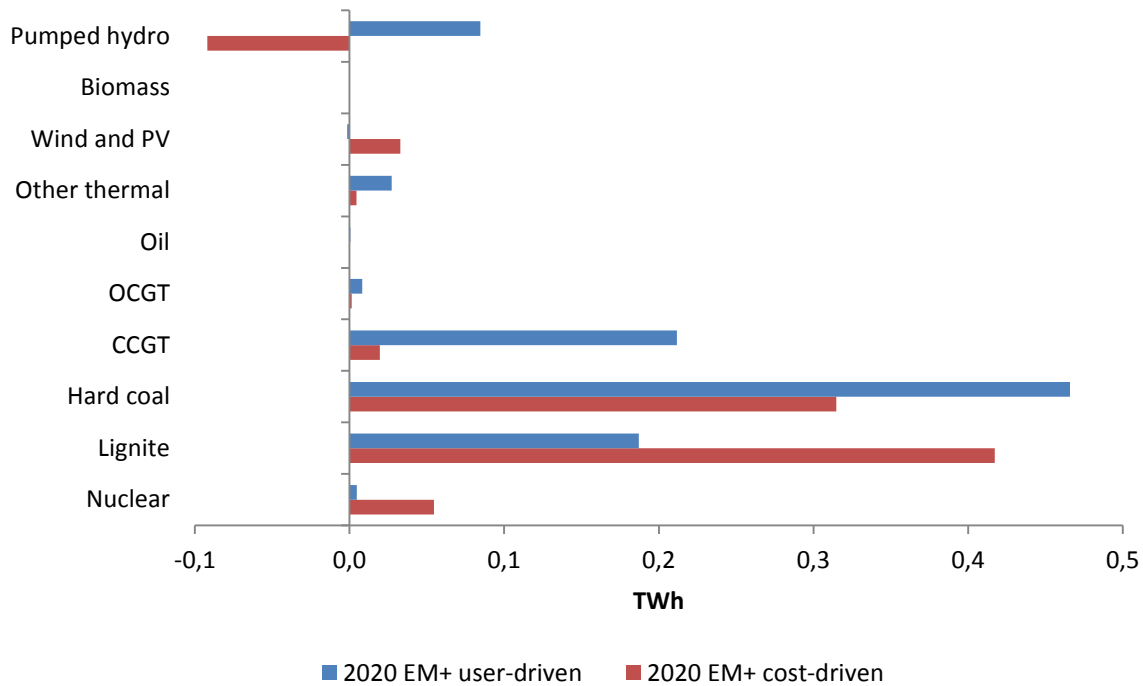


Figure 5: Dispatch changes relative to scenario without EV (2020, EM⁺)

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 user-driven charging, this effect—which can be explained by an exogenous decrease of lignite plants and a corresponding increase of gas-fired generation capacities (cf. 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. It can also be seen that reducing the fast charging requirement from 100% to 75% strongly alters the dispatch into the direction of the cost-driven outcomes. Reducing the requirement to 50% entails largely the same dispatch as the fully cost-driven charging mode.

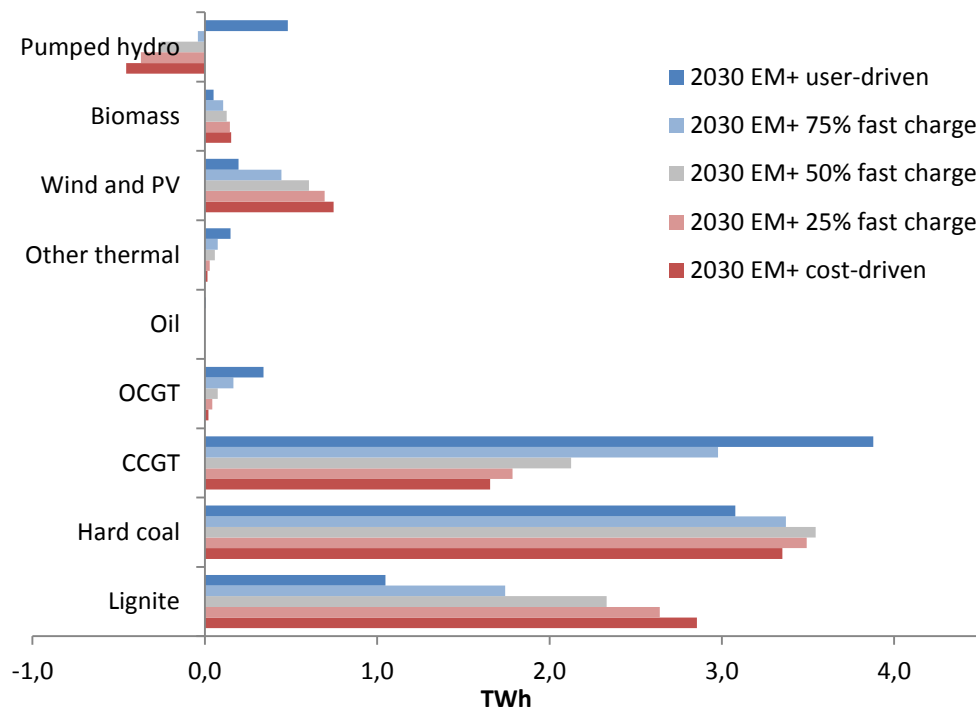


Figure 6: Dispatch changes relative to scenario without EV (2030, EM⁺)

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 electric mobility. While there are many thinkable changes to the generation portfolio¹⁰, we are particularly interested in cases in which the introduction of electric vehicles goes along with 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 compare the outcomes of the RE+ cases to the 2030 scenario without EVs and without additional renewables.¹² 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 electric mobility. Figure 7 shows the dispatch changes induced by electric vehicles and additional renewables for the three cases 100% Wind, 100% PV, and 50% Wind/PV each. Not surprisingly, the additional energy is predominantly provided by the exogenously added renewable capacities in all cases. Under user-driven charging, lignite plants are used less, while gas-fired plants and pumped hydro stations 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.

In contrast, dispatch of thermal generators changes substantially under cost-driven charging. Power generation from lignite increases compared to the case without electric vehicles, 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 at the same time increase generation from rather inflexible lignite plants at the same time. This flexibility also allows slightly increasing the overall utilization of renewables as compared to the user-drive mode.

¹² An additional comparison of RE+ results to the respective 2030 EM+ outcomes allows separating the effects of introducing EV and additional renewable capacities. A comparison of the user-driven cases shows that additional renewables mainly substitute hard coal and CCGT, while lignite is substituted to a minor extent. Comparing RE+ to EM+ under cost-driven charging leads to similar results, yet the substitution effect is slightly stronger as cost-driven charging allows increasing the integration of fluctuating renewables, in particularly PV.

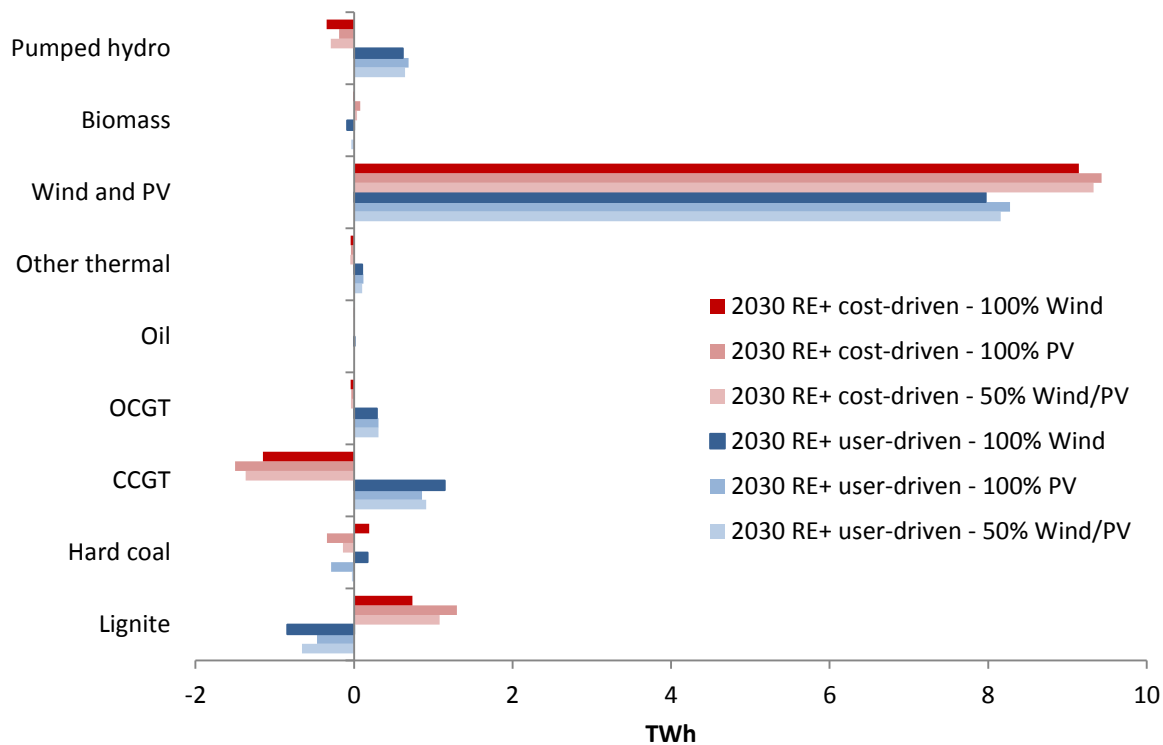


Figure 7: Dispatch changes relative to scenario without EV (2030, RE+)

Finally, we compare the cases with respect to the integration of fluctuating renewables. It has often been argued that future electric vehicle fleets may help to foster the system integration of fluctuating renewables (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 8).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.

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.

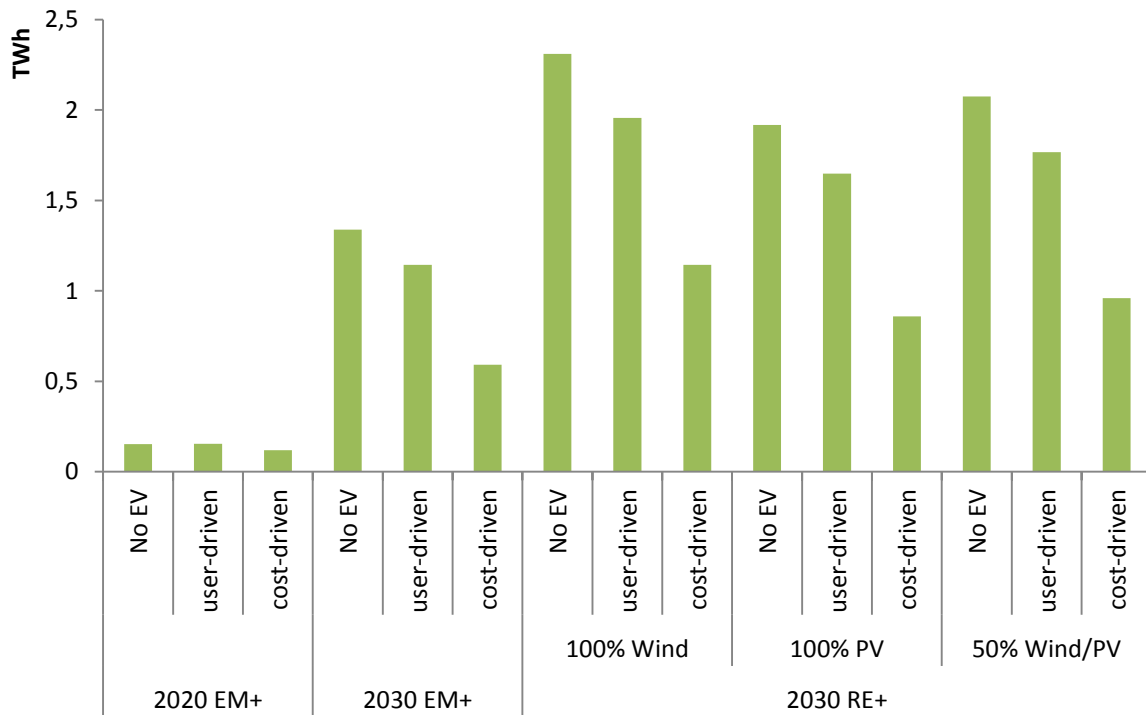


Figure 8: Renewable curtailment

4.3 Charging costs

The previously discussed differences in power plant dispatch are reflected by substantial differences in the charging costs of EVs. Here, average costs of charging are calculated by comparing overall dispatch costs of the respective scenario to the costs of the scenario without EVs and relating the difference to the overall power consumption of EVs.¹⁴

In the 2020 EM⁺ scenarios, moving from user-driven to cost-driven charging decreases average EV loading costs from nearly 44 €/MWh to around 29 €/MWh. In the 2030 EM⁺ scenarios, there is a similar effect on a somewhat higher level, with average costs of 56 €/MWh in the user-driven mode and 42 €/MWh in the cost-driven mode. From a vehicle owner perspective, the cost advantages of optimized charging have to be compared to real or perceived benefits of the user-driven mode, for example, not handing over control of charging to a third party, or the flexibility to use the car sooner than previously planned. Interestingly, requiring only 75% of the battery to be charged as soon as possible instead of 100% already reduces average loading costs in the 2030 EM⁺ scenarios from 56 €/MWh to 49 €/MWh, i.e., roughly the average of the outcomes for fully cost-driven and fully user-driven charging. Reducing *fastchargegoal* to 50% further reduces costs to 45 €/MWh.

When calculating the charging costs of the 2030 RE⁺ cases, we proceed as described above, but also take into account the investments required for the additional wind and PV capacities. To do so, we calculate investment annuities, drawing on the cost projections of Schröder et al. (2013), an econom-

¹⁴ Alternatively, hourly power prices—i.e., the marginal values of equation (14) in the Appendix—in the periods of vehicle loading could be used. Prices in unit commitment models, however, do not include start-up costs.

ic lifetime of 20 years and an interest rate of 4%. It should be noted that this approach attributes the dispatch cost changes of introducing both additional renewables and electric vehicles fully to EV charging costs. Average EV charging costs in the cost-driven mode are around 58 €/MWh for the 100% Wind case (61 €/MWh for 100% PV, and 59 €/MWh for 50% Wind/PV). The difference to average charging costs in the EM+ scenario may be interpreted as the additional cost of linking EVs to renewables. In the user-driven mode, average charging costs are much higher with 93 €/MWh for the 100% Wind case (120 €/MWh for 100% PV, and 118 €/MWh for 50% Wind/PV). Accordingly, linking the introduction of electric vehicles to an according additional system integration of renewables becomes much cheaper if the vehicles are charged in a cost-optimized way.

4.4 CO₂ emissions

The changes in dispatch, which are discussed in detail in section 4.2, are reflected by changes in CO₂ emissions.¹⁵ 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 CO₂ emissions, the latter has an opposite effect. Both effects overlap. The net effect on emissions is shown in Figure 9, which features specific emissions of both overall power consumption and EV's charging electricity. The latter are calculated as the difference of overall CO₂ emissions between the respective case and the scenario without electric vehicles, related to the overall power consumption of EVs.

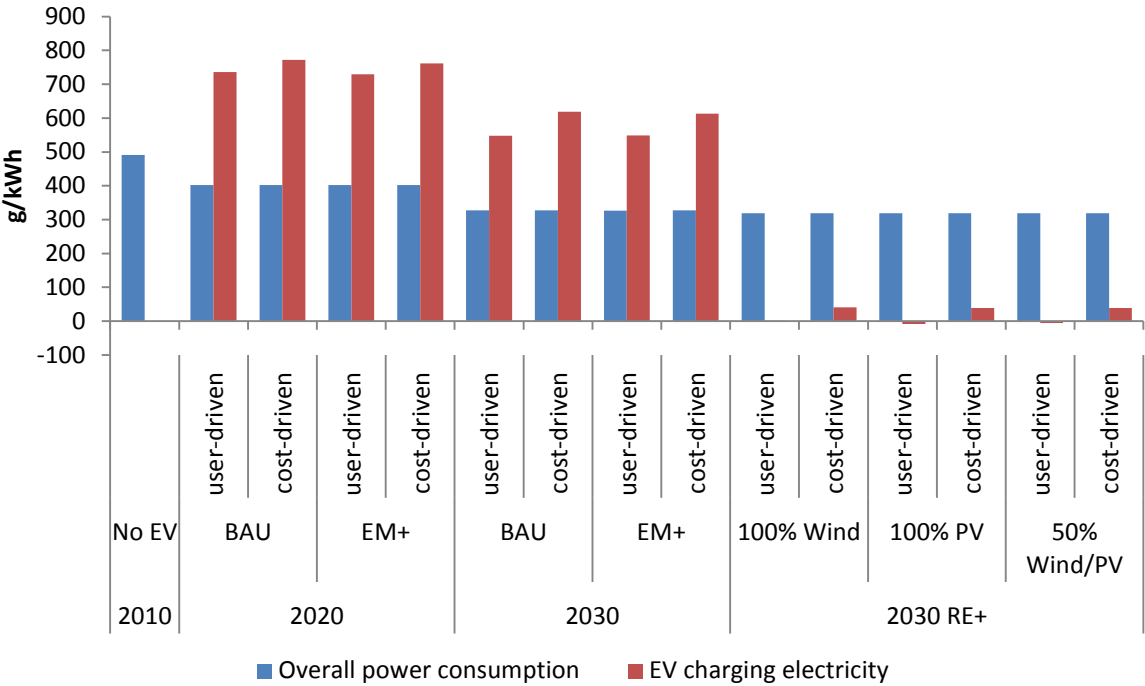


Figure 9: Specific CO₂ emissions

¹⁵ It should be noted that the dispatch model not only considers CO₂ emissions related to the actual generation of power, but also to the start-up of thermal power plants.

Due to ongoing deployment of renewable generators, specific CO₂ emissions of the overall power consumption change from around 490 g/kWh in 2010¹⁶ 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.¹⁷ In terms of CO₂ emissions, the slight improvements in renewable integration related to EVs are by far outweighed by 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 electric mobility, 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 CO₂ 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-

¹⁶ According to our model results. The officially reported CO₂ intensity for 2010 is slightly higher. Yet in this context, only the relation between different scenarios is relevant, and not so much absolute emission levels.

¹⁷ This finding relativizes a qualitative argument brought forward by Schill (2010), according to which future improvements in CO₂ emissions of the overall power system should have a positive influence on the emission balance of EVs.

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, CO₂ prices, or diverging EV profiles, 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. In case of binding distribution network restrictions, both extreme modes of charging may not be fully realizable.

In addition, we abstract from interactions with neighboring countries. In the context of existing interconnection and European plans for further 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. It would also require making detailed assumption on the development of neighboring countries' power systems as well as on their deployment of electric vehicles. Solving 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, i.e., not considering the option of power exchange with neighboring European countries, 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. Our results may thus be interpreted as an upper boundary for the flexibility impacts of EVs on the German power system.

Next, 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). Including the provision of 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 4.4). An according analysis would require extending the model to also

incorporate the provision and activation of reserves of different qualities – most importantly, secondary control reserves and minute reserve – by electric vehicles. This interesting task is left for future research. Likewise, future model analyses may shed light on possible interactions of EVs with other flexibility options such as demand-side management or power-to-heat.

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. As for exogenous input parameters, we largely draw on public and/or semi-governmental data, as well as on EV profiles derived by Kasten and Hacker (2014).

We find that 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 we find substantial impacts on the system's load duration curve which differ strongly between charging 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 mainly carried out during night-time, and thus leads to a much flatter charging profile and to a smaller increase of the system peak load.

The 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 changing power plant fleet and the increased number of EVs. The potential to reduce renewable curtailment is higher in case of cost-driven charging. Likewise, average charging costs are lower in the cost-drive mode.

Using a novel model formulation that allows for intermediate charging modes, we find that even a slight relaxation of fully user-driven charging leads to much smoother—and cheaper—charging profiles. That is, EV impacts on the system peak load could be substantially reduced if vehicle owners would agree to have not the full battery capacity charged as quickly as possible after connecting to the grid, but only a fraction of it. We show that a large part of the system benefits generated by fully cost-driven charging could already be realized with a fast charging requirement of around 50%. This suggests that EV user preferences—such as being able to make previously unplanned trips—and power system requirements could be reconciled by a charging strategy which makes sure that at least a fraction of the battery—say, half of it—is charged as soon as possible.

In additional model runs, we link the introduction of electric mobility 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.

The CO₂ emission balance of EVs strongly 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 CO₂ 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 several 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 impact on peak loads should be. With respect to system security, cost-driven charging is clearly preferably to the user-driven mode. Because of generation adequacy concerns, user-driven charging may have to be restricted 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-optimized charging not only increases the utilization of renewable energy, but also of low-cost emission-intensive plants. If the introduction of electric mobility 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 renewables is added to the system. With respect to CO₂ 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. 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 charging; rather, the net balance of the combined introduction of electric mobility *and* renewables compared to a baseline without EVs *and without* additional renewables is relevant.

Third, 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 the user-driven mode. Accordingly, policy makers should make sure that CO₂ 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. 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 the charging mode.

Appendix

Table 7: Sets, parameters, and variables not related to electric vehicles

Sets	Description	Unit
$i \in I$	Set of thermal power plant blocks of various technologies	
$j \in J$	Set of thermal storage technologies	
$res \in RES$	Set of fluctuating renewable technologies	
$t, tt \in T$	Time set	hours
Parameters		
$avail_{i,t}$	Availability of thermal blocks	%
$availbio_t$	Availability of biomass generation	%
dem_t	Hourly power demand (without EV consumption)	MWh
$energymaxbio$	Yearly biomass power generation budget	MWh
$othergen_t$	Exogenous other hourly power generation (hydro, waste)	MWh
$penalty^{Peak}$	Penalty for use of backstop peak technology	€/MWh
$qmax_i$	Hourly Generation capacity of thermal blocks	MWh
$qmaxbio$	Hourly biomass generation capacity	MWh
$qmin_i$	Minimum hourly generation of thermal blocks	MWh
$resavail_{res,t}$	Hourly availability of fluctuating renewables	MWh
sc_i	Start-up costs of thermal blocks	€
$stinmax_j$	Hourly storage loading capacity	MWh
$stime_i$	Start-up time of thermal blocks	Hours
$stlevmax_j$	Maximum storage level	MWh
$stoutmax_j$	Hourly storage discharging capacity	MWh
vc_i	Variable generation costs of thermal blocks	€/MWh
$vstc_j$	Variable generation costs of storage technologies	€/MWh
Binary variables		
$ST_{i,t}$	Start-up variable of thermal blocks (1 if block is started up in period t, 0 otherwise)	
$U_{i,t}$	Status variable of thermal blocks (1 if block is generating, 0 otherwise)	
Continuous variables		
Bio_t	Generation from biomass	MWh
$Cost$	Total dispatch costs	€
$Rescurt_{res,t}$	Hourly curtailment of fluctuating renewables	MWh
$Resint_{res,t}$	Hourly system integration of fluctuating renewables	MWh
$Peak_t$	Hourly generation of backstop peak technology	MWh
$Q_{i,t}$	Quantity of power generated by thermal block i in hour t	MWh
$Stin_{j,t}$	Hourly power fed into storage	MWh
$Stlev_{j,t}$	Hourly storage level	MWh
$Stout_{j,t}$	Hourly power generation from storage	MWh

Complementary to Table 1, which focuses on electric vehicles, Table 7 list all other relevant sets, parameters and variables of the dispatch model. EV-related equations have already been described in section 3. In the following, we provide the analytical formulation of the remainder of the model.

$$Cost = \sum_{i,t} (vc_i Q_{i,t} + sc_i ST_{i,t}) + \sum_{j,t} vstc_j Stout_{j,t} + \sum_t penalty^{Peak} Peak_t + \sum_{ev,t} penalty^{Phevfuel} Phevfuel_{ev,t} \quad (1)$$

$$Q_{i,t} \leq qmax_i avail_{i,t} U_{i,t} \quad \forall i, t \quad (2)$$

$$Q_{i,t} \geq qmin_i avail_{i,t} U_{i,t} \quad \forall i, t \quad (3)$$

$$ST_{i,t} \geq U_{i,t} - U_{i,t-1} \quad \forall i, t \quad (4)$$

$$U_{i,t-1} - U_{i,t} \leq 1 - U_{i,t} \quad \forall i, t \text{ with } t \leq tt \leq t + stime_i - 1 \quad (5)$$

$$Resint_{res,t} + Rescurt_{res,t} = resavail_{res,t} \quad \forall res, t \quad (6)$$

$$Rescurt_{res,t} \leq resavail_{res,t} \quad \forall res, t \quad (7)$$

$$Bio_t \leq qmaxbio * availbio_t \quad \forall t \quad (8)$$

$$\sum_t Bio_t \leq energymaxbio \quad (9)$$

$$Stlev_{j,t} = Stlev_{j,t-1} + Stin_{j,t} \eta_j - Stout_{j,t} \quad \forall j, t \quad (10)$$

$$Stlev_{j,t} \leq stlevmax_j \quad \forall j, t \quad (11)$$

$$Stin_{j,t} \leq stinmax_j \quad \forall j, t \quad (12)$$

$$Stout_{j,t} \leq stoutmax_j \quad \forall j, t \quad (13)$$

$$\sum_i Q_{i,t} + \sum_{res} Resint_{res,t} + Bio_t + Peak_t + othergen_t + \sum_j (Stout_{j,t} - Stin_{j,t}) = dem_t + \sum_{ev} Charge_{ev,t} \quad \forall t \quad (14)$$

The objective function (1) sums up variable generation costs of thermal plants, including start-up costs of single blocks, variable storage costs as well as penalties for using the backstop peak load technology and for non-electric operation of PHEV/REEV. Equations (2) and (3) establish maximum and minimum generation levels for thermal blocks. Note that the binary status variable $U_{i,t}$ is 1 if the plant is online and 0 otherwise. Equation (4) ensures consistency between the binary status and start-up variables of thermal generators. (5) enforces a start-up time restriction. Equations (6) and (7) determine hourly system integration as well as curtailment of fluctuating renewables such as on-shore and offshore wind power and solar PV. Equation (8) is an hourly power generation capacity restriction for biomass, whereas (9) constrains overall biomass utilization, for example, because of resource constraints. Equation (10) connects storage levels of subsequent periods, given inflows and outflows. Here, roundtrip efficiency losses are attributed to storage loading. (11) to (13) establish upper limits on the storage level, the loading capacity as well as the discharging capacity. Finally, the market clearing condition (14) ensures that overall supply equals demand in all hours.

Thermal power plants are modeled as single blocks in a unit commitment formulation with respective start-up costs and start-up times; in contrast, other generation technologies such as storage, biomass and variable renewables are modeled in a linear way as aggregated capacities which are assumed to be perfectly flexible. Only in the 2010 scenario, we assume generation from biomass to be completely inflexible, i.e., fixed to average levels. In addition, we include inflexible power genera-

tion from run-of river hydro and waste incineration as an exogenous parameter $othergen_t$, drawing on historic data.

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