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

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HIGHLIGHTS

- We analyze the impacts of electric vehicles (EVs) on the German power system.
- In a fully user-driven charging mode, peak load concerns arise.
- Under cost-driven charging, emission-intensive power generation is increased.
- An intermediate charging mode may reconcile user preferences and system needs.
- With respect to CO_2, EVs should be linked to additional renewable deployment.

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ABSTRACT

We analyze the impacts of future scenarios of electric vehicles (EVs) on the German power system, drawing on different assumptions on the charging mode. We find that the impact on the load duration curve strongly differs 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 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 simulating intermediate charging modes, we show that even a slight relaxation of fully user-driven charging results in much smoother load profiles. Further, cost-driven EV charging strongly increases the utilization of hard coal and lignite plants in 2030, whereas additional power in the user-driven mode is predominantly generated from natural gas and hard coal. Specific CO_2 emissions of EVs are substantially higher 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 renewables, electric vehicles become largely CO_2-neutral.

1. Introduction

The use of electric vehicles (EVs) is set to increase substantially in many countries around the world [1]. EV may bring about numerous benefits, such as lower emissions 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. A massive uptake of electric vehicles may also have a strong impact on the power system. The effects on power plant dispatch, system peak load, and carbon emissions depend on both the power plant fleet and the charging mode of electric vehicles (cf. [2]).

In this paper, we study possible impacts of future electric vehicle fleets on 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 [3]. Moreover, the German power system undergoes a massive transformation from coal and nuclear toward 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. We are particularly interested in the impacts of electric vehicles on the system's load duration curve, the dispatch of power plants, the integration of

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fluctuating renewables, and CO_2 emissions under different assumptions on the mode of vehicle charging.

Previous research has analyzed various interactions of electric mobility and the power system, covering purely battery-electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), and/or range extender electric vehicles (REEV). Kempton and Tomić [4] 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. [2] 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.

One strand of the literature deals with power system implications of different charging strategies. Wang et al. [5] examine interactions between PHEVs and wind power in the Illinois power system with a unit commitment approach. They show that smart coordinated charging leads to a reduction in total system cost and smoother conventional power generation profiles. Kiviluoma and Meibom [6] model the power costs that Finnish owners of electric vehicles would face by 2035. In case of optimized charging, power prices turn out to be rather low as cheap generation capacities can be used. Loisel et al. [7] analyze the power system impacts of different charging and discharging strategies of battery-electric vehicles for Germany by 2030. Distinguishing between grid-to-vehicle (G2V) and vehicle-to-grid (V2G), they also highlight the benefits of optimized charging, yet conclude that V2G is not a viable option due to excessive battery degradation costs. Kristoffersen et al. [8] as well as Juul and Meibom [9] and Juul and Meibom [10] 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 fluctuating renewables and emission impacts. Lund and Kempton [11] analyze the integration of variable renewable sources into both the power system and the transport sector. They find that EVs with high charging power can substantially reduce renewable curtailment and CO_2 emissions. Göransson et al. [12] carry out a comparable case study for Denmark, also concluding that system-optimized PHEV charging can decrease net CO_2 emissions. In a more stylized simulation for Denmark, Ekman [13] highlights the potential of EVs to take up excess wind power. Guille and Gross [14] focus their analysis on PHEV-related potentials for smoothing variable wind generation. Sioshansi and Miller [15] apply a unit commitment model to analyze the emission impacts of PHEVs 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. For the case of Ireland, Foley et al. [16] show that off-peak charging is the most favorable option with respect to cost and CO_2 emissions. Using an agent-based model, Dallinger et al. [17] find that smart EV charging can facilitate the integration of intermittent renewables both in California and Germany by 2030. Schill [18] analyzes the impacts of PHEV fleets in an imperfectly competitive power market with a Cournot model and finds that both welfare and emission impacts depend on the agents being responsible for charging the vehicles, and on the availability of V2G. Doucette and McCulloch [19] notes that the CO_2 mitigation potential of EVs is highly dependent on the existing power plant portfolio and concludes that additional decarbonization efforts might be needed to obtain CO_2 emission reductions.

We aim to contribute to the cited literature in several ways. First, the unit commitment approach used here is particularly suitable for studying the interactions of EVs with fluctuating renewables. It considers the limited flexibility of thermal power generators and is thus more suitable to capture the potential flexibility benefits of EVs compared to linear dispatch models such as [11–13,18,7]. 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., [13,16]. In contrast to, for example, Loisel et al. [7], 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., [5]), but apply the model to all subsequent hours of a full year. We further present a topical case study of the German *Energiewende* 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. Next, we do not only distinguish between the two stylized extreme cases of fully cost-optimized and completely non-coordinated 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, but also for cases with adjusted renewable generation capacities. 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. The final section concludes. The Appendix A.1 presents a description of the optimization model, dispatch outcomes without EVs, and the results of additional sensitivity analyses.

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 several inter-temporal constraints on thermal power plants, such as minimum load restrictions, minimum down-time, and start-up costs. The model is formulated as a mixed integer linear program (MILP) with binary variables on the status of thermal plants. 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 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 [20]. Hourly demand is assumed not to be price-elastic. Endogenous model variables include the dispatch of all generators, electric vehicle charging patterns, dispatch costs, and CO_2 emissions.[1]

[1] We only consider G2V and abstract from V2G applications, as previous analyses have shown that the potential V2G revenues are unlikely to cover related battery degradation costs (cf. [7]). Kempton and Tomić [21], Andersson et al. [22], Lopes et al. [23], and Sioshansi and Denholm [24] argue that V2G may be viable for providing spinning reserves and other ancillary services.

We use a standard unit commitment model approach. The basic formulation is provided in Appendix A.1. In the following, we highlight the equations that deal with electric vehicles. EV-related sets, parameters and variables are listed in Table 6 in Appendix A.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.The set ev represents the different EV profiles in the model. Eq. (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 (price-inelastic) 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, so $Phevfuel_{ev,t}$ 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 (Eq. (1) in Appendix A.1). Eqs. (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 $chargemax_{ev,t}$ assumes positive values only in periods in which the EV is connected to the grid. Non-negativity of the variables representing charging, charge level, and conventional fuel use is ensured by Eqs. (EV5)–(EV7). In addition, the model's energy balance (Eq. (14) in Appendix A.1) considers the additional electricity that is required for charging electric vehicles $\sum_{ev} Charge_{ev,t}$ in each hour.

$$Chargelev_{ev,t} = Chargelev_{ev,t-1} + Charge_{ev,t}\eta_{ev} - cons_{ev,t}n_{ev} + Phevfuel_{ev,t} \quad \forall ev,t \tag{EV1}$$

$$Phevfuel_{ev,t} = 0 \quad if\ phev_{ev} = 0 \quad \forall ev,t \tag{EV2}$$

$$Charge_{ev,t} \leqslant chargemax_{ev,t}n_{ev} \quad \forall ev,t \tag{EV3}$$

$$Chargelev_{ev,t} \leqslant batcap_{ev}n_{ev} \quad \forall ev,t \tag{EV4}$$

$$Charge_{ev,t} \geqslant 0 \quad \forall ev,t \tag{EV5}$$

$$Chargelev_{ev,t} \geqslant 0 \quad \forall ev,t \tag{EV6}$$

$$Phevfuel_{ev,t} \geqslant 0 \quad \forall ev,t \tag{EV7}$$

Eqs. (EV8) and (EV9) are only relevant in the case of not fully cost-driven charging, i.e., if *fastchargegoal* is exogenously set to a positive value. Eq. (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. Eq. (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[2] 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-optimal 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 additional analyses with values of 0.25, 0.5 and 0.75 (see Section 3).

[2] According to the objective function (1) presented in Appendix A.1, the model minimizes the costs of dispatch. This includes fuel and CO_2 costs as well as start-up costs. Capital costs are not relevant for the optimization under the assumption of existing generation capacities.

$$fastchargegoal * batcap_{ev}n_{ev} - Chargelev_{ev,t} \leqslant (batcap_{ev}n_{ev} + 1)FULLCHARGE_{ev,t} \quad \forall ev,t \tag{EV8}$$

$$FULLCHARGE_{ev,t}chargemax_{ev,t}n_{ev} \leqslant Charge_{ev,t} \quad \forall ev,t \tag{EV9}$$

3. Scenarios and input parameters

We apply the dispatch model to various scenarios. First, we distinguish different developments with regard to electric vehicle deployment:[3] 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 CO_2 emission targets (for further details, see [20]). 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 their yearly generation exactly matches the yearly power demand of 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.

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 recharged 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 modes 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. Table 1 gives an overview of all model runs.

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 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. We largely draw on the 2013 version [25] regarding thermal and renewable generation capacities, fuel and carbon prices (Table 2), and specific carbon emissions.[5]

[3] In doing so, we draw on the scenarios developed by Kasten and Hacker [20] in the context of the European research project DEFINE. https://www.ihs.ac.at/projects/define/.

[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 [26,27].

Table 1
Scenario matrix.

EV scenario	Charging mode	Generation capacities		2010	2020	2030
No EVs		Baseline		×	×	×
		RE+	100% Wind			×
			50% Wind/PV			×
			100% PV			×
			100% Wind			×
			50% Wind/PV			×
			100% PV			×
BAU	User-driven	Baseline			×	×
	Cost-driven				×	×
EM+	User-driven	Baseline			×	×
	75% fast charge					×
	50% fast charge					×
	25% fast charge					×
	Cost-driven				×	×
	User-driven	RE+	100% Wind			×
			50% Wind/PV			×
			100% PV			×
	Cost-driven		100% Wind			×
			50% Wind/PV			×
			100% PV			×

Table 2
Fuel and carbon prices.

	Unit	2010	2020	2030
Lignite	$EUR_{2010}/MW\,h_{th}$	1.5	1.5	1.5
Hard coal	$EUR_{2010}/MW\,h_{th}$	10.4	9.9	10.5
Natural gas	$EUR_{2010}/MW\,h_{th}$	21.0	24.8	26.2
Oil	$EUR_{2010}/MW\,h_{th}$	38.3	46.7	57.0
CO_2 certificates	EUR_{2010}/t	13.0	23.8	40.8

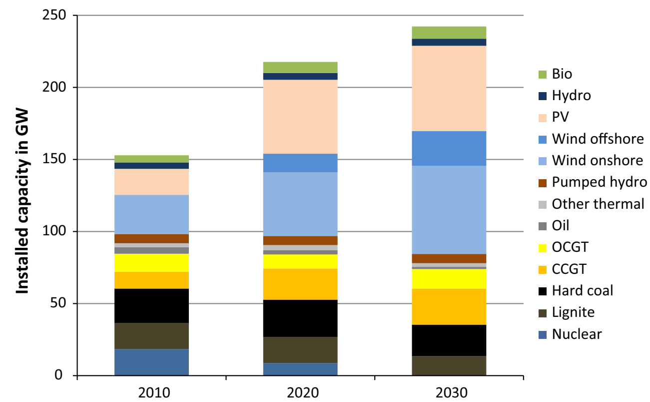

Fig. 1. Installed net generation capacities.

Table 3
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 (GW h)				
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

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. Nuclear power is phased-out according to German legislation. Pumped hydro storage capacity is assumed to stay constant. Overall, thermal generation capacities slightly decrease until 2030, whereas installed renewable capacities increase substantially (Fig. 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.

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.[6] Hourly power demand is assumed not to change compared to 2010 levels. We assume a total yearly net consumption of around 561 TW h, 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 largely draw on Egerer et al. [28].

All exogenous model parameters related to electric vehicles – except for the parameter *fastchargegoal* – are provided by Kasten and Hacker [20]. The input data includes aggregate hourly power consumption and maximum charging profiles of 28 vehicle categories, of which 16 relate to BEV and 12 to PHEV/REEV. Vehicle categories 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 they are assumed to be connected to (semi-)public fast-charging stations at least occasionally. Table 3 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. Table 3 also includes an indicative yearly average value of hourly recharging capacities, which reflects different hourly connectivities to charging stations and different charging power ratings.

4. Results

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 4). In 2020, the EV fleet accounts for only around 0.1–0.2% of total power consumption. In 2030, EV-related power consumption gets more significant with up to 7.1 TW h in BAU and nearly 9.0 TW h in EM+, which corresponds to around 1.3% of total power consumption, or 1.6%, respectively. In the user-driven charging modes, the values are generally slightly lower compared to cost-driven charging because the electric shares of PHEV/REEV are 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. For comparison, Kelly et al. [29] estimate a utility factor of around 67% based on data

[6] Offshore wind feed-in data is available for selected projects in the North Sea only. We derive hourly availability factors from 2012 feed-in data provided by the transmission system operator TenneT.

Table 4
Power consumption of electric vehicles.

EV scenario	Charging mode	Generation capacities		EV consumption (TW h) 2020	EV consumption (TW h) 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
	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
	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

from 170,000 vehicles in the U.S. Weiller [30] also determines utility factors for U.S. PHEVs between 50% and 70%, depending on the battery size and car usage.

While overall power consumption of the assumed EV fleets is relatively small, 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.[7] Fig. 2 exemplarily shows the average charging power over 24 h for the 2030 EM+ scenario for the two extreme charging cases as well as for the 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. 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 evening trip. In contrast, the cost-driven charging mode allows charging EVs during hours of high PV availability, and shifting 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.

Even a slight relaxation of the fully user-driven mode, i.e., reducing *fastchargegoal* 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.

From a power system perspective, average charging levels of electric vehicles are less relevant than the peak loads which EVs induce on the system. Fig. 3 shows the electricity system's load duration curve without electric vehicles, i.e., all observed hourly loads in descending order (right axis). In addition, the sorted additional loads related to EVs for different charging modes are shown (left axis).[8]

Fig. 3 shows that fully user-driven charging generally steepens the load duration curve of the system, 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 during off-peak hours. We again find a strong effect of even slightly deviating from the fully user-driven mode: reducing *fastchargegoal*

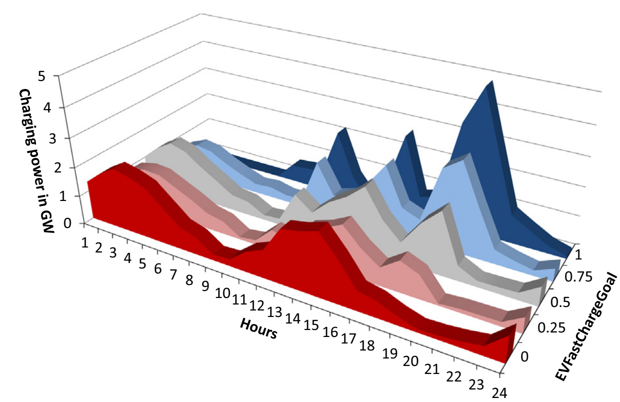

Fig. 2. Average EV charging power over 24 h (2030, EM+).

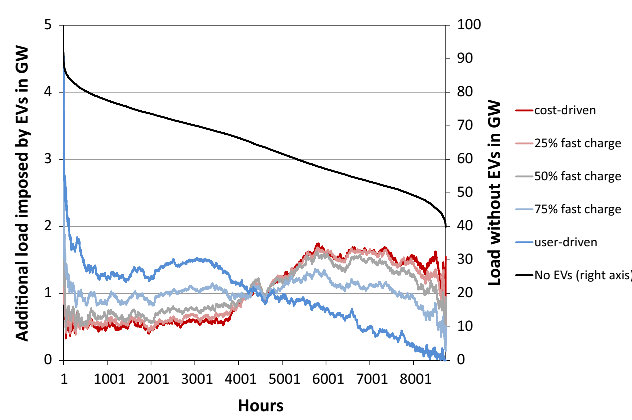

Fig. 3. Impacts of EVs on the load duration curve under different charging modes (2030, EM+).

[7] 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.

[8] The Figure shows the differences between sorted load duration curves with and without EVs for different charging modes. That is, the differences 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.

from 1 to 0.75 results in substantial smoothing of the residual load curve. If this parameter is further reduced to 0.5, 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 Fig. 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 with the assumed EV fleets.

4.2. Power plant dispatch

The differences in hourly EV charging patterns discussed above go along with 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 (Fig. 4).[10] 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.

Fig. 5 shows respective changes in dispatch outcomes for the 2030 EM+ scenario. Compared to 2020, the introduction of electric vehicles has a much stronger 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. Fig. 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. Pumped storage, which is another potential source of flexibility, is accordingly 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.

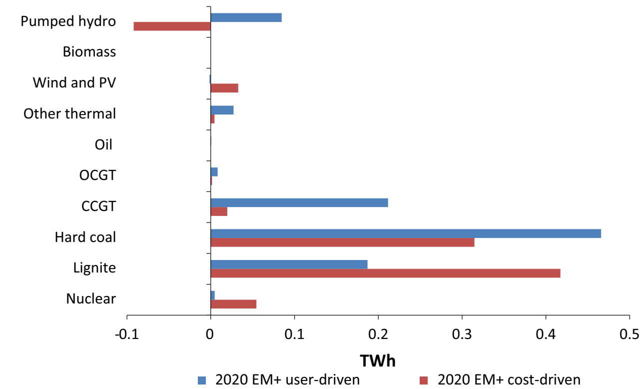

Fig. 4. Dispatch changes relative to scenario without EVs (2020, EM+).

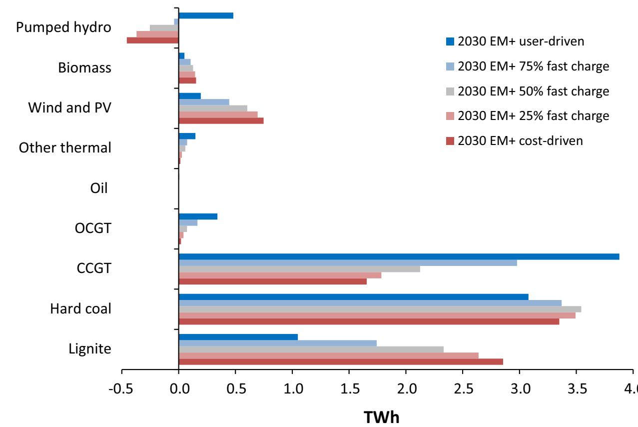

Fig. 5. Dispatch changes relative to scenario without EVs (2030, EM+).

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 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 portfolio,[11] 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 [3]. Yet results presented so far have shown that the additional energy used to charge EVs is mainly provided by conventional power plants, and

[9] We only present dispatch 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.

[10] Fig. 8 in the Appendix A.2 shows the dispatch results of the scenarios without EVs, against which the EV-related dispatch changes presented in Figs. 4–6 may be compared.

[11] For example, additional open cycle gas turbines may be beneficial under user-driven charging, while additional base-load 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.

Table 5
Additional generation capacities in RE$^+$ scenarios (in MW).

Charging mode	100% Wind	100% PV	50% Wind/PV	
			Wind	PV
User-driven	6176	13,235	3088	6617
Cost-driven	6438	13,795	3219	6897

particularly by emission-intensive lignite plants in the cost-driven charging mode.

In the 2030 RE$^+$ model runs, 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 with 100% onshore wind, 100% PV, or fifty-fifty (Table 5).[12] 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 slightly higher than in the user-driven mode, as the overall power consumption of PHEV and REEV is higher.

The outcomes of the RE$^+$ cases may be compared to the 2030 scenario without EVs *and* without additional renewables. This may be interpreted as if the deployment of EVs was strictly linked to an additional deployment of renewables, which would not have occurred without the introduction of electric mobility. 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) EVs and fluctuating renewables. In contrast, power generation from lignite increases under cost-driven charging, whereas gas-fired plants and pumped hydro facilities are used less. This is because system-optimized EV charging 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.

Finally, we provide further details on 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 [2]). 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 (Fig. 6).[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 TW h 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 TW h (0.55%), while only 0.6 TW h of renewables have to be curtailed under cost-driven charging (0.29%). Accordingly, optimized EV charging allows slightly increasing the overall utilization of renewables. 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 TW h or 0.89% in the case without electric vehicles), while curtailment is highest in the one with 100% onshore wind (2.3 TW h or 1.07%). Cost-driven charging results in much lower levels of renewable curtailment compared to user-driven charging.

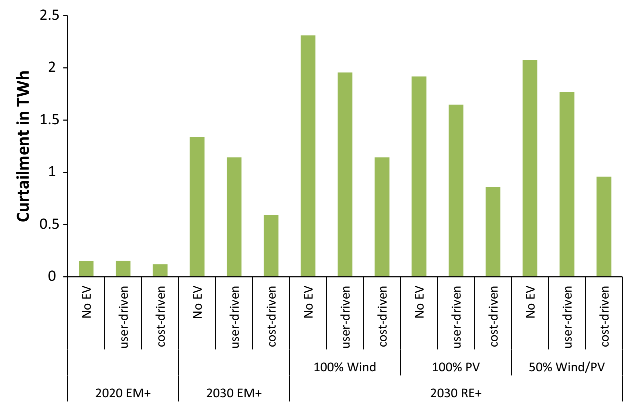

Fig. 6. Renewable curtailment.

4.3. CO_2 emissions

We have shown that EVs may increase the utilization of base-load capacities as well as fluctuating renewables.[14] 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 Fig. 7, which features specific emissions of both overall power consumption and EV charging electricity. The latter are calculated as the difference of overall power plants' CO_2 emissions between the respective case and the scenario without electric vehicles, related to the overall power consumption of EVs.[15]

Due to ongoing deployment of renewable generators, specific CO_2 emissions of the overall power consumption decrease from around 490 g/kW h in 2010[16] to around 400 g/kW h in 2020, to less than 330 g/kW h in the 2030 BAU and EM$^+$ scenarios, and to around 320 g/kW h 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 it is largely generated from emission-intensive technologies like lignite and hard-coal. The 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. 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. [12], which show for a Danish case study that user-driven charging increases system-wide CO_2 emissions, whereas

[12] Additional deployment of renewables involves additional capital and fixed costs. These are not considered here. Onshore wind and PV as well incur different capital costs. Yet we do not aim to determine a cost-minimizing portfolio; rather, we are interested in the effects of different technology choices on dispatch outcomes.

[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.

[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] The analysis accordingly focuses on direct CO_2 emissions from the operation of power plants, and is not based on a full life-cycle assessment of electric vehicles.

[16] According to model results. The officially reported CO_2 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.

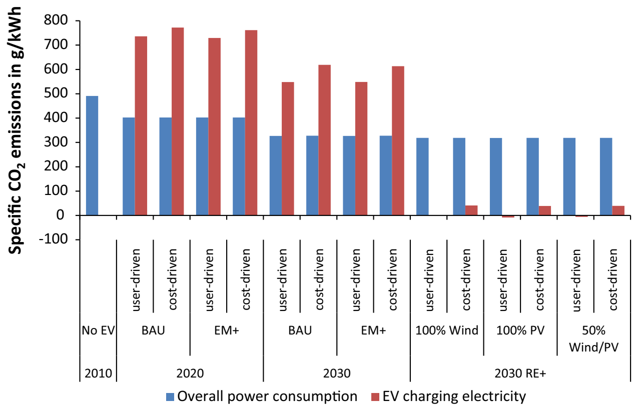

Fig. 7. Specific CO_2 emissions.

cost-driven charging decreases 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.

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 future power plant fleet. We have thus decided to largely draw on the assumptions of a well-established scenario [25]. 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 Appendix A.3, we provide the dispatch outcomes for additional sensitivity analyses that include alternative assumptions on the power plant fleet, higher CO_2 prices, and cross-border exchange. We find that general dispatch results hardly change in most sensitivity runs, except for the case in which CO_2 prices are assumed to double, as this reverses the merit order of gas- and coal-fired plants.

While using projections of future power generation from fluctuating renewables, drawing on historic feed-in data of other years than 2010 may lead to slightly different dispatch results. What is more, calculating availability factors from 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 [31].

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 perfect network expansion. Yet on the distribution level, a massive deployment of electric vehicles may lead to local congestion. Such effects can hardly be considered in a power system model. 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 addition, we abstract from interactions with neighboring countries. In the context of existing interconnection and plans for further European market integration, 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, and according parameters on future power system and EV developments in these countries. Solving a large European unit commitment model for a full year and various scenarios 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. Our results may thus be interpreted as an upper boundary for the flexibility impacts of EVs on the German power system. In fact, the effects of EVs on lignite-fired power generation are mildly mitigated compared to the EM^+ runs in a sensitivity analysis in which we fix the hourly pattern of net power exchange with neighboring countries to 2010 levels.

Next, we only consider G2V power flows and abstract from V2G flows. 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 [7,18]. The provision of reserves and other ancillary services by V2G, however, appears to be more promising [22,23,24]. We also abstract from the provision of reserves, which may result in underestimated levels of conventional generation, and accordingly underestimated renewable curtailment.

Finally, it should be noted that cost-driven charging generally reduces the utility of vehicle owners compared to the user-driven mode. Under cost-driven charging, users would have to make regular forecasts about when they use their cars again, and how long the next trips will be. In the real-world, this may pose a considerable barrier to the adoption of a purely cost-driven charging mode. On the other hand, charging costs are lower in the cost-driven mode, as the EV owner – or the retailer, or some other service provider, respectively – can make use of lower wholesale prices. Further savings should be possible if not only the wholesale market, but also reserve markets and other ancillary services could be accessed, probably in combination with V2G applications. Yet the feasibility of such strategies as well as the quantification of utility losses and cost savings remain questions for future research. In any case, a partly cost-driven charging mode as modeled here (for example, with *fastchargegoal* of 50%), may provide a feasible middle ground between users' preferences and power system requirements.

6. Conclusions

We analyze the integration of future fleets of electric vehicles into the German power system for various scenarios of 2020 and 2030. We use a numerical dispatch model with a unit commitment formulation which minimizes overall dispatch costs over a full year to study the effects of different charging modes on the load curve, dispatch, costs, and emission. By applying a novel model formulation, we are able not only to simulate extreme charging modes, but also more realistic intermediate ones.

Based on our 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. Not only with respect to costs, but also 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, at the latest if the vehicle fleet gets as large as in our 2030 scenarios, unless high charging tariffs 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 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. From a system perspective it does not matter if these additional renewables are actually fully utilized by EVs 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 – as, for example, in a sensitivity analysis that assumes double CO_2 prices. 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 CO_2 emissions are adequately priced. Otherwise, some kind of emission-oriented charging strategy would have to be applied, which is possible in theory (cf. [15]), but very unlikely to be implemented in practice.

Fourth, 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 in the cost-driven mode compared to user-driven charging. The same may hold for other storage technologies and load shifting. Accordingly, the viability of such flexibility options depends on the size of the future EV fleet, as well as on the charging mode.

Finally, we conclude that even a slight relaxation of fully user-driven charging leads to much smoother charging profiles. That is, undesirable 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 (possibly large) 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% or even 75%. This suggests that EV user preferences – such as not giving control over charging away completely, or being able to make previously unplanned trips – and power system requirements could be reconciled by a charging strategy which makes sure that not the full battery capacity is charged as soon as possible.

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Appendix A

A.1. The model

Table 6 lists all sets, parameters, and variables related to electric vehicles. The complementary Table 7 includes all other sets, parameters, and variables of the basic dispatch model. EV-related equations have already been described in Section 2. In the following, we provide the analytical formulation of the remainder of the model.

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

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

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

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

$$U_{i,t-1} - U_{i,t} \leqslant 1 - U_{i,tt} \quad \forall i,t \text{ with } t \leqslant tt \leqslant t + s\ time_i - 1 \quad (5)$$

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

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

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

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

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

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

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

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

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

Table 6
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	kW h
$chargemax_{ev,t}$	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	kW h
η_{ev}	EV charging efficiency	%
$fastchargegoal$	Restricts the relative battery charge level that should be reached as fast as possible (1 for fully user-driven charging, 0 for cost-driven)	
$penalty^{Phevfuel}$	Penalty for non-electric PHEV operation mode	€/MW h
$phev_{ev}$	Defines whether an EV is a PHEV/REEV (1 if yes, 0 otherwise)	
n_{ev}	Number 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	MW h
$Phevfuel_{ev,t}$	Cumulative PHEV conventional fuel use	MW h

Table 7
Sets, parameters, and variables of the basic model.

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	h
Parameters		
$avail_{i,t}$	Availability of thermal blocks	%
$availbio_t$	Availability of biomass generation	%
dem_t	Hourly power demand (without EV consumption)	MW h
$energymaxbio$	Yearly biomass power generation budget	MW h
$othergen_t$	Exogenous other hourly power generation (hydro, waste)	MW h
$penalty^{Peak}$	Penalty for use of backstop peak technology	€/MW h
$qmax_i$	Hourly Generation capacity of thermal blocks	MW h
$qmaxbio$	Hourly biomass generation capacity	MW h
$qmin_i$	Minimum hourly generation of thermal blocks	MW h
$resavail_{res,t}$	Hourly availability of fluctuating renewables	MW h
sc_i	Start-up costs of thermal blocks	€
$stinmax_j$	Hourly storage loading capacity	MW h
$stime_i$	Start-up time of thermal blocks	h
$stlevmax_j$	Maximum storage level	MW h
$stoutmax_j$	Hourly storage discharging capacity	MW h
vc_i	Variable generation costs of thermal blocks	€/MW h
$vstc_j$	Variable generation costs of storage technologies	€/MW h
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	MW h
$Cost$	Total dispatch costs	€
$Rescurt_{res,t}$	Hourly curtailment of fluctuating renewables	MW h
$Resint_{res,t}$	Hourly system integration of fluctuating renewables	MW h
$Peak_t$	Hourly generation of backstop peak technology	MW h
$Q_{i,t}$	Quantity of power generated by thermal block *i* in hour *t*	MW h
$Stin_{j,t}$	Hourly power fed into storage	MW h
$Stlev_{j,t}$	Hourly storage level	MW h
$Stout_{j,t}$	Hourly power generation from storage	MW h

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. Eqs. (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. Eq. (4) ensures consistency between the binary status and start-up variables of thermal generators. Eq. (5) enforces a start-up time restriction. Eqs. (6) and (7) determine hourly system integration as well as curtailment of fluctuating renewables such as onshore and offshore wind power and solar PV. Eq. (8) is an hourly power generation capacity restriction for biomass, whereas (9) constrains overall biomass utilization, for example, because of resource constraints. Eq. (10) connects storage levels of subsequent periods, given inflows and outflows. Here, roundtrip efficiency losses are attributed to storage loading. Eqs. (11)–(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 generation from run-of river hydro and waste incineration as an exogenous parameter $othergen_t$, drawing on historic data.

A.2. Dispatch outcomes without EVs

Fig. 8 shows power plant dispatch of the scenarios without electric vehicles for 2020, the 2030 baseline, and the 2030 RE^+ sensitivities. Between 2020 and 2030, generation from wind and PV as well as CCGT plants increases, as the respective capacities grow (cf. Fig. 1). On the contrary, generation from lignite and hard coal goes down and nuclear power is phased out completely.

A.3. Sensitivity analyses

Results of dispatch models generally depend on the input parameters used. This concerns, for example, assumptions on the power plant fleet, future CO_2 prices, and power exchange with neighboring countries. In fact, the uncertainties concerning the future development of the German power plant portfolio may be larger than the size of the EV fleet assumed here. We thus carry out additional sensitivity analyses for the year 2030 to study the effect of such parameter variations.

Two sensitivities deal with changes of the power plant fleet: "No lignite" assumes that all lignite plants are shut down by 2030 and fully substituted by CCGT plants with block sizes of 500 MW each. This sensitivity is of interest against the background of the ongoing debate on the compatibility of lignite-fired power generation with German CO_2 emission targets. In a sensitivity "20% more RES", we assume the capacities of onshore and offshore wind power as well as PV to be 20% larger compared to EM^+. This assumption reflects the fact that renewable expansion was much faster in the last decade compared to what was planned by the government.[17] In another sensitivity called "Double CO_2 price" we assume that CO_2 prices double compared to what is assumed in EM^+ for 2030, i.e., reach 82 Euro per ton. A fourth sensitivity deals with the simplifying assumption of treating the German power system as an island: In "Exchange", we fix the hourly net power exchange with neighboring countries to 2010 levels. The respective time series is derived from data published by the four German transmission system operators.[18]

For each of these sensitivities, we carry out three model runs: a reference case without electric vehicles, a fully user-driven case, and a fully cost-driven one. We then compare dispatch outcomes of the EV scenarios to the respective runs without EVs. Results presented in Fig. 9 shows that major changes of general dispatch outcomes occur only under the assumption of double CO_2 prices.

In "No lignite", additional generation from hard coal and CCGT plants substitutes for the phased-out lignite plants. The relative share of CCGT under the cost-driven charging mode is higher than in EM^+, as the hard coal plants are often producing at full capacity even in the case without EVs. Accordingly, specific CO_2 emissions of EVs also decrease compared to EM^+. Yet the general finding that cost-driven charging involves more power generation from

[17] In contrast to the RE^+ scenario, we do not link the renewable expansion to the introduction of electric vehicles, i.e., the additional renewable capacities are also foreseen in the respective reference scenario without electric vehicles.

[18] We chose the year 2010 because it is consistent with the load data and the renewable feed-in patterns. According to data provided by 50Hertz, Amprion, TenneT TSO, and TransnetBW, net exports amounted to around 5 TW h in 2010, with hourly maximum net exports of 6 TW h and maximum net imports of 7 TW h.

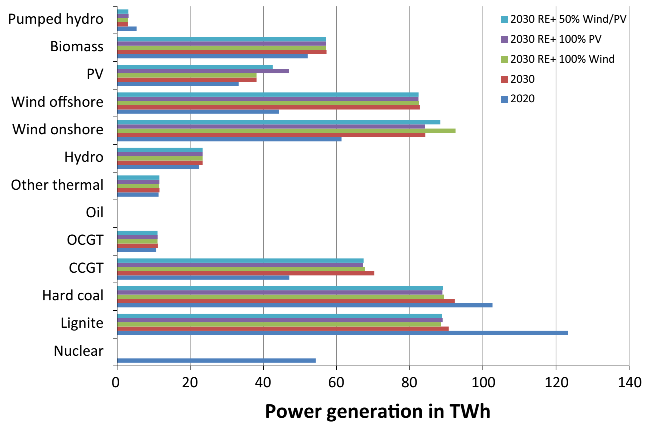

Fig. 8. Dispatch outcomes for scenarios without EVs.

emission-intensive coal plants and less from CCGT compared to user-driven charging also holds in this sensitivity.

A major change occurs in the sensitivity "Double CO_2 price". Under this assumption, the merit order changes such that CCGT plants provide the cheapest option to charge EVs. Accordingly, CCGT is now the predominant source of charging electricity in the cost-driven mode, while lignite and hard coal achieve only minor shares. In contrast, user-driven charging now involves larger amounts of electricity from lignite and hard coal plants, as cheaper CCGT plants are already producing at full capacity in many hours of vehicle charging. This sensitivity also indicates that cost-driven charging goes along with less carbon-intensive power generation if CO_2 is priced sufficiently.

In the "20% more RES" sensitivity, results generally do not change much compared to EM+. EVs lead to some additional integration of wind power and PV; yet most of the charging electricity still comes from lignite and hard coal plants in the cost-driven mode, and from hard coal and CCGT plants in the user-driven mode, respectively. The reason is that most of the additional renewable power is already used in the reference scenario without electric vehicles.

Finally, "Exchange" only leads to minor changes compared to EM+. Assuming hourly net power exchange with neighboring countries as in 2010 leads to slightly higher full-load hours of lignite and hard coal plants compared to EM+ already in the case without electric vehicles. The effect of EV charging on lignite is thus mildly mitigated: in the cost-driven mode, charging power from lignite now amounts to 2.6 TW h, compared to 2.9 TW h in EM+. Yet the overall change remains small because of the rather low historic exchange levels. The effect should become stronger if further renewable expansion in Germany, combined with increased interconnector capacity, leads to higher cross-border power exchange.

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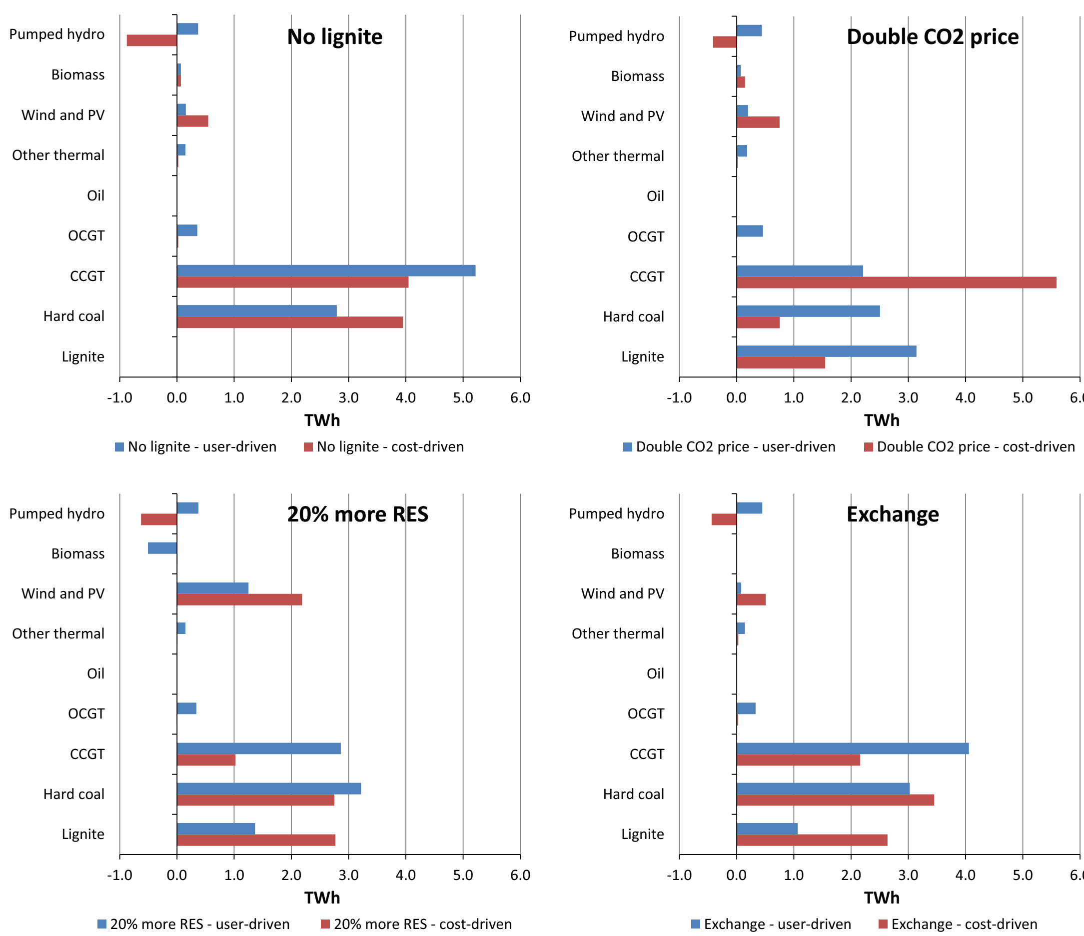

Fig. 9. Sensitivity analyses: dispatch changes relative to respective scenarios without EVs.

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