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Electrical energy storage in highly renewable European energy systems: Capacity requirements, spatial distribution, and storage dispatch

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ABSTRACT

One of the major challenges of renewable energy systems is the inherently limited dispatchability of power generators that rely on variable renewable energy (VRE) sources. To overcome this insufficient system flexibility, electrical energy storage (EES) is a promising option. The first contribution of our work is to address the role of EES in highly renewable energy systems in Europe. For this purpose, we apply the energy system model REMix which endogenously determines both capacity expansion and dispatch of all electricity generation as well as storage technologies. We derive an EES capacity of 206 GW and 30 TWh for a system with a renewable share of 89%, relative to the annual gross power generation. An extensive sensitivity analysis shows that EES requirements range from 126 GW and 16 TWh (endogenous grid expansion) to 272 GW and 54 TWh (low EES investment costs). As our second contribution, we show how the spatial distribution of EES capacity depends on the residual load, which—in turn—is influenced by regionally predominant VRE technologies and their temporal characteristics in terms of power generation. In this sense, frequent periods of high VRE excess require short-term EES, which naturally feature low power-related investment costs. In contrast, long-term EES with low energy-related costs are characteristic for regions where high amounts of surplus energy occur. This relationship furthermore underlines how EES capacity distribution is implicitly influenced by technical potentials for VRE expansion.

1. Introduction

The reduction of greenhouse gas emissions is one of the main challenges of our society towards more sustainable energy supply [1]. Electricity generation from renewable resources represents a promising option to tackle this problem. However, the mismatch of electricity generation and load caused by the limited dispatchability of intermittent electricity generation such as photovoltaic (PV) or wind power—hereinafter referred to as variable renewable energies (VRE)—requires an increase of flexibility of future energy systems. While various definitions of flexibility exist (see Refs. [2,3]), the term is commonly understood as the ability of technical devices to contribute to the balancing of the residual load [4] (which, in turn, is defined as the electricity load minus the generation from VRE). More specifically, flexibility might be provided e.g. by electrical energy storage (EES) or the electricity grid. While the former option provides flexibility on a temporal level, i.e. allows shifting of energy from one point in time to another, grid expansion can be considered as a spatial flexibility, since it enables large-scale balancing of generation and demand between different regions which otherwise have to balance their internal mismatches themselves. Additional technical solutions for flexibility are demand side management, in particular in combination with new loads (electric heating, electric cooling, e-mobility, and power-to-gas) and supply-side flexibility (flexible

Abbreviations: AC, alternating current; aCAES, adiabatic compressed air storage; CCGT, combined cycle gas turbine; CSP, concentrated solar power; DC, direct current; E2P, energy-to-power-ratio; EES, electrical energy storage; EEX, European energy exchange; EnDAT, energy data analysis tool; ENTSO-E, European network of transmission system operators for electricity; GAMS, general algebraic modeling system; GT, open cycle gas turbine; H_2, hydrogen storage; Li-Ion, stationary lithium-ion battery; NC, number of cycles; NFC, number of full cycles; PHS, pumped hydro storage; PV, photovoltaic; RE, renewable energy; REMix, renewable energy mix model; SOC, state of charge; VRE, variable renewable energy.

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Table 1
Observation areas and spatial resolutions in different analyses which focus on flexibility demand calculations (number of model-regions in brackets).

Author	Model type	Observation area	Spatial resolution
[10]	Optimization	Small exemplary region	Single node
[19]	Simulation	Texas	Single node[a]
[24]	Optimization	California	Multi node (12)
[42]	Optimization	Germany	Multi node (440)
[48]	Optimization	Germany	Single node
[49]	Optimization	US: Western Electricity Coordinating Council	Multi node (50)
[4]	Simulation	Ireland, Germany, Italy[b]	Single node[c]
[20]	Simulation	EU 27 + offshore regions	Single node[c]
[11,12]	Optimization	Europe, Middle East, North Africa	Multi node (21)
[50]	Simulation	Worldwide	Single node[c]

[a] Small import and export capacities <1 GW exist.
[b] The study includes 27 European countries, excluding Malta and Cyprus and including Norway and Switzerland, focuses, however, on the three countries listed in the table.
[c] Although the observation area includes several regions, each region is analyzed isolated as one model-region (no grid).

power-plants, curtailments of VRE) [5,6]. In this work, we focus on flexibility provided by EES which is characterized both in terms of necessary power and energy related capacity.

1.1. Literature review

Current research addresses the question of future EES requirements typically via model-based analyses, often emphasizing the quantification of EES capacity for different energy scenarios [7–13]. Reviews for the required EES capacity in Europe are, for example, provided by Kondziella and Bruckner [6] or Droste-Franke et al. [14]. These publications show broad ranges of required EES capacity[2] in the current research, highlighting the necessity of a thorough examination of the underlying assumptions in the original studies.

In this sense, storage requirements have been studied with regard to different renewable energy (RE) shares [7,16–20], wind-to-PV generation ratios [4,13,21], weather years or climate effects [22,23], cost assumptions [8,12], and the representation of the electric grid [12,16,24]. Moreover, the resulting EES capacities in model-based assessments are influenced by the applied modeling approach (I), different temporal (II), technological (III), and spatial resolutions (IV). A profound review of methods, challenges, and trends for flexibility requirements (including EES) is provided by Haas et al. [25].

(I) Storage requirements have been analyzed with the help of various modeling approaches; some of the most prominent ones are optimizations (e.g. in [8,9,13,24,26–30]) and simulations (e.g. in [17,18,31–33]). While optimizations derive an ideal energy system under the premise of their objective function (e.g. minimal system costs [13] or efficient RE integration [26]), simulations have a predictive or explorative view [34], relying on energy balance accounting methods, dispatch strategies (*merit order*), or time-series analyses. By this means, simulations might not find the optimal solution, however, typically enable a higher temporal (e.g. 6 min in [33]), technological (e.g. multi-sectoral approaches in [35,36]), or spatial resolution (e.g. 146 regions in [32]).

(II) The influence of the temporal resolution has been studied in an optimization model for ramp flexibility as well as for system costs in Deane et al. [37]. Pandzic et al. [38] and O'Dwyer and Flynn [39] use a unit-commitment model to study day-ahead utility scheduling of power plants. The studies find that sub-hourly resolutions are desirable for assessing the ramping flexibility of power plants. However, if system costs are the main evaluation criterion, hourly resolutions are sufficient. Pfenninger [40] uses down-sampling, clustering, and heuristics to reduce the temporal resolution (initial time-series in hourly resolution) in energy systems models and studies their effects on computational performance, dispatch, installed capacities, and system costs for a UK power system. The author concludes that—particularly in energy scenarios with high VRE shares—the temporal resolution should be preferably on an hourly basis or better. In the contrary, Pfenninger points out that if the modeling includes EES, the need for high sequential temporal resolutions can be reduced. However, the author also states that there are no clear recommendations regarding which temporal resolution is most suitable and emphasizes that the influence strongly depends on the model setup as well as the input parameters.

(III) Technological resolution can either refer to the abstraction level in the modeling approach to characterize the technologies or to the considered energy sectors in the model-based analysis.

With regard to the technological representation of storage, the literature shows numerous approaches, ranging from representations of a single generic storage [41], to storage classes (e.g. short-, mid-, long-term, without further details on the assumed technologies, see Ref. [11]), or detailed representations of actual storage technologies [9,13,27,42].

Model-based quantifications of EES requirements typically only analyze the power sector. If other sectors are included (e.g. with transportation, heating, or cooling), the approaches typically rely on accounting frameworks on an annual basis (e.g. in [35], [36]) or optimizations which use a simplified temporal resolution in terms of representative time periods (e.g. in [43,44]). Multi-sectoral analyses based on an hourly basis, for example, can be found in the work of Thellufsen and Lund [45], Lund et al. [46], or Schaber et al. [47].

(IV) Storage requirements have been analyzed for several observations areas with different spatial resolutions within the models, i.e. the number of model-regions. The latter plays an important role, as it defines the distribution of capacities, generation, electricity load, and transmission grid topology within the observation area. Table 1 gives an overview regarding spatial examination areas and resolution in different studies (number of model-regions in brackets).

1.2. Contributions and novelty

As illustrated in the literature review, the question of the required EES capacity has been tackled by a substantial amount of studies for various energy scenarios and under different assumptions, applying a broad spectrum of methods. Additionally, several valuable insights can be derived from the literature review.

First, current research indicates that the importance of EES will rise significantly with higher shares of VRE power (>80%) and analyses, therefore, should emphasize such systems.

[2] For a fully renewable European energy system the storage power capacities range from 500GW to 900 GW and 80 to 400 TWh [14].

Second, for an appropriate representation of the dynamics of VRE power generation, hourly resolutions are desirable. Moreover, the benefits of sub-hourly modeling are marginal and such temporal resolutions are only essential when assessing ramp flexibility or in short-term analyses.

Third, research recognizes the importance of joint optimization of several flexibility options (e.g. EES, grid, curtailments) when analyzing future energy systems.

Despite these manifold analyses in the literature, the number of studies which derive the EES capacity for Europe with an adequate spatial resolution is limited. Furthermore, recent research rarely assesses the reasons for the *optimum* spatial distribution of storage expansion and its dispatch but takes the model results as granted. One exception is a recently published paper by Schlachtberger et al. [51], who study the complementarity of transmission grid and EES for a similar energy system (30 European countries, CO_2 reduction target of 95%). The authors find how wind generation is highly correlated with hydrogen storage (H_2) utilization, whereas batteries balance power generation from PV systems. Our analysis enhances this discussion and sheds light on the underlying causes of both the optimum spatial distribution of storage capacity and storage dispatch for European energy systems with high shares of non-dispatchable renewable power production. In particular, we provide a more granular technological resolution and test the robustness of our results via an extensive sensitivity analysis.

For this purpose, we apply the linear, cost minimizing optimization model REMix (**R**enewable **E**nergy **Mix**), which endogenously determines all generation and storage capacities as well as their dispatch.

2. Methodology

2.1. Model

The energy system model REMix was developed in the department of Systems Analysis and Technology Assessment at the German Aerospace Center [29,30,52,53]. The model minimizes the system costs under perfect foresight, considering pre-defined techno-economic constraints for the expansion and dispatch of technologies, such as resource availability for RE or cost and efficiency assumptions for generation technologies. The system costs include the annuities of the overnight investment costs of capacity expansion as well as the operating costs of the utility dispatch. The latter consist of fuel, emission certificate as well as operations and maintenance costs (O&M). The model's decision variables are capacity dispatch and expansion, optimized together during one model run. REMix is developed in the mathematical programming language GAMS [54] and solved with CPLEX [55]. An overview of the model functions is provided by Fig. 1, whereas a detailed model description including the mathematical framework can be found in Gils et al. [56].

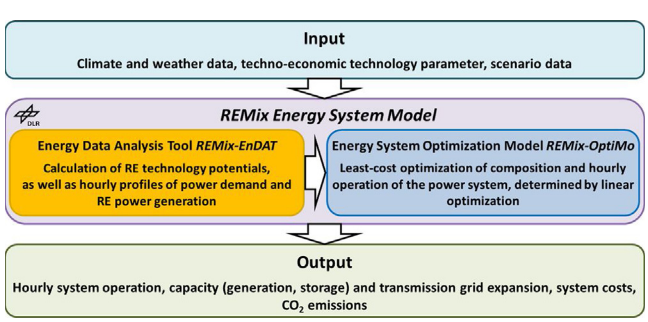

Fig. 1. Fundamental structure of the REMix optimization model based on [57].

2.2. Scenario assumptions

The main application of REMix is the dimensioning of a least cost supply system that can reliably cover the electric load at any time. For this analysis, we incorporate a partial greenfield approach, which optimizes the expansion and dispatch of all storage and most of the power generation capacities for the year 2050. Optimized power technologies comprise VRE technologies (PV, onshore and offshore wind, run-of-the-river hydroelectricity), dispatchable RE (biomass, reservoir hydroelectricity, geothermal and concentrated solar power systems (CSP)), fossil-fired power-plants (lignite, hard coal, natural gas), and nuclear power plants. For natural gas-fired plants we distinguish between open cycle gas turbines (GT) and combined cycle gas turbines (CCGT). The capacities of geothermal, CSP, and nuclear power plants are exogenously pre-defined (based on Ref. [58]). Since the installed capacities of those technologies are relatively small (see Table A3), their influence on the storage capacity distribution is expected to be marginal. Furthermore, this simplification reduces the solving time of the model. Curtailments of electricity generation from VRE technologies are possible at zero costs. Therefore, the model first uses curtailments of VRE at times of negative residual loads to reduce the surplus of electricity. In detail descriptions of the modeling approach and the underlying assumptions for each technology are provided in the Supplementary material.

The partial greenfield methodology is based on the assumption that almost no capacities are installed at the beginning of the observation year and investments are necessary to reliably cover the electric load at any time. The approach is valid since most of the existing capacities at the present will not last until the observation year 2050. However, due to their long life time, some technologies will prevail until 2050, including some fossil-fired and reservoir hydro power-plants. For this purpose, we consider the decommissioning of generation capacity based on its technology-specific life time (see Table A4).

The analysis focusses on the electricity sector and excludes interactions with the transportation and heat sector.

Current research agrees that the importance of storage will rise significantly with higher shares of VRE power (e.g. >80% [13]). Therefore, we include a model constraint which enforces at least 80% of electricity generation to come from VRE (averaged over the whole observation area), hereinafter denoted by $80\%_{constr}$. Although dispatchable RE (e.g. biomass or CSP with thermal storage) can also reduce CO_2 emissions, their availability in Europe is limited and $80\%_{constr}$ is, therefore, a valid assumption. For a detailed analysis of the influence of this model constraint see Sec. 10.5 of the Supplementary material.

For the analyzed year 2050, the optimization period is divided into 8760 hourly time-steps. The observation area comprises northern, western, and central Europe (see Fig. 2). While larger countries are generally represented by individual model-regions, smaller European countries are aggregated. In contrast, Germany is split into 20 sub-regions, resulting in 29 overall model-regions for this analysis (see Fig. A1).

The model uses exogenously, hourly and model-region-specific load profiles of the electricity demand. They are based on the load profiles from 2006 of the European Network of Transmission System Operators for Electricity (ENTSO-E) [59,60]. All profiles are scaled through estimates of the development of the total electricity demand for the year 2050 for each country based on Refs. [61–63] (see Table A14).

A simplified representation of the transmission grid (exogenously specified in the standard analysis) allows electricity import and export between the model-regions (see Sec. 2 in the Supplementary material). The exogenous grid capacities are based on today's net transfer capacities (NTC) of the ENTSO-E [64] and

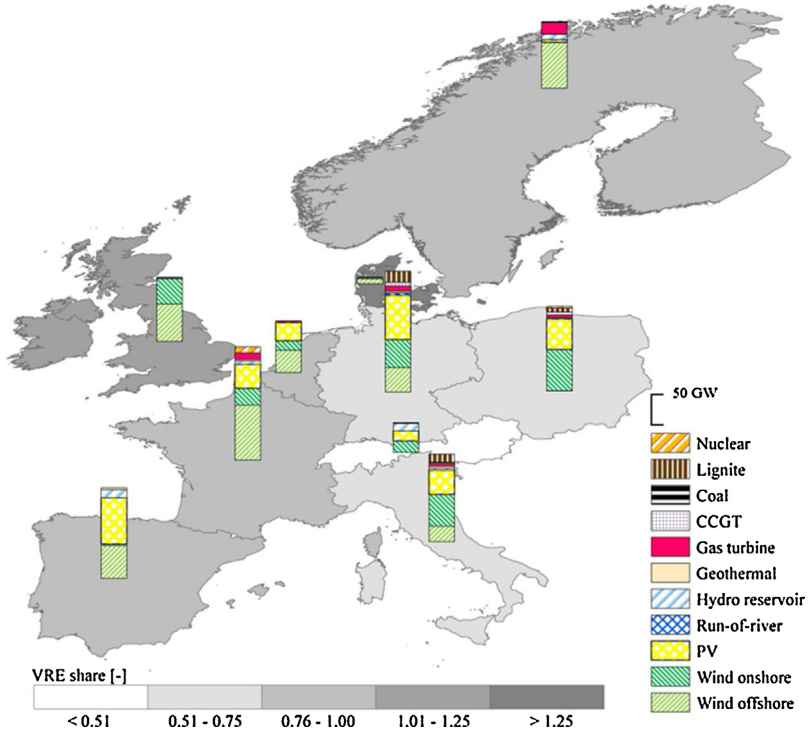

Fig. 2. Technology-specific installed generation capacities for Europe in 2050. VRE shares are depicted in relation to the annual gross electricity generation. VRE shares >1 indicate model-regions which export electricity (i.e. generation > demand). All numerical values also can be found in Table A 18 of the Supplementary material.

include all planed grid expansion projects of the Ten Year Network Development Plan (TYNDP) 2012 [65]. Based on this setup, an initial model run provided information regarding frequently overloaded transmission lines. As a consequence, the NTC's of these lines were increased (see Sec. 2 of the Supplementary material). Still, this approach is a rather conservative estimate for the grid of 2050 and we therefore allow for an endogenously calculated transmission grid expansion between the model-regions in the sensitivity analysis (see Sec. 2 and Sec. 10.3 of the Supplementary material). Within each region, a perfect grid without any transmission constraints is assumed (*copper plate*).

The model includes five storage technologies which are characterized by different charging and discharging efficiencies, investment costs for the power and energy capacity, and O&M costs. Represented EES technologies are pumped hydro power (PHS), H_2, adiabatic compressed air (aCAES), stationary lithium-ion (Li-ion), and redox-flow batteries. H_2 storage is considered for power-to-power applications. In this sense, electricity is converted to H_2 via alkaline water electrolysis, stored in underground salt caverns and reconverted via a CCGT. An overview of all relevant technology parameters can be found in Table A15.

Apart from storage expansion, REMix also optimizes the storage dispatch and furthermore allows an individual and independent dimensioning of the storage power (GW_{el}) and energy capacity (GWh_{el}), implying no pre-defined energy to power ratio (E2P),[3] sometimes referred to as *disjoint capacity*. A detailed description of the methodology for storage modeling is provided in Gils et al. [56], whereas the main techno-economic parameters are shown in Table 2. All cost assumptions as well as the existing capacities of PHS, aCAES, and H_2 are discussed in Sec. 8 in the Supplementary material. For Li-ion and redox-flow batteries it is assumed that there are no constraints regarding their technical potential (both maximal installable storage power and energy capacity).

Although the techno-economic input parameters are carefully chosen and based on a broad literature review as well as expert assessments, we are aware that their exact values are highly uncertain for the observation year 2050. We therefore include a broad sensitivity analysis in the discussion section and the Supplementary material to validate our key results. The scenario setup as described above serves as the reference scenario for those sensitivity tests.

3. Results

3.1. Generation capacity expansion

Fig. 2 shows the endogenously derived total generation capacities for all renewable and fossil-fired technologies in 2050. Moreover, the VRE share with respect to the gross annual electricity generation for each model-region is depicted. Unless otherwise stated, the 20 German model-regions are aggregated in the following sections. Furthermore, the analysis concentrates on the technologies with the highest installed capacities and neglects technologies with smaller amounts of installed capacities, such as run-of-the-river hydroelectricity or biomass systems.

The overall VRE capacity is 1185 GW, mainly provided by offshore wind (465 GW), PV (392 GW), and onshore wind (328 GW). Fossil-fired technologies (lignite, CCGT, GT) sum up to 119 GW, mainly provided by GT's (58 GW). In terms of annual electricity generation, offshore wind systems generate 1482 TWh, whereas onshore wind and PV result in 624 TWh and 419 TWh, which equals 47%, 20%, and 13% of the overall gross electricity generation.

Naturally, the optimization favors technologies which are (regionally) cost-effective regarding capacity expansion and

[3] The E2P describes the time in hours a storage needs for a complete cycle with its nominal power and allows an identification whether a storage technology is mainly used for short, mid, or long-term applications.

Table 2
Main techno-economic parameters for the storage technologies.

Technology	$Invest_{power}$ [€/kW_{el}]	$Invest_{energy}$ [€/kWh_{el}]	η_{charge} [-]	$\eta_{discharge}$ [-]
H_2	1200	1	0.75	0.62
Li-ion	50	150	0.97	0.97
aCAES	570	47	0.84	0.89
Redox-flow	630	100	0.92	0.92
PHS	450	10	0.91	0.91

dispatch. In consequence, investments for VRE happen predominantly in regions with high technical potentials and high full load hours. Regions with high solar irradiation for example—such as Iberia—show comparatively high installations of PV systems, whereas high wind speeds—as in the UK + IE or in Northern Europe—will foster the installation of wind power-plants. Furthermore, region-specific technical potentials restrict the capacity expansion of VRE, as this is, for instance, the case for onshore wind (in AT + CH, BeNeLux, PL + CZ + SK, Italy, Germany, UK + IE) and for PV (in BeNeLux, PL + CZ + SK, Iberia, Italy) (see Fig. 3). Relaxing these resource constraints would result in higher installations of onshore wind as well as PV and is likely to substitute some of the offshore wind capacity.

The high share of electricity generation from PV, onshore and offshore wind reflects the VRE constraint ($80\%_{constr}$) set for the reference scenario (see Sec. 2.2). More specifically, power generation from VRE accounts for exactly 80 % (2547 TWh/a), whereas dispatchable technologies—including electricity generation from biomass, geothermal systems, CSP, and conventional hydroelectricity—contributes by 9 % (289 TWh/a). Without this constraint, the VRE share in Europe would be much smaller: Assuming the same CO_2 certificate prices and fuel costs as well as identical investment and O&M costs, calculations without $80\%_{constr}$ result in a significant lower VRE share (42%) on the European average (see Sec. 10.5 in the Supplementary material). However, if a very high CO_2 certificate price is chosen (130€/t CO_2 instead of 57€/t CO_2 as in the standard case), optimum capacity expansion leads to a VRE share that is close to the one of the reference scenario (75%).

3.2. Storage capacity expansion

Fig. 4 depicts the total installed EES power capacity for all storage options for the European model-regions, as obtained from

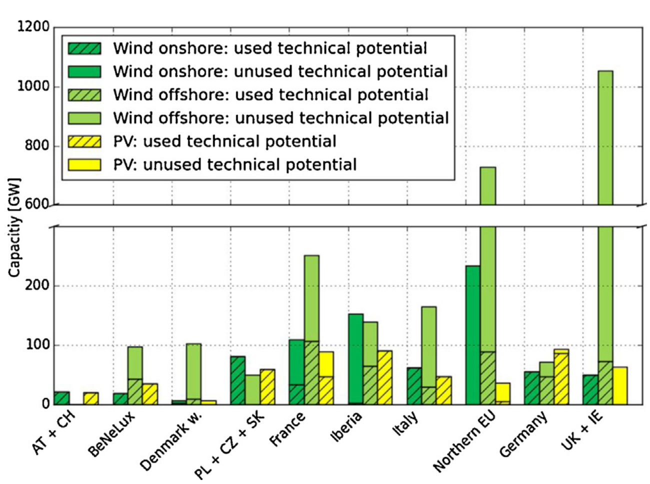

Fig. 3. Used and unused technical potential of VRE capacity for each model-region. The sum of used and unused technical potential defines the total technical potential.

our calculations. For PHS this includes today's existing capacities (39 GW and 271 GWh, see Tables A16 and A17) as we assume that these will not be retired until 2050 due to the long life time of the water reservoir. Additionally, a simulation run with no existing capacities of PHS was performed as part of the sensitivity analysis. This scenario confirms that a stock of PHS capacities does not influence the installed PHS, as both model runs result in an identical expansion of PHS capacities (see Sec. 10.7 in the Supplementary material). Apart from redox-flow batteries, the model derives investments into every storage technology. The endogenously determined storage power capacities result in 166 GW. The largest share is provided by H_2 storage with 86 GW, whereas capacities from Li-on batteries account for 58 GW.

The lack of redox-flow storage can be explained by the cost optimizing model logic. For mid-term applications, i.e. the balancing of surplus energy and deficits of time periods up to several days (*synoptic*), redox-flow batteries compete with aCAES which have rather similar techno-economic characteristics (see Table 2). Despite the favorable efficiencies of redox-flow batteries, their higher energy capacity investment costs (at similar storage power costs) prevent the expansion as long as aCAES expansion limits are not reached.

This hypothesis has been validated with model-runs where the energy capacity investment costs for redox-flow batteries were set to the respective value for aCAES. The results confirm that mid-term storage applications of aCAES could be substituted by redox-flow batteries if battery costs improve to the level of aCAES (see Sec. 10.7 in the Supplementary material). Because of negligible installed capacities of redox flow batteries, this storage type is not taken into account in the remainder of this paper.

While the majority of storage power capacity is provided by H_2 storage and Li-ion batteries, aCAES and PHS also play an important role in certain regions. In the model-region Iberia, for example, the installed capacities of PHS reach the technical potential of 137 GWh (see Table 3) and 12 GW of storage power. Italy is another region where the capacity expansion of PHS reaches its technical potential (77 GWh). Notable capacities of aCAES occur in UK + IE, resulting in 5 GW and 72 GWh.

For the German model-regions (see Fig. 5) the optimization results in 30 GW of EES power. The largest share is provided by Li-ion batteries and H_2 storage with 16 GW and 10 GW respectively. The highest power capacities can be observed in Tennet2, Amprion2, and 50 Hertz1 (6.80 GW, 5.03 GW, 3.70 GW), mainly providing flexibility for the integration of offshore wind generation (Tennet2, 50 Hertz1) and additionally high amounts of PV and onshore wind capacities (50 Hertz1). In this regard, the favorable transmission grid infrastructure between Tennet2 and 50 Hertz1 fosters the storage capacity expansion in these regions.

Particularly in regions with high shares of electricity from wind turbines—such as 50Hertz1 or Tennet2—higher amounts of aCAES expansion were observed, resulting in 1.38 GW, 0.59 GW respectively. All model-region and technology-specific EES power capacity expansion is also shown in Tables A19 and A20 of the Supplementary material.

Table 3 lists the model results for storage energy capacities for each region. While the quantity, technology-specific composition

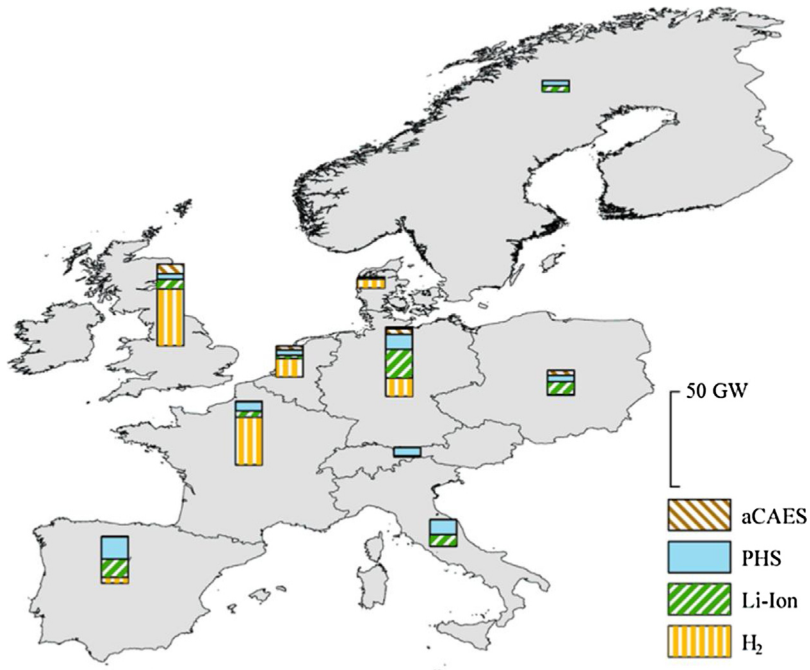

Fig. 4. Technology-specific storage power for Europe in 2050 (see Table A19 for all numerical values).

Table 3
Installed storage energy capacity for all model-regions in 2050.

	Storage energy capacity [GWh_{el}]			
	H_2	Li-ion	aCAES	PHS
AT + CH	36	–	1	40
BeNeLux	3117	4	44	22
Denmark w.	2264	1	4	–
PL + CZ + SK	86	30	48	25
France	6927	6	5	37
Iberia	901	38	3	137
Italy	38	16	2	77
Northern Europe	–	13	–	27
Germany	3671	32	58	54
UK + IE	12578	10	72	22
Total	29618	150	237	441

and spatial distribution of the *storage power* is quite diverse over the observation area, *storage energy capacity* is, as expected, mainly provided by H_2 long-term storage (29616 GWh). We observe the highest energy capacities in the regions UK + IE, France, Germany, and BeNeLux respectively (12578 GWh, 6927 GWh, 3671 GWh, 3117 GWh). With respect to energy capacity, aCAES, PHS, and Li-ion batteries play only a minor role (236 GWh, 168 GWh, 151 GWh, together less than 3% of the total energy capacity), since these technologies mainly provide short and mid-term flexibility in the model to compensate diurnal (1 h–1 d) and synoptic (2 d–10 d) fluctuations from VRE. H_2, in contrast, serves as long-term storage (>10 d) for electricity from offshore wind turbines. Note that both storage power (GW) and storage energy capacity (GWh) are endogenously derived by REMix for each storage technology. A more detailed analysis of storage dispatch and its spatial distribution is provided by the following section.

3.3. Spatial distribution of storage capacity

For each model-region the technology-specific storage expansion depends on the hourly power generation from VRE sources and their regional capacity mix (limited by the technical storage potentials). Moreover, storage requirements are implicitly affected by the spatial balancing ability of the transmission grid between the regions.

Previous research showed that storage portfolios depend on the level of wind and PV penetration within the system [21,66], where a predominance of one generation technology can influence the overall storage design. Our results indicate that high shares of wind generation tend to require more long-term storage, while, in contrast, larger amounts of short-term storage (e.g. Li-ion batteries) seem to be characteristic for regions which are mainly supplied by electricity from PV systems.

Therefore, we compare the hourly time-series of the residual load (electrical load minus VRE feed-in) with the hourly cumulative charging power of all storage technologies for the model-regions France, PL + CZ + SK, and Iberia (Fig. 6). More specifically, the hourly values depicted in this figure are normalized regarding the total VRE and storage power capacity. A negative residual load indicates a VRE surplus, while positive values indicate a VRE deficit which requires further generation from dispatchable technologies (e.g. fossil-fired power-plants or biomass systems), storage discharging, or electricity import.

We chose these specific regions due to their different generation and storage mixes (see Fig. 2, Table 3). Moreover, each region is characterized by one predominant VRE Source: France is mainly supplied by electricity from offshore wind power (74%), PL + CZ + SK largely by onshore wind (50%), and Iberia shows high shares of PV generation (34%).

The plots show a distinct correlation between VRE surpluses and storage charging. Within the regions PL + CZ + SK and Iberia, daily VRE peaks caused by PV generation occur, which, in consequence, foster daily charging of storage. The PV-dominated pattern in PL + CZ + SK is superimposed by a short onshore wind event of a few days (14th–17th June). In the offshore wind region France, in contrast, we do not observe daily storage charging but patterns that correlate on a more synoptic and seasonal basis.

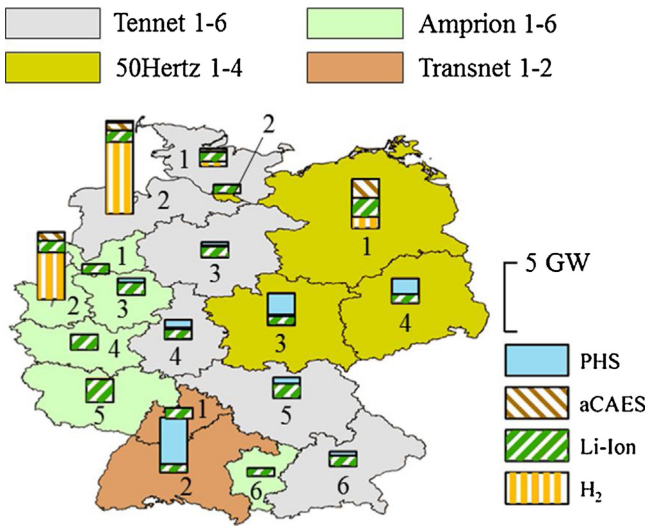

Fig. 5. Technology-specific storage power for Germany in 2050 (see Table A20 for all numerical values).

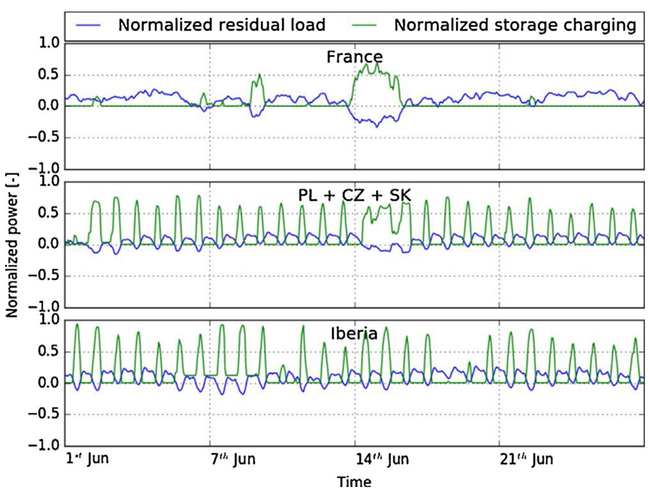

Fig. 6. Model endogenously determined hourly residual load and hourly cumulated charging capacity of all storage technologies for the model-regions France, PL + CZ + SK, and Iberia. Storage charging is normalized to the total storage power capacity; the residual load to the region-specific, total VRE capacity.

To support these findings, we analyze the linear correlation coefficient ρ between VRE surpluses (i.e. negative residual loads) and the hourly storage charging capacity (cumulated over all storage technologies) for each model-region (Pearson product-moment coefficient, Fig. 7). Additionally, Fig. 7 depicts the VRE share of each model-region on the color axis.

A significant correlation ρ between VRE excess and storage charging can be observed in all regions, indicating that regional VRE generation that exceeds the electrical load mostly is used for storage charging. In this sense, storage is dispatched to integrate power generation from VRE technologies, and does not, as for example shown for scenarios with lower shares of VRE penetration (see e.g. [67,68]), ensure the continuous dispatch of thermal power plants and subsequently leads to higher CO_2 emissions. Alternatively to storage charging, generation surplus can be curtailed or exported to other regions where an additional demand exists. The results also show that the correlation ρ tends to increase with higher VRE share.

Yet, Figs. 6 and 7 do not explain why we obtain distinct EES mixes for different model-regions. The reasons are twofold and elaborated subsequently.

(1) As shown previously, storage charging strongly correlates with negative residual loads. In this sense, the shape of the residual load of each model-region directly influences which EES technologies are built to which extent. Residual loads that are characterized by high powers with short time periods require short-term EES (low E2P). In contrast, longer time periods of negative residual loads foster the expansion of EES with high E2P ratios.

Whether an EES is used for short or long-term balancing is primarily defined by the investment costs assumptions; the crucial parameter is the ratio between power-specific and energy-specific investment costs (*energy-to-power-investment-ratio*). On the one hand, EES with low energy investment costs favor large amounts of stored energy and hence long-term applications. On the other hand, low power investment costs foster EES expansion which is preferred for the balancing of high power and short-term usage. Therefore, the charging times-series of H_2 correlate significantly with the electricity generation from offshore wind. In general, also Li-ion storage charging is correlated with PV power production and aCAES charging with onshore wind.

(2) Second, limited regional technical potentials for EES expansion will directly affect the storage portfolio. The optimization approach favors the storage expansion of cost-effective technologies, such as PHS. Provided that further storage is required to meet $80\%_{constr}$, the model will pursue the expansion of such technologies as long as the technical potential is not reached. Table 4 underlines that effect, showing that nearly all model-regions exploit their technical potential of PHS.[4] In contrast, large amounts of unused technical potential still remain for aCAES and H_2.

The technical potentials for storage expansion are discussed in more detail in Sec. 8 of the Supplementary material.

3.4. Storage dispatch

The following section takes a closer look at storage utilization in terms of hourly charge and discharge; it addresses two main questions:

(1) Is the temporal storage dispatch pattern technology-specific?
(2) If so, are those patterns region-specific or do similar patterns occur in all regions?

(1) For the analysis of the hourly dispatch patterns the subsequent metrics are introduced: total number of cycles (NC), number of full cycles (NFC), number of typical cycles (NC_{typ}), representative length (Φ) of one typical cycle.
   i NC describes each change from charging to discharging and is a measurement of the annual utilization of the storage.
   ii The NFC is defined as the ratio of the sum of annual storage energy (electrical output) and load (electrical input) to the storage energy capacity divided by two. The difference between NC and NFC helps to assess the intensity of the storage utilization.
   iii NC_{typ} is defined as the number of charge and discharge processes going through the following states of charge (SOC): $SOC \leq 0.2 \rightarrow SOC \geq 0.8 \rightarrow SOC \leq 0.2$. It is the precondition for defining Φ.

[4] An exception is the model-region Austria + Switzerland, which, additionally to the existing PHS capacities, provides flexibility mainly through dispatchable reservoir hydroelectricity (49 GWh, resp. 40% of the annual demand).

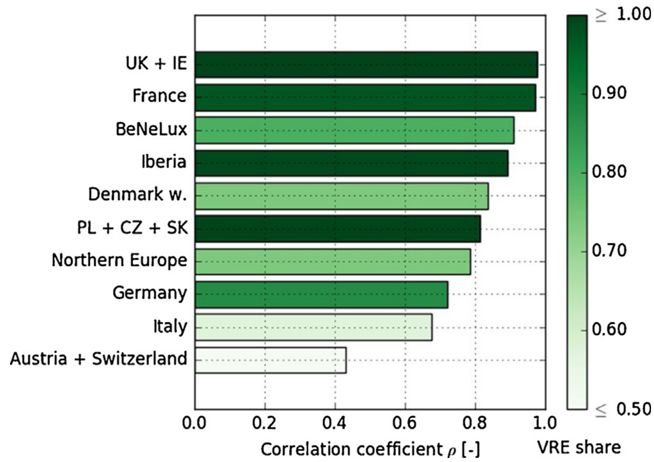

Fig. 7. Correlation coefficients (ρ) (x-axis) of the model-endogenous, hourly times-series of VRE surplus with the model-endogenous, hourly storage charging times-series for all regions. Moreover, the figure depicts the VRE shares (color axis).

iv Φ denotes an average length (e.g. in hours or days) of a typical cycle NC_{typ}.

For the regions Iberia, PL + CZ + SK, and France, Fig. 8 displays the relative storage charge, discharge, and the fill level for Li-ion, aCAES, and H_2 respectively.

The expansion of short-term storage technologies, such as Li-ion batteries, is typical for regions with high shares of PV generation. The dispatch of these batteries in the model-region Iberia (upper panel in Fig. 8) shows the most distinct cyclicality of all EES technologies. Daily cycles can be observed, where charging mainly occurs in times of high PV feed-in, as a single peak around noon. Furthermore, the high charging power is striking which usually reaches almost 100% (in absolute terms ≈10 GW, see Fig. 4). Discharging of Li-ion batteries in Iberia usually occurs during morning and evening hours. Opposed to the charging process, discharging of Li-ion batteries also occurs with partial power. This implies that the power capacity is mainly optimized to balance surplus PV production and less to balance nocturnal deficits. A complete discharge (SOC = 0) is usually reached at night times; the typical cycle duration Φ is around one day.

The middle panel of Fig. 8 represents the dispatch pattern of aCAES in the model-region PL + CZ + SK. Φ is around three to five days. Opposed to Li-ion batteries in Iberia, aCAES charging and discharging also occurs with partial storage power. Moreover, the cyclicality of the storage dispatch is not as distinctive as for stationary Li-ion batteries, mainly since aCAES charging correlates on a more synoptic basis with the feed-in of onshore wind.

Regions with high shares of offshore wind penetration—namely the model-regions Denmark west, Northern Europe, UK + IE, and France—require large amounts of H_2 long-term storage, provided that the technical potential of the storage energy capacity, i.e. salt caverns, is sufficient (see Table 4). The lower panel of Fig. 8 shows the dispatch behavior of H_2 storage in France. Since charging strongly correlates with offshore wind generation, rather seasonal changes of the storage fill level are characteristic. This is also indicated by a high E2P ratio (mean over all regions = 316). A typical cycle lasts ≈45 days and charging as well as discharging usually occurs with high power.

(2) In the following section, we investigate to what extent storage dispatch patterns (characterized by NC and NFC) for individual EES technologies are either model-region-specific or similar in all model-regions. For this purpose, we compare the number of storage cycles (NC) to the storage full cycles (NFC) for all storage technologies (except for redox-flow batteries) for four regions (see Fig. 9).

The NC of H_2 storage is between 80 and 100, for aCAES between 250 and 320, for PHS between 360 and 380, and for Li-ion batteries between 540 and 860. Regarding the NFC, model results range from 10 to 12 for H_2, 90–130 for aCAES, 140–170 for PHS, and 420–730 for Li-ion storage. For each storage technology, similar values for NC and NFC are observed in all model-regions, however, with one exception: Li-ion storage shows notable differences between the regions with regard to the NC and the NFC. The model-regions Iberia and PL + CZ + SK, for example, exhibit rather low NC (≈500), whereas France and 50Hertz1 show relatively high NC (≈750). This also can be supported by the coefficient of variation (cv), which is shown in Table 5 for the NFC of each storage technology of all model-regions with non-marginal installed storage capacities. Here, Li-ion batteries show the highest cv (0.67), indicating the regional differences in the utilization of this technology.

This behavior could be explained by the fact that Li-ion batteries with low NC primarily balance electricity from PV. High NC in contrast, indicate that Li-ion does not exclusively store PV feed-in (daily cycling), but additionally balances electricity from wind power. To validate this hypothesis, we analyze the region and technology-specific storage dispatch of Li-ion batteries in detail by using heat maps.

Fig. 10 shows the normalized charge (left panels) and discharge power (right panels) of Li-ion storage over the hours of a day on the abscissa and over the days of the year on the ordinate for the same model-regions as in Fig. 9.

In all regions shown in Fig. 10, storage loading processes generally occur daily and primarily in the hours of the highest PV power generation, while discharging mainly takes place during hours of high electricity demand and low PV power production. However, some differences exist. For the regions shown in Fig. 10, low PV shares—as in France or 50 Hertz1—are associated with high

Table 4
Model-region and technology-specific used and unused technical potential of the storage energy capacity. Note that we assumed unlimited storage energy capacity potentials for Li-ion and redox-flow batteries. .

	Used technical potential [GWh_{el}]			Unused technical potential [GWh_{el}]		
	PHS	aCAES	H_2	PHS	aCAES	H_2
AT + CH	40	1	36	22	137	13155
BeNeLux	22	44	3117	–	269	26838
Denmark w.	–	4	2264	–	183	15709
PL + CZ + SK	25	48	86	–	1577	155691
France	37	5	6927	–	620	52982
Iberia	137	3	901	–	1397	133304
Italy	77	2	38	–	123	11944
Northern Europe	27	–	–	–	–	–
Germany	54	58	3671	–	1192	116161
UK + IE	22	72	12578	–	403	32959

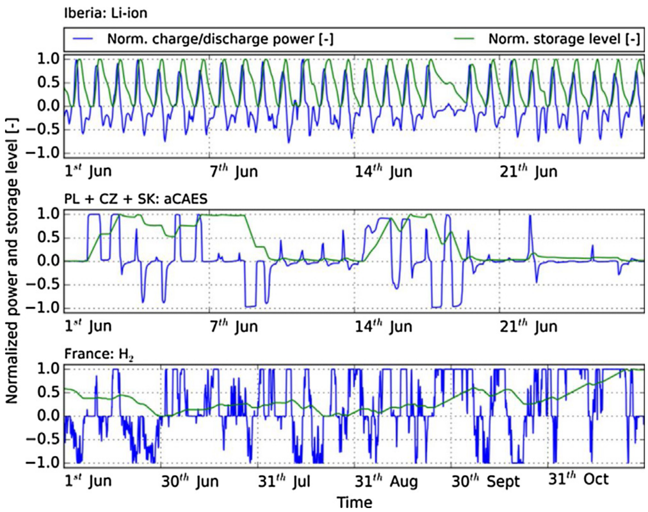

Fig. 8. Storage level as well as charge and discharge power for the storage technologies Li-ion battery (Iberia), aCAES (PL + CZ + SK), and H_2 (France). Storage level is normalized to the total storage energy capacity; charge and discharge power are normalized to the total installed storage power. Note that the plots show different temporal intervals on the abscissa to illustrate the typical dispatch for each storage technology.

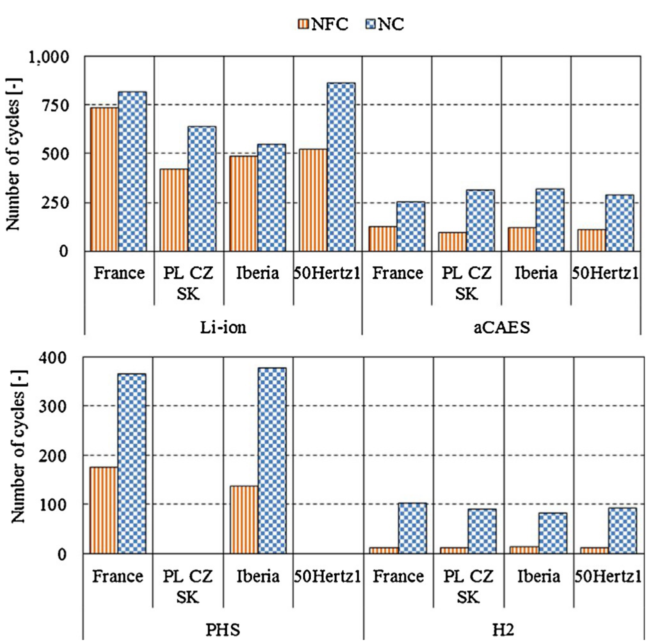

Fig. 9. Number of cycles (NC) and full cycles (NFC) for each storage technology for the model-regions France, PL + CZ + SK, Iberia, and 50 Hertz1.

Table 5
Mean values, standard deviation, and coefficient of variation (cv) of the number of full cycles (NFC) over all model-regions. Note that these values were only derived for model-regions with a considerable amount of storage capacity.

	Number of full cycles (NFC)		
	Mean [-]	Std. deviation [-]	cv [-]
H_2	9	1.5	0.17
Li-Ion	817	550	0.67
aCAES	119	19	0.16
PHS	117	56	0.18

amounts of electricity generation from wind power due to the required high share of VRE. In consequence, France and 50 Hertz1 are characterized by a higher number of charging processes during the night times when compared with Iberia or PL + CZ + SK. This, in turn, again leads to a higher NC of Li-ion batteries in France and 50 Hertz1 (see Fig. 9).

Furthermore, we observe that higher wind shares and hence increasing NC lead to lower relative charge powers. Consequently, for PV regions which are characterized with higher Li-ion battery capacities and lower NC, the relative charge power is significantly higher than in wind-dominated regions.

In conclusion, Fig. 10 underlines the assumption that Li-ion batteries do not exclusively balance short-term diurnal fluctuations from PV generation, but also are charged in times of high wind penetration. Naturally, this effect is more distinctive with increasing wind shares. In these cases, Li-ion batteries complement mid and long-term storage with the balancing of synoptic and seasonal fluctuations from wind energy (*dual use* of Li-ion batteries).

In contrast to Li-ion batteries, the dispatch of PHS, aCAES, and H_2 storage is largely region-independent (see Fig. 9).

4. Discussion

4.1. Sensitivity analysis

To validate the model results with respect to EES requirements, an extensive sensitivity analysis has been carried out. Here, we summarize results for a selection of sensitivity tests. The detailed analysis, which furthermore includes model runs for variations in operating costs (fuel costs, CO_2 prices) and different weather years, along with all underlying assumtions, can be found in Sec. 10 of the Supplementary materials. The sensitivity tests discussed here include:

i StorInv_high, StorInv_low: 50% higher (lower) specific investment costs for storage than in the reference case.
ii VREInv_high, VREInv_low: 50% higher (lower) specific investment costs for PV, onshore wind, and offshore wind than in the reference case.
iii Cur.003: technology- and model-region-specific curtailment limited to 3% of technology-specific gross power production.
iv G+: endogenously optimized power grid expansion.

Fig. 11 shows the differences in installed storage power capacity in the selected sensitivity tests compared to the reference scenario (Ref) (sum over all model-regions).

First, reduced storage investment costs (StorInv_low) lead to an increased EES expansion; in contrast, higher storage costs reduce EES expansion compared to the reference run (StorInv_high). Second, higher costs for VRE (VREInv_high) lead to reduced installed capacities of VRE and in consequence will foster higher EES capacities through reduced curtailments of VRE (to meet $80\%_{constr}$). Third, more restrictive curtailment requirements (Cur.003) mainly lead to reduced curtailments of offshore wind generation. The wind power otherwise curtailed has to be stored in Cur.003. This results in increased H_2 storage capacities (as charging of these capacities mainly correlates with offshore wind, see Sec. 3.3) in this scenario. Finally, we see that endogenously determined grid expansion (G+) can substitute large amounts of EES capacity, in particularly H_2. These storage capacities are replaced since in the reference case EES primarily integrates offshore wind power production which otherwise would have to be curtailed due to grid limitations. However, as also shown in other studies (see e.g. [69]), storage capacities are not completely interchangeable by transmission grid. In fact, this complementary of both flexibility options

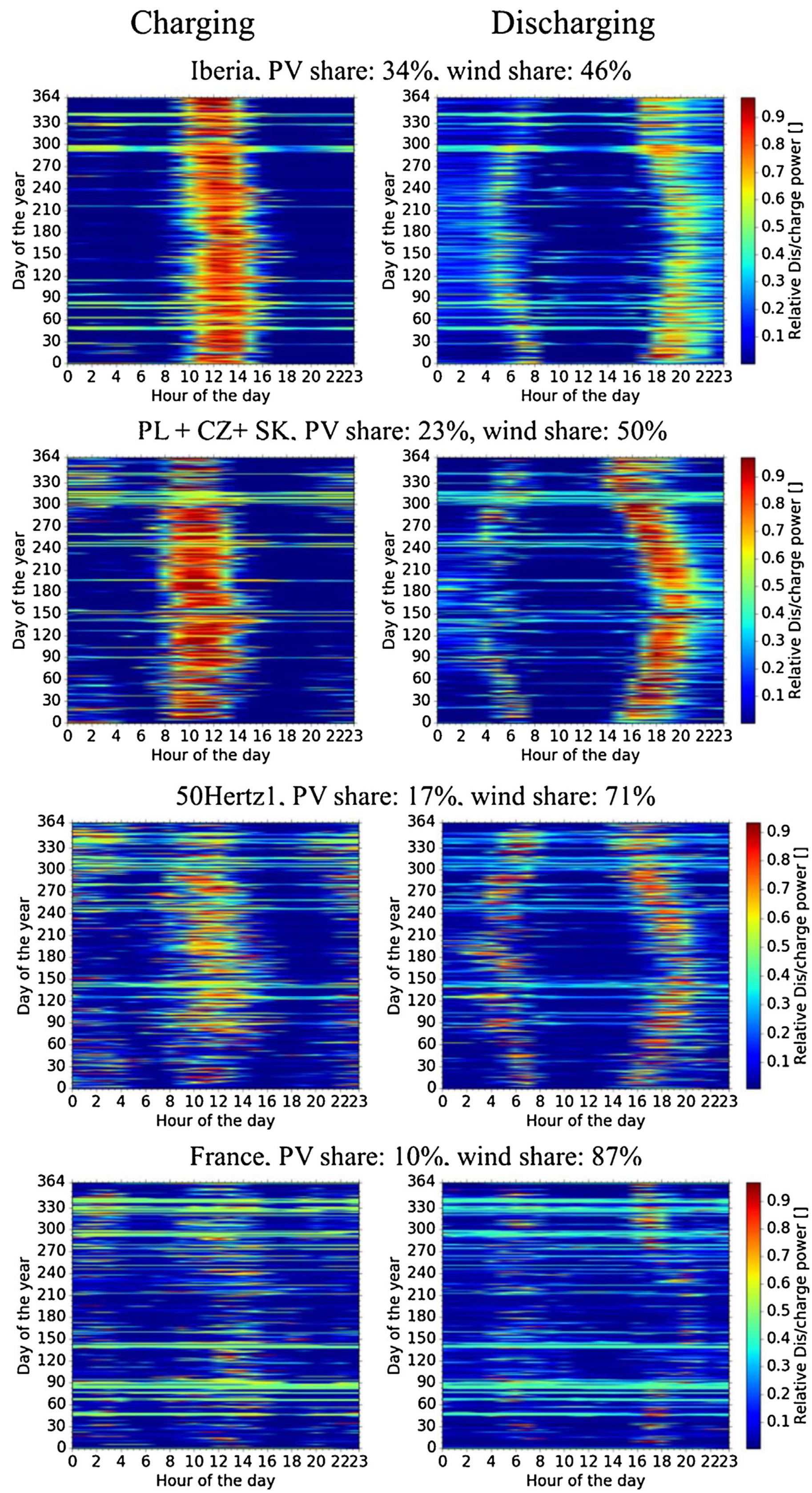

Fig. 10. Normalized charge (left panels) and discharge power (right panels) over the hours of the day and over the days of the year of Li-ion batteries in the model-regions Iberia, PL + CZ + SK, 50 Hertz1, and France.

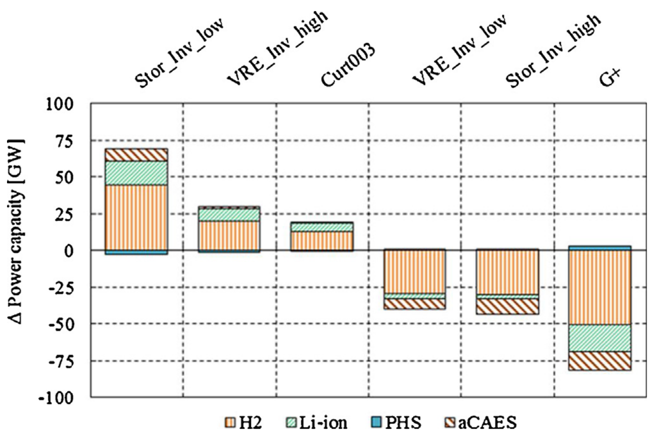

Fig. 11. Selected sensitivity tests: differences in the installed capacity of storage power capacity compared to the reference scenario aggregated over all model-regions.

is caused by the ability of trans-continental grids and medium-term storage to balance the synoptic variability of wind, whereas daily fluctuations of PV can only be smoothed by short-term storage (or a global grid, which, most likely, is economically not feasible).

The outcome of the sensitivity analysis supports the coherence of the optimization results and the underlying model assumptions. In comparison to the overall installed EES capacity in the reference scenario (166 GW, see Sec. 3.2), the variations shown in Fig. 11 are notable (for StorInv_low +32% and for G+ -39%). Nevertheless, Fig. 11 only depicts the most influential scenarios (regarding storage capacity); other sensitivity cases—such as fuels or CO_2 emission certificate variations—only show minor effects (see Sec. 10 of the Supplementary material). Moreover, the findings from Sec. 3 (spatial storage distribution and dispatch) remain robust over all scenarios.

4.2. Limitations and outlook

Ranges for EES capacity in the literature vary widely, driven by different methodologies, as well as model and data assumptions. The endogenously derived EES capacities aggregated over all model-regions (166 GW, 30 TWh, excluding existing capacities) are in line with some studies (I), while others result in significantly lower (II), or higher (III, IV) storage capacities.

(I) Scholz et al. [13] use the same model as this study, assume similar model-regions, and quantify EES capacities for various theoretical (before curtailment) VRE shares and solar-(PV and CSP)-to-wind ratios, including endogenously derived transmission grid capacities. We, therefore, compare their results to scenario G+. The latter is characterized by a theoretical VRE share of 87% and a storage power (endogenously expansion, no stock capacities) of 87 GW. The authors derive similar results for storage power; 93 GW in a 100% VRE share scenario and 58 GW in a 80% VRE share scenario, both assuming solar-to-wind ratios of 0.25.

(II) Though analyzing a larger observation area (EU27), the cost minimizing model of Bertsch et al. [28] results in lower EES power (68 GW, scenario B: high CO_2 prices), which mainly can be explained by the lower VRE share of 75%.

(III) The analysis of Bussar et al. [12] results in 1060 GW of EES power, including PHS, battery systems, and the capacity of CCGT for the reconversion of H_2 (excluding the electrolyzer capacity). Again, we stress that comparability is limited, as Ref. [12] assumes a 100% VRE share and analyzes a larger observation area, which, compared to this study, additionally includes East and South-East Europe, Turkey, North Africa, and the Middle East. Furthermore, the model assumes that at least 80% of each country's electricity demand is supplied by national resources. This assumption limits long-range load and generation balancing and thus increases the demand for EES.

(IV) The analysis of Hartman [48] derives storage requirements for Germany, assuming no transmission grid restrictions within the model-region (*copper plate*). While storage energy capacity is similar (5.4 TWh, in the scenarios with unrestricted curtailments), storage power is more than double (66 GW), even though the renewable share (regarding the annual gross electricity demand) is lower (80%) than in our calculations. However, Hartman [48] does not include power exchange via the transmission grid to neighboring countries. The latter has—as shown in our analysis and in other recent literature (see e.g. [13,51])—a major impact on storage requirements.

Subsequently, we discuss whether some aspects of the chosen methodology and the assumptions might influence the derived EES capacity.

First, the results of the sensitivity analysis already indicate that grid expansion reduces the demand for EES (see Fig. 11, scenario G+). Including more flexibility options (e.g. demand side management) and incorporating the coupling to other energy-related sectors (e.g. heating, cooling, and transportation) is likely to decrease the demand for EES (see e.g. [29]).

Second, the proposed method solely includes the high voltage transmission grid and, in consequence, neglects distribution grid restrictions within the defined model-regions (*copper plates*). Thus, additional EES requirements on the distribution grid level are not taken into account. We tackle this issue by using a high number of model-regions which reduces the size of each copper plate. However, the uneven disaggregation of countries into model-regions (e.g. 20 German model-regions compared to one model-region for France) might lead to over- or underestimation of grid restrictions and thereby affects EES requirements. A recent paper by Hörsch and Brown [70] studies the effect of spatial aggregation, clustering Europe into different numbers of model-regions. The authors find that—in case of no transmission grid expansion (which is comparable to our reference scenario)—the amount of model regions does not influence storage requirements significantly. In the light of existing research, the effect of distribution grids and spatial resolution has not yet been analyzed for European long-term energy scenarios.

To answer the question of *optimal* spatial distribution of storage capacity, the simultaneous endogenous capacity expansion and dispatch optimization for generation technologies and flexibility options using a high level of temporal, spatial, and technological resolution is a novelty. Despite the aforementioned limitations, the analysis, therefore, is an adequate remedy to answer the research question. Additionally, promising research topics include the question whether storage power capacity is mainly determined by charging or discharging power. This could be achieved by enhancing the modeling approach to two decision variables for storage power capacity.

5. Summary and conclusions

We applied the linear, cost minimizing optimization model REMix which endogenously determines the installed capacities and dispatch of all power generation and electrical energy storage in a system with at least 80% power production from variable renewable energies. The analysis region comprises northern, western, south, southwest, and central Europe. Furthermore, we investigated the spatial distribution of those storage capacities and their dispatch in detail.

The model results in storage power capacity that is mainly provided by hydrogen storage and lithium-ion batteries. Adiabatic compressed air and pumped hydro storage can play a role for regions with higher shares of mid-term fluctuations through onshore wind, provided that sufficient energy capacity expansion potentials are available (e.g. salt caverns or water reservoirs). In this analysis, redox-flow batteries only play an insignificant role for power balancing, mainly due to the more favorable techno-economic parameters of lithium-ion batteries and compressed air storage.

From this analysis, we also conclude that the spatial distribution of storage capacity expansion is mainly influenced by two factors (see next paragraphs); model-based quantifications, therefore, should carefully consider these aspects in their assumptions.

First, the temporal characteristics of the electricity generation from variable renewable energy sources heavily influence the expansion of storage. In general, surpluses from variable renewable power, i.e. negative residual loads, highly correlate with storage charging in all model-regions. In this sense, the shape of the negative residual load—typically defined by the predominance of a certain variable renewable energy technology—triggers the need for either short, mid, or long-term storage (or a combination of all three if the residual load is characterized by multiple VRE technologies). More precisely, we observed high correlations between the generation of offshore wind and hydrogen storage charging, onshore wind with hydrogen and compressed air, and, finally, between PV generation and lithium-ion battery charging. These correlation coefficients can be explained by the energy-to-power-investment-ratio of each storage technology.

Second, the results further show that limited technical potentials with respect to storage energy capacity of one technology have an influence on the local, region-specific allocation of other storage technologies. In particular, limited technical potentials for pumped hydro can be substituted by compressed air and stationary lithium-ion storage, if necessary.

For storage utilization, the results show typical dispatch patterns of different storage technologies: while lithium-ion batteries in PV dominated regions (e.g. Iberia) generally cycle daily, onshore wind regions (e.g. PL + CZ + SK) are characterized by mid-term balancing of compressed air storage with typical cycle lengths of three to five days. In contrast, hydrogen storage shows a more seasonal behavior with typical cycle lengths around 45 days. Our results highlight that all three storage technologies have similar characteristic dispatch patterns in all model-regions. The utilization of lithium-ion batteries, however, depends on the generation share of wind and PV generation. In regions with high shares of wind we observed a dual use of lithium-ion storage, where this technology not only balances the daily fluctuation of PV feed-in but additionally is used to level the more diurnal and seasonal volatile generation from wind power.

Our results have a number of implications for policy makers and long-term energy system planning.

First, we underline the need for electricity storage in energy systems characterized by high shares of VRE (>80%). Even if such systems are highly interconnected, electricity storage is still required. Storage becomes yet more valuable if grid expansion projects get delayed.

Second, while short and medium-term storage is required to balance daily and weekly fluctuations from PV and onshore wind, hydrogen storage is particularly important for longer periods of low solar irradiation and wind speeds (*dark doldrums*). Therefore, and, as an ideal storage technology does not exist, support schemes for R&D should not only focus on a limited set of technologies, but rather support a broad range of options to find an optimal storage mix.

Third, our analysis indicated promising storage options. However, some, in our results under-represented technologies (e.g. redox-flow), can become cost-competitive, if experience curves enable future cost reductions. In this sense, particular R&D efforts exist to decrease storage costs, increase efficiencies, and to address limiting aspects, such as life time (batteries), flexibility (electrolyzers), and demand for critical resources (batteries).

Finally, policy support mechanisms for storage should not be limited to mere investment grants, but rather incentivize the system friendly operation of storage and reduce regulatory barriers.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.est.2017.10.004.

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