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Wind power decreases the need for storage in an interconnected 100% renewable European power sector

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Abstract

The massive expansion of wind power and solar PV is the primary strategy to reduce greenhouse gas emissions in many countries. Due to their variable generation profiles, power sector flexibility needs to increase. Geographical balancing enabled by electricity grids and temporal flexibility enabled by electricity storage are important options for flexibility. As they interact with each other, we investigate how and why interconnection with neighboring countries reduces storage needs. To do so, we apply a cost-minimizing open-source capacity expansion model to a 100% renewable energy scenario of central Europe. We use a factorization method to disentangle the effect of interconnection on optimal storage through distinct channels: differences in (i) countries' solar PV and wind power capacity factors, (ii) load profiles, as well as (iii) hydropower and bioenergy capacity. Results show that geographical balancing lowers aggregate storage capacities by around 30% in contrast to a similar system without interconnection. We further find that the differences in wind power profiles between countries explain, on average, around 80% of that effect. Differences in solar PV capacity factors, load profiles, or country-specific capacities of hydropower together explain up to 20%. Our analysis improves the understanding of the benefits of geographical balancing for providing flexibility and its drivers.

Keywords: variable renewable energy sources, electricity storage, interconnection, numerical optimization, 100% renewable energy

JEL: C61, Q42, Q49

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1. Introduction

The massive expansion of renewable energy sources is a major strategy to mitigate greenhouse gas emissions [1]. Thus, many countries have ambitious targets for increasing renewable shares in the power sector [2]. For example, the G7 countries aim for “achieving a fully or predominantly decarbonised power sector by 2035” [3]. As the potentials for firm renewable generation technologies such as geothermal and bioenergy are limited in most countries, much of the projected growth needs to come from variable renewable energy sources, i.e., wind power and solar photovoltaics (PV) [4]. As these depend on weather conditions and daily and seasonal cycles, their electricity generation potential is variable [5]. Increasing their share in the electricity supply thus requires additional flexibility of the power system to deal with their variability [6]. Spatial balancing, i.e. transmission of electricity between different regions and countries, is a particularly relevant flexibility option [7]. This allows for balancing renewable variability over larger areas, using differences in temporal load and generation patterns. Aside from such spatial flexibility, various temporal flexibility options can be used to manage the variability of wind and solar power, particularly different types of electricity storage [8]. Both geographical and temporal balancing can help to integrate renewable surplus generation and to meet positive residual load that could not be supplied by variable renewable sources available at a particular location.

From a techno-economic perspective, geographical balancing, using the electricity grid, and temporal balancing, using electricity storage, are substitutes to a certain degree. Therefore, the need for storage capacities in a specific region decreases if electricity can be exchanged with neighboring areas that have different weather and demand patterns. In an application to central Europe, we investigate the interactions between geographical and temporal balancing, enabled by electricity storage, in a future 100% renewable energy scenario. We analyze how interconnection with neighboring countries mitigates electricity storage requirements. First, we quantify the substitution effect between interconnection and storage, define several factors driving the decline in optimal storage capacities in a larger balancing area, and then quantify their importance. We differentiate between “short-duration” storage, parameterized as lithium-ion batteries, and “long-duration” storage, parameterized as power-to-gas-to-power storage.

We focus on five different factors to explain the storage-reducing effect of geographical balancing: differences between countries in hourly capacity factors of (1) wind and (2) solar power, which are a function of spatially heterogeneous weather patterns and daily and seasonal cycles; (3) hourly time series of the electric load; and the availability of specific technologies such as (4) hydropower and (5) bioenergy that differ due to geographic or historical factors.

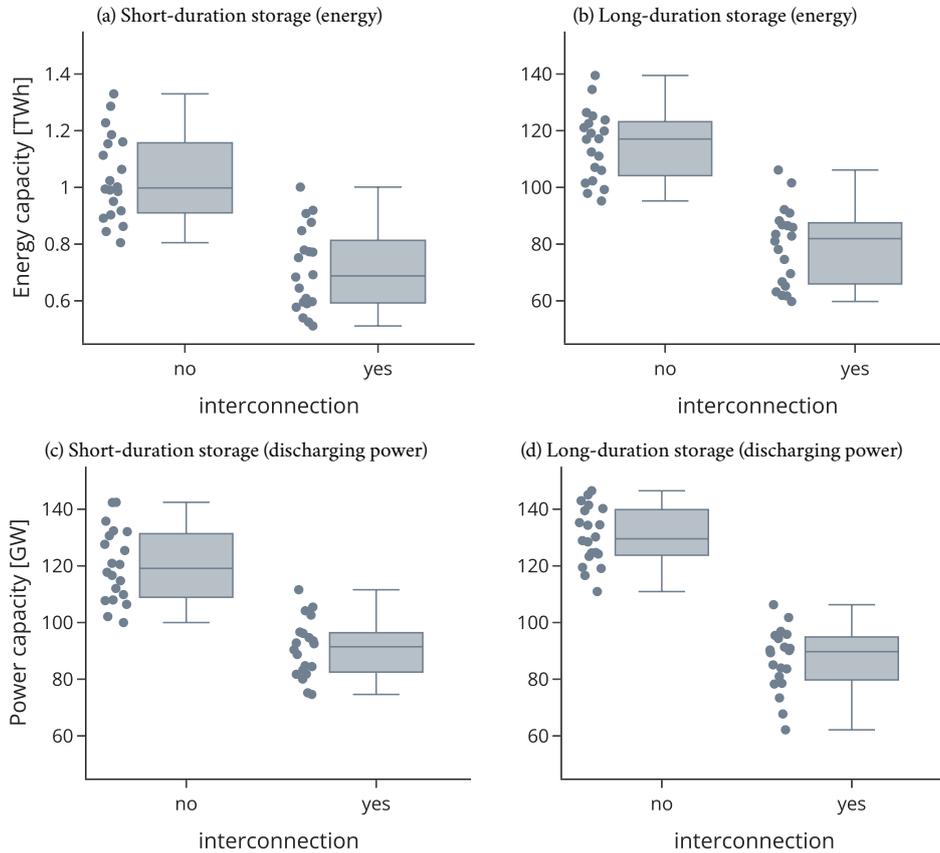
We use an open-source numerical capacity expansion model of the European electricity system that minimizes total system costs of providing electricity for one year in an hourly resolution. The model endogenously determines the optimal dispatch and investment, considering hourly market clearing and a range of technical and policy-related constraints. We focus on central Europe, covering twelve European countries connected in a net transfer capacity model. For increased robustness, our analysis considers ten weather years from a 30-years period.

Several studies have estimated electricity storage needs in Europe in scenarios with high shares of renewables. Literature reviews identify a positive, linear relationship between renewable electricity shares and optimal electricity storage deployment [9, 10]. Focusing on single countries, such as Germany, various analyses find that storage needs depend on the model scope and the availability of other flexibility options [11–14]. Other studies investigate how much storage is needed in the wider European power sector. While results again depend on model and technology assumptions, studies covering several European countries imply relatively lower storage needs than analyses focusing on a single country only [4, 15–17]. Other analyses investigate the need for electricity storage in the U.S. For instance, long-duration storage requirements in Texas increase with growing penetration of variable renewable energy sources [18, 19]. Related studies derive similar findings and also conclude that interconnection decreases storage needs, focusing on other parts of the U.S. [20] or the whole of the United States [21–23]. Similarly, geographical balancing and electricity storage are identified as partial substitutes in a model analysis of the North-East Asian region [24]. This substitution is considered to be particularly feasible for long-duration storage technologies [25]. However, none of these studies focuses primarily on quantifying the effect of interconnection on storage needs or on isolating individual drivers.

Hence, we contribute to the literature by, first, illustrating how spatial flexibility influences the need for temporal flexibility in Europe. Second, to the best of our knowledge, we are the first to quantify how different factors contribute to the reduction in storage capacity caused by geographical balancing. Third, to identify the magnitude of the different channels, we use an adapted “factor separation” method that is used to explain climate model outcomes [26, 27]. As there is so far no established method to attribute outcomes of power market models to changing parameters, we propose a modified procedure that builds on counterfactual scenarios and factor separation, which could also be used in other energy modeling applications. To the best of our knowledge, we are the first to employ factor separation in the context of energy modeling.

2. Results

2.1. Geographical balancing reduces optimal storage power and energy capacity



Notes: The figure shows storage capacities (energy and discharging power) aggregated over all countries. Every dot is the scenario result based on one weather year. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile.

Figure 1: Aggregate installed storage energy and discharging power capacity

We find that aggregated optimal storage capacity is substantially lower in an inter-connected system than in a system of isolated countries (Figure 1). This applies to both short- and long-duration storage, as well as to storage discharging power and energy. Interconnection reduces optimal energy capacity need of short- and long-duration storage on average by 31% over all years modeled. Discharging power, on

average, decreases by 25% for short-duration and by 33% for long-duration storage. This translates to a reduction of 36 TWh in storage energy and 74 GW in storage discharging power (short- and long-duration storage combined) for the modeled interconnected central European power sector with 100% renewable energy sources.

These results confirm previous findings in the literature that a system with interconnection requires less storage than a system without, or put differently, that a larger balancing area mitigates storage needs. We show that this also holds in a 100% renewable energy scenario. Even if the variation of results between weather years is substantial, our results further indicate that this effect is robust to different weather years. For instance, optimal long-duration storage energy varies between 95 TWh and 140 TWh depending on the weather year.

2.2. Wind power is the largest driver for mitigating storage needs

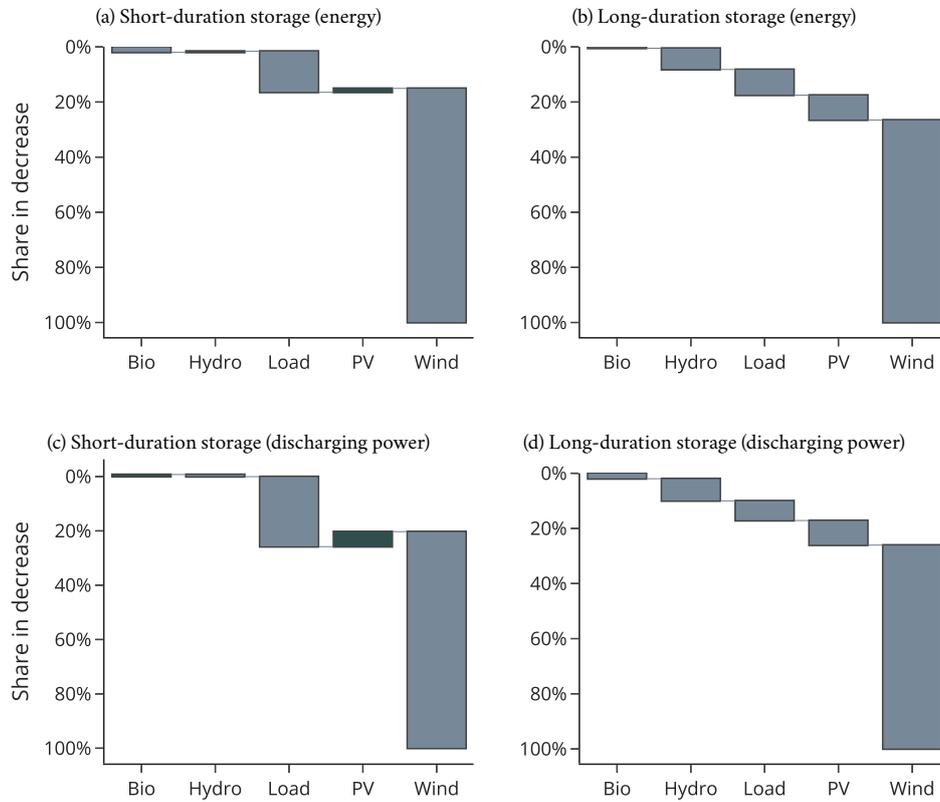


Figure 2: Average (of all weather years) relative contribution of different factors to the change in storage energy and discharging power capacity related to interconnection.

Using counterfactual scenarios and a factorization method (more information on that in Section 4.2), we can attribute the decrease in optimal storage needs to individual factors. Wind power contributes by far the most, namely 80%, to reducing storage discharging power and energy (Figure 2).

Especially for short-duration storage, differences in load profiles also contribute substantially to the storage-mitigating effect of interconnection. These account for 26% of the decrease in short-duration storage discharging power (Figure 2c). In contrast, differences in PV even have a small increasing effect on short-duration storage energy and discharging power. Allowing for transmission between countries may increase

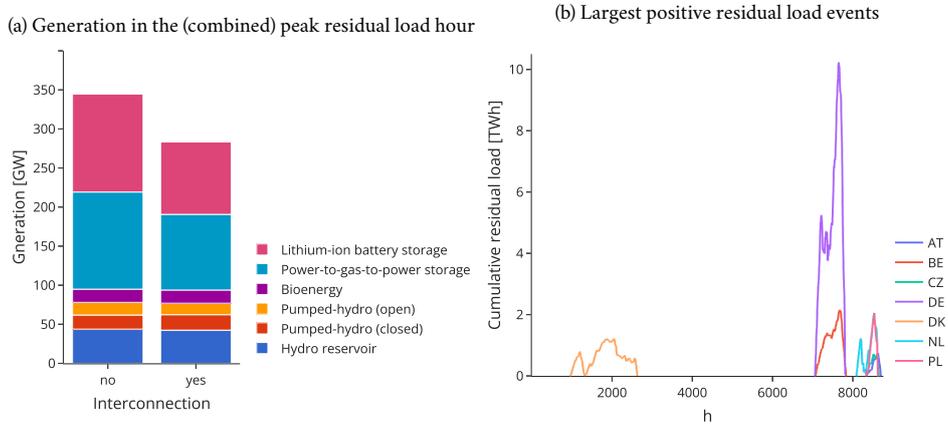
optimal overall PV investments, all other factors being constant and homogenized; this is because capacities grow in countries with higher PV full load hours, i.e., with lower PV costs. In turn, the need for short-duration storage then increases compared to a setting without transmission between countries because of higher diurnal fluctuations.

In the case of long-duration storage, all investigated factors contribute to the reduction of optimal storage investments enabled by interconnection. While wind power is again clearly dominating, differences in hydropower capacity, load curves, and PV time series almost equally contribute to reducing storage needs.

While Figure 2 depicts average values, using ten weather years, results for individual years vary (Figure SI.I). Especially the contribution of wind power strongly differs between weather years. However, the relative contributions of the factors are qualitatively robust. In all analyzed weather years, we find that wind power is the dominating factor.

Figure 2 (and Figure SI.I) show the already aggregated factors. In the supplemental information SI.5, Figure SI.II shows the magnitude of all factors from the factorization in all weather years, Figure SI.III of the weather year 2016.

2.3. An explanation of key mechanisms



Notes: Both panels show data for the weather year 2016. Left panel: The left bar shows the sum of electricity generation in the different countries' peak residual load hours, and the right bar shows the system-wide generation in the peak residual load hour of the interconnected system. Both bars depict the aggregate values of all countries. Right panel: The largest positive residual load event and the shape of each country is shown. Countries with large hydro reservoirs are excluded as they have fundamentally different residual load events. Due to the existence of reservoirs, they accumulate large positive residual load events over the year.

Figure 3: The drivers of reduced storage need: peak residual load hours and positive residual events

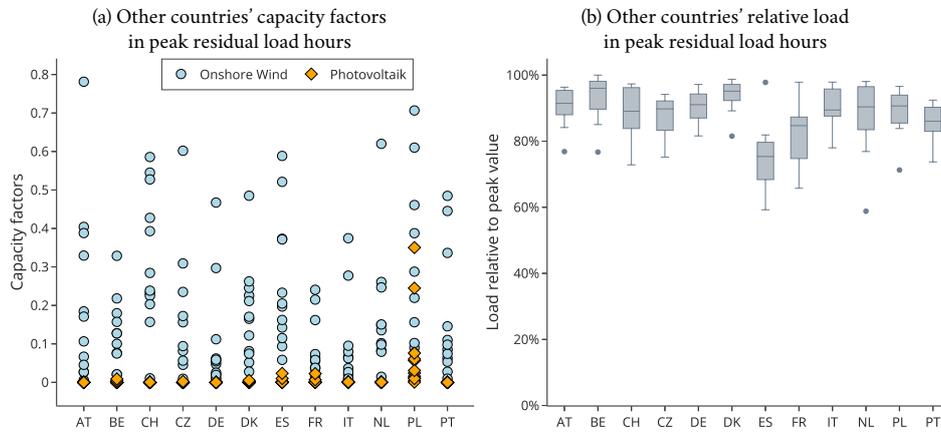
To explain these results, we illustrate the key mechanisms using the weather year 2016. We turn to the peak residual load hour as a central driver to explain the drop in optimal storage discharging power capacity through interconnection. The peak residual load hour is defined as the hour in which residual load (i.e., load minus generation by variable renewable sources) is largest in a year. In an energy system based on 100% renewables and high shares of wind and solar power, load in that critical hour has to be provided mainly by storage. Hence, the residual load peak hour determines the required storage discharging power capacity.

An energy system with interconnection needs less storage discharging power because the peak residual load hours do not necessarily coincide in all countries. The overall needed storage discharging power in a system without interconnection is the sum of the countries' individual peak residual loads. In contrast, in an interconnected system, peak residual load hours in individual countries could be balanced out by

geographical balancing. The left bar of Figure 3a shows the sum of electricity generation in the different countries' peak residual load hours, while the right bar shows the system-wide generation in the peak residual load hour of the interconnected system. The two differ because peak residual load hours do not align in the different countries. Implicitly, this reasoning assumes that there would be no limit on interconnection capacity between countries. In our case, net transfer capacities (NTC) are limited, so the residual peaks cannot be balanced out completely. Yet, even with limited interconnection, the non-aligned peak residual load hours of the different countries help to reduce residual storage discharging power needs.

Regarding the need for storage energy, a similar reasoning applies. The size of needed storage energy is (roughly) determined by the largest positive residual load event. We define a positive residual load event as a series of consecutive hours in which the cumulative residual load stays above zero. It may be interrupted by hours of negative residual load as long as the cumulative negative residual load does not outweigh the positive one. As soon as it does, the positive residual load event is terminated. These events typically occur when sunshine and wind are absent for long periods.

An energy system with interconnection needs less storage energy if the countries' largest positive residual load events do not fully coincide. In this case, geographical balancing can help to flatten out these events. Yet, in a system without interconnection, all these events have to be covered in each country individually; hence the aggregate storage energy need in a system without interconnection is the sum of every country's largest positive residual load event and, therefore, higher than in a system with interconnection. Figure 3b depicts the large positive residual load events for the year 2016 for different countries. Although some events overlap between the countries, many do not and thus help reduce the need for storage energy capacity.



Notes: Both panels show data for the weather year 2016. Right panel: The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile.

Figure 4: Illustration of main drivers: wind power, PV, and load

The decrease in peak residual load and also in the largest residual load events are, in turn, largely driven by the heterogeneity of wind power between countries. In the hour of a country's highest residual load, onshore wind power capacity factors of most countries are still relatively high, so geographical balancing could help to make use of them (Figure 4a). In contrast, this is hardly the case for PV capacity factors. The peak residual load hour of most European countries is likely to be in the winter when demand is high, but PV feed-in is low. Thus, wind power can contribute more to covering the peak residual hour than PV.

Load profiles also differ to some extent, such that relatively lower loads in other countries in combination with transmission can help to relieve the peak demand in a given country. During a peak residual load hour in a given country, we show the load (not residual load) relative to its maximal value in that year (Figure 4b). Most values range above 80%, indicating a positive but limited flexibility potential related to (peak) residual load balancing using interconnection.

Hydropower, a combined factor of hydro reservoirs, pumped-hydro, and run-of-river, has only a limited influence on storage reduction through interconnection. It

could, in general, be an important provider of flexibility to the system. Yet, the reason for its limited importance is that installed hydro capacities are not big enough to substantially reduce the need for storage power and energy capacity (see Table SI.III). This result may change under the assumption that the capacity of hydropower could be extended far beyond current levels. Then, this factors hydropower could play a bigger role. This is also true for bioenergy, which we do not discuss here explicitly due to its minor effect.

3. Discussion

Identifying future electricity storage needs is highly relevant for planning deeply decarbonized, 100% renewable power systems [28]. Using an open-source numerical model, our results show that optimal electricity storage capacity in central Europe substantially decreases when interconnection between countries is allowed. Compared to a setting without interconnection, short- and long-duration storage energy capacity decreases by 31%; storage discharging power, on average, declines by 25% and 33%, respectively. These values hold for an average of ten weather years, covering three decades of historical data. Our outcomes corroborate and extend findings in the previous literature and show that the storage-mitigating effect of geographical balancing also holds in a 100% renewable energy scenario. Yet, we go a step further by also disentangling and quantifying how the mitigation of storage needs is driven by different factors. To do so, we use a factorization approach used, for instance, in climate modeling [27]. To the best of our knowledge, this is the first time such an approach is adapted to a quantitative power sector model analysis.

We find that wind power is by far the most important factor in reducing optimal storage needs through geographical balancing. Its heterogeneity between countries accounts, on average, for around 80% of reductions in storage energy and discharging power capacity needs. The main reason is that during peak residual load hours of a given country, which largely determine electricity storage needs, wind power availability in neighboring countries is still relatively high. Accordingly, geographical balancing helps to make better use of unevenly distributed wind generation potentials in an interconnected system during such periods. Differences in the profiles of solar PV and load, as well as in power plant portfolios (hydropower and bioenergy),

contribute to the mitigation of storage needs to a much smaller extent. Though our analysis focuses on central Europe, we expect that qualitatively similar findings could also be derived for other non-island countries in temperate climate zones where wind power plays an important role in the energy mix.

As with any numerical analysis, our investigation comes with some limitations. First, we may underestimate storage needs due to averaging over specific weather years. In the real world, system planners may pick only scenarios with the highest storage need to derive robust storage capacity needs. Likewise, planners may also want to consider an extreme renewable energy drought for storage dimensioning, i.e. a period with low wind and solar availability. In case such a renewable energy drought similarly affects all countries of interconnection, the storage-mitigating effects may decrease. Second, we exclude demand-side flexibility options. In particular, we do not consider future sector coupling technologies such as battery-electric vehicles or heat pumps, which may induce substantial additional electricity demand, but possibly also new flexibility options. Temporally inflexible sector coupling options may substantially increase storage needs [8]. Thus, we might overestimate the role of interconnection in mitigating storage. To investigate how this would interact with storage mitigation via geographical balancing is a promising area for future research. Third, optimization model results depend on input parameter assumptions. For instance, we assume fixed interconnection capacities (Table SI.IV). Larger NTC values may even increase the storage-mitigating effect of interconnection as additional flexibility from other countries would become available. Moreover, our analysis does not differentiate between the “level” and “pattern” effects of wind and solar PV profiles. In our counterfactual scenarios, we implicitly change both the patterns and the levels of wind and solar PV availability. Further analysis could disentangle these two factors and quantify this relative importance to better understand what exactly drives storage mitigation through wind and solar PV.

Our analysis fosters an understanding of the benefits of geographical balancing and its drivers. The findings may also be useful for energy system planners and policymakers. We reiterate the benefits of the European interconnection and argue that strengthening it should stay an energy policy priority if a potential shortage of electricity storage is a concern. Then, policymakers and system planners may particularly

focus on such interconnection projects that facilitate the integration of wind power.

Finally, some modeling-related conclusions can be drawn. Any model analysis where wind power plays a role should properly consider geographical balancing in case storage capacities are of interest. Our analysis also indicates the importance of using more than one weather year in energy modeling with high shares of variable renewables. Not least, we hope to inspire other researchers to use factorization methods in energy modeling applications more widely.

4. Experimental procedures

4.1. Definition of factors

The basic principle to quantify how different factors impact optimal storage through interconnection is the use of counterfactual scenarios, in which the state of these factors is varied. In general, two states *not harmonized* and *harmonized* exist, in which, in the latter, all countries are made equal to eliminate the variation between countries.

We define five factors within three channels we believe are most relevant. Within in channel “supply”, there are the two factors “wind” and “PV”, the channel load coincides with the factor “load”, and the channel “power plant portfolios” contains the factors “hydropower” and “bioenergy”. A sixth factor “interconnection” is defined not for explanation but only for the operationalization of the analysis.

4.1.1. Interconnection

This factor, like all factors investigated, has two possible states: if interconnection is allowed, the interconnection capacities between countries are fixed, as given in Table SI.IV. If interconnection is not possible, no electricity can flow between countries.

4.1.2. Supply: wind and PV patterns

The factor related to PV and wind patterns are operationalized with the help of capacity factors and can take two different states: *not harmonized* or *harmonized*. In the state *not harmonized*, every country has its own capacity factor time series, as given for that specific weather year. In the state *harmonized*, capacity factors are equal in all countries. In the case of *harmonized* solar PV, PV capacity factors are equal in all countries using those of pour reference country Germany. Hence, all variation between countries in solar PV capacity factors is taken away.

In general, the same logic applies to wind power, but here we also have to account for offshore wind power, which cannot be deployed in all countries. In the state *harmonized*, we apply German offshore wind capacity factors using German values in all countries. In addition, we assume a fixed share of wind offshore capacity for every country. That means that even countries without sea access, e.g., Austria or Switzerland, deploy offshore wind in these counterfactual settings.

That share is defined as installed capacity divided by the total yearly load. We use the total yearly load as the denominator as it is not related to the power plant fleet but is still country-specific. If we used the share of installed power plant capacity, the model would be incentivized to change the total power plant fleet.

This share is the optimal share of offshore wind power that Germany would install in a counterfactual scenario without interconnection in a 100% renewable setting. Applying this share to all countries, we treat them as “clones” of our reference country Germany and thereby, we “switch off” the effect of offshore wind within the wind factor.

4.1.3. Demand: load patterns

The operationalization of the load factor is similar to solar PV and wind power. In the state *harmonized*, all countries have the same load time series as our reference country, yet scaled to their original total yearly demand. Therefore, in the state *harmonized*, all countries have the same load profile (same as the reference country Germany) but on country-specific levels.

4.1.4. Power plant portfolios

With the “portfolio” channel, we aim to quantify how much of the storage capacity reduction can be attributed to specifics of the existing power plant portfolios because of legacy capacities and limited potentials. We focus on two power plant technologies we assume to be exogenous and dependent on geographic factors: (1) hydropower, comprising reservoirs, pumped-hydro, and run-of-river, and (2) bioenergy. These are considered to be exogenous, some countries happen to have them while others do not, and their potentials can be (largely) regarded as exogenous.

In the state *harmonized*, all countries have the same share of installed power plant

capacities of the respective technologies. We make all countries “as if they had a power plant portfolio like Germany in isolation”. In the case of hydropower, we also assume the German hydro times series for the other countries. For bioenergy, we only impose shares and do not constrain the generation pattern.

These shares are determined based on a scenario run of our reference country Germany in isolation. We calculate the relative weight of the exogenous technologies as a share of installed capacity over the total yearly load. In the state *harmonized* of the factors “hydropower” and “bioenergy”, this share is applied to all countries.

4.2. Factorisation method

Factorization (also known as ‘factor separation’) is used to quantify the importance of different variables concerning their changes in a system. In complex systems, where more than one variable is altered simultaneously, it can be used to identify the importance of these variables for the changes in outcomes. Therefore, it can be used to analyze the results of numerical simulations [27].

There are several factorization methods, and our analysis builds on the factorization method by “Stein and Alpert (1993)” [26] and its extension, the “the shared-interactions factorization” [27]. The basic principle of factorization relies on comparing the results of various counterfactual scenarios to separate the influence of different factors on a specific outcome variable. For a broader introduction to factor separation, we refer to the Supplemental Information (SI.3) and to a recent paper providing an excellent introduction and overview [27].

To decompose the changes in storage needs, we define six factors that will impact the need for storage. Each factor can take two different states:

- (1) Interconnection: allowed / not allowed
- (2) Wind: harmonized / not harmonized
- (3) PV: harmonized / not harmonized
- (4) Load: harmonized / not harmonized
- (5) Hydropower: harmonized / not harmonized
- (6) Bioenergy: harmonized / not harmonized

In contrast to typical previous applications of factorization, we are not interested in the *entire* effect of each factor on storage needs. To identify which factors are most important in influencing storage needs through interconnection, we focus on the “interaction terms” between interconnection (1) and the other factors (2)-(6).

To identify the influence of the factors, we run several counterfactual scenarios. For example, in one extreme scenario, denoted as f_0 , all factors are “harmonized” and no interconnection is possible. This makes all modeled countries very similar, e.g., they have the same capacity factors, load patterns, and equal relative installed hydropower and bioenergy capacities. A similar system, yet with interconnection allowed, is noted as f_1 . Following that logic, scenario f_2 resembles f_0 , except for factor (2), i.e., wind power is not harmonized. In the same fashion, we can define all other scenarios. For instance, f_{12} denotes the scenario where interconnection is allowed, and wind capacity factors are not harmonized, yet the rest is. Of all possible scenarios, two are of special interest:

- f_{123456} : This scenario can be regarded as our “default” scenario with no capacity factors or power plant portfolios being harmonized and interconnection between countries allowed.
- f_{23456} : This scenario equals the previous, with the only difference that interconnection between countries is not allowed. Thus, all countries operate as electric islands.

We aim to explain the difference in optimal storage energy and power between these two scenarios f_{123456} and f_{23456} , and to attribute it to the different factors (2)-(6). For this, we calculate the size of interaction factors between factor (1), interconnection, and the other factors (2)-(6).

The size of the individual factors can be calculated as differences between different scenario runs. These are denoted $\hat{f}_1, \hat{f}_2, \dots, \hat{f}_{12}, \dots$, etc. \hat{f}_1 is the sole effect of factor (1) by comparing the scenarios f_0 and f_1 :

$$\hat{f}_1 = f_1 - f_0. \quad (1)$$

The definition of interaction effect is more complicated and takes several scenarios

into account. For instance, the combined effect of the factors (1), (2), and (3), denoted \hat{f}_{123} , is defined as:

$$\hat{f}_{123} = f_{123} - (f_{12} + f_{13} + f_{23}) + (f_1 + f_2 + f_3) - f_0 \quad (2)$$

Put in words, \hat{f}_{123} measures *only* the *combined* influence of (1) interconnection, (2) wind, and (3) PV on storage need, hence the interaction effect. The (direct) effects of the factors (such as \hat{f}_1) are not comprised.

To quantify the importance of different factors of interconnection on storage, we want to separate the “difference of interest” (INT), which we define as:

$$\text{INT} = f_{123456} - f_{23456}. \quad (3)$$

It can be separated into the sum of all interaction factors between the different factors (2)-(6) and the interconnection factor (1), hence comprising at least factor (1). It can be shown that the difference INT is just the sum of all the interaction factors where interconnection is involved in:

$$\begin{aligned} \text{INT} = & \hat{f}_1 + \hat{f}_{12} + \hat{f}_{13} + \cdots + \hat{f}_{16} + \hat{f}_{123} + \cdots + \hat{f}_{156} \\ & + \hat{f}_{1234} + \cdots + \hat{f}_{1456} + \hat{f}_{12345} + \cdots + \hat{f}_{13456} + \hat{f}_{123456}. \end{aligned} \quad (4)$$

To calculate the contribution of one of the factors on the difference of interest, INT, we “collect” all interaction effects between the factor interconnection (1) and that other factor. For instance, to quantify the contribution of the factor wind (2), we sum up all interaction effects that include the factors interconnection (1) and wind (2). The principal interaction effect \hat{f}_{12} is part of it, but, e.g., also the interaction effects between interconnection, wind, and PV: \hat{f}_{123} . To avoid double-counting, we have to distribute these shared interactions between - in this case - the factors wind and PV. There are different ways to distribute these effects. We use the “shared-interactions factorization” as defined by [27] that distributes the interaction effects equally be-

tween the different factors. Hence, the “total” interaction effect between interconnection and wind can be defined as follows:

$$\hat{f}_{12}^{total} = \hat{f}_{12} + \frac{1}{2}\hat{f}_{123} + \frac{1}{2}\hat{f}_{124} + \dots + \frac{1}{3}\hat{f}_{1234} + \dots + \frac{1}{5}\hat{f}_{123456} \quad (5)$$

Similarly, we can define the interactions between interconnection and PV \hat{f}_{13}^{total} , load \hat{f}_{14}^{total} , hydropower \hat{f}_{15}^{total} , and bioenergy \hat{f}_{16}^{total} .

All these interaction terms add up to our difference of interest:

$$INT = \hat{f}_{12}^{total} + \hat{f}_{13}^{total} + \hat{f}_{14}^{total} + \hat{f}_{15}^{total} + \hat{f}_{16}^{total}. \quad (6)$$

To determine the importance of each factor (wind, PV, load, etc.) in the change of optimal storage need through interconnection, we can calculate their share s . For wind, this shares reads as $s_{wind} = \hat{f}_{12}^{total} / INT$.

As we have defined six factors, we need to run $2^6 = 64$ scenarios for a complete factorization of one weather year. As we perform our analysis for ten weather years, we run 640 different scenarios (see Table SI.V for an illustrative overview).

4.3. Model

We use the open-source capacity expansion model DIETER [29, 30], which has previously been used for various long-term electricity sector planning analyses [e.g., 8, 14, 31–33]. It minimizes total power sector costs for one year, considering all 8760 consecutive hours. DIETER focuses on the temporal flexibility of renewable integration. It assumes unconstrained electricity flows within countries. The model covers 12 central European countries (Figure 5). These are connected with a transport model based on Net Transfer Capacity (NTC).

Endogenous model variables of interest are the installed capacity of on- and offshore wind power and solar PV and the installed capacity of short- and long-term storage, differentiated by storage energy, as well as charging and discharging power. Further model outputs are hourly patterns of electricity generation and curtailment (of renewables), the charging and discharging patterns of storage, and the power exchange

between countries.

Exogenous model inputs include techno-economic parameters such as investment and variable costs, the time series of capacity factors of wind and solar PV, and electricity demand. Electricity demand is assumed to be price-inelastic. To ensure the relevance of our results, we impose certain bounds on the investments of some generation technologies. In particular, we consider the installed storage energy and power capacities of different types of hydropower plants (run-of-river, reservoir, pumped-hydro) and the installed power capacity of bioenergy to be exogenous, without any possibility of additional investments. For bioenergy, there is no cap on produced energy, though. Only a subset of countries can install offshore wind power. In Section SI.1, we provide more details on assumptions and the input data.

For robustness, we do not perform our analysis only for one weather year only but for ten different ones, i.e., 1989, 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, and 2016. Between these weather years, the time series of renewables, load, and hydro-inflow time series differ.

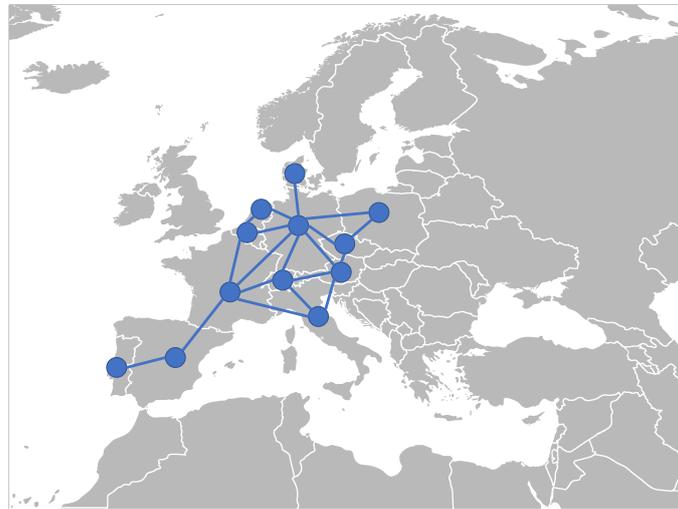


Figure 5: Geographic scope and interconnections

5. Acknowledgments

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GC Workshop 2021, the FSR Summer School 2021, and the YEEES 2022 Copenhagen.
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6. Author contributions

Alexander Roth: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization. **Wolf-Peter Schill:** Conceptualization, Methodology, Investigation, Writing - Original Draft, Funding acquisition.

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SI. Supplemental Information

SI.1. Assumptions and data

SI.1.1. Time series

All time series concerning generation (capacity factors for solar PV, wind on- and off-shore, inflow series for hydropower plants) are taken from ENTSO-E’s “Pan-European Climate Database (PECD)” [1]. The load data is taken from ENTSO-E’s “Mid-term Adequacy Forecast (MAF) 2020” [2].

SI.1.2. Techno-economic parameters for technologies with endogenous capacities

Technology	Thermal efficiency [%]	Overnight investment costs [EUR/kW]	Technical Lifetime [years]
Bioenergy	0.487	1951	30
Run-of-river	0.9	600	25
PV	1	3000	50
Wind offshore	1	2,506	25
Wind onshore	1	1,182	25

Table SI.I: Technical and costs assumptions of installable generation technologies

Technology	Marginal costs of storing in [EUR/MW]	Marginal costs of storing out [EUR/MW]	Efficiency storing in [%]	Efficiency storing out [%]	Efficiency self-discharge [%]	Overnight investment costs in energy [EUR/kWh]	Overnight investment costs in capacity charge [EUR/kW]	Overnight investment costs in capacity discharge [EUR/kW]	Technical lifetime [years]
Lithium-Ion	0.5	0.5	92	92	100	200	150	150	13
Power-to-gas-to-power	0.5	0.5	50	50	100	1	3000	3000	20
Pumped-hydro	0.5	0.5	80	80	100	80	1100	1100	60
Reservoir	-	0.1	-	95	100	10	-	200	50

Table SI.II: Technical and cost assumptions of installable storage technologies

For the principal technical and cost parameters, we rely on previous research [3], and these are shown in Tables SI.I and SI.II. For all technologies (generation and storage), we assume an interest rate for calculating investment annuities of 4%. The assumed power of installed bioenergy capacities is provided by ENTSO-E [4].

SI.1.3. Exogenous generation and storage capacities

Technology	Variable	AT	BE	CH	CZ	DE	DK	ES	FR	IT	NL	PL	PT
Bioenergy	Power [GW]	0.50	0.62	0	0.40	7.75	1.72	0.51	1.93	1.54	0.46	0.85	0.61
Run-of-River	Power [GW]	5.56	0.17	0.64	0.33	3.99	0.01	1.16	10.96	10.65	0.04	0.44	2.86
Pumped-hydro (closed)	Discharging power [GW]	0	1.31	3.99	0.69	6.06	0	3.33	1.96	4.01	0	1.32	0
	Charging power [GW]	0	1.15	3.94	0.65	6.07	0	3.14	1.95	4.07	0	1.49	0
	Energy [GWh]	0	5.30	670	3.70	355	0	95.40	10	22.40	0	6.34	0
Pumped-hydro (open)	Discharging power [GW]	3.46	0	0	0.47	1.64	0	2.68	1.85	3.57	0	0.18	2.95
	Charging power [GW]	2.56	0	0	0.44	1.36	0	2.42	1.85	2.34	0	0.17	2.70
	Energy [GWh]	1722	0	0	2	417	0	6185	90	382	0	2	1966
Reservoir	Discharging power [GW]	2.43	0	8.15	0.70	1.30	0	10.97	8.48	9.96	0	0.18	3.49
	Energy [GWh]	762	0	8155	3	258	0	11840	10000	5649	0	1	1187

Table SI.III: Assumptions on exogenous generation and storage capacities

SI.1.4. Interconnection capacities

link	Installed capacity [MW]
AT_CH	1700
AT_CZ	1100
AT_DE	7500
AT_IT	1470
BE_DE	1000
BE_FR	5050
BE_NL	4900
CH_DE	5300
CH_FR	4000
CH_IT	4850
CZ_DE	2300
CZ_PL	700
DE_DK	4000
DE_FR	4800
DE_NL	5000
DE_PL	3750
DK_PL	500
ES_FR	9000
ES_PT	4350
FR_IT	3255

Table SI.IV: Installed Net Transfer capacities (NTC) in model runs with interconnection

The assumed Net Transfer capacities (NTC) provided in Table SI.IV are taken from [4] (Appendix IV – Cross-border capacities, NTC ST 2040).

SI.2. Model

Our analysis is model-based, using the open-source capacity expansion model DIETER. A short introduction is provided in section 4.3, more details are provided in previous publications [3, 5].

For illustrative reasons, we provide below the formulation of two key equations of the model: the objective function and the energy balance. Before, we provide a non-exhaustive nomenclature of sets, variables, and parameters used in these equations. Variables are defined with uppercase letters and parameters with lowercase letters.

Sets. n is the country set, h the hour set, dis the set of dispatchable generators, nd the set of non-dispatchable generators, and sto the set of storage technologies.

Electricity generation and flows [MW]. $G_{n,dis,h}$ is the generation of the dispatchable generation technology dis in country n in hour h . STO^{out} is the electricity generation (by discharge) of storage technologies, STO^{in} is the charging, and RSV^{out} is the electricity generation (by outflows) of reservoirs. $F_{l,h}$ is the electricity sent over line l in hour h .

Installed generation capacities [MW]. N is the installed capacity of a generation technology. N^{p-out} is the installed discharging capacity of storage technologies, N^{p-in} is the installed charging capacity of storage technologies.

Energy installation variables [MWh]. N^e is the installed energy capacity of storage technologies.

Costs [Euro/MW(h)]. c^m are marginal costs of generation, c^i annualized investment costs of installation power and energy capacities (generation and storage), c^{fix} are the respective annual fixed costs.

Objective function. DIETER minimizes the total cost Z , consisting of variable generation costs (first term), investment costs of dispatchable and non-dispatchable generators (second term), as well as fixed and variable costs of storage (third term). The objective function of the model is given as:

$$\begin{aligned}
Z = & \sum_n \left[\sum_h \left[\sum_{dis} c_{n,dis}^m G_{n,dis,h} + \sum_{sto} c_{n,sto}^m (STO_{n,sto,h}^{out} + STO_{n,sto,h}^{in}) \right. \right. \\
& + c_{n,rsv}^m RSV_{n,rsv,h}^{out} \left. \right] \\
& + \sum_{dis} \left[(c_{n,dis}^i + c_{n,dis}^{fix}) N_{n,dis} \right] + \sum_{nd} \left[(c_{n,nd}^i + c_{n,nd}^{fix}) N_{n,nd} \right] \\
& + \sum_{sto} \left[(c_{n,sto}^{i,p-out} + c_{n,sto}^{fix,p-out}) N_{n,sto}^{p-out} + (c_{n,sto}^{i,p-in} + c_{n,sto}^{fix,p-in}) N_{n,sto}^{p-in} \right. \\
& \left. + (c_{n,sto}^{i,e} + c_{n,sto}^{fix,e}) N_{n,sto}^e \right] \quad (A.1)
\end{aligned}$$

Those fixed variables (NTC capacities, installed capacities of hydro and bioenergy), and some nomenclature details, are omitted in the objective function for the reader's convenience. The full objective function is provided in the model code.

Energy balance. The wholesale energy balance reads as follows:

$$\begin{aligned}
& d_{n,h} + \sum_{sto} STO_{n,sto,h}^{in} \\
= & \\
& \sum_{dis} G_{n,dis,h} + \sum_{nd} G_{n,nd,h} + \sum_{sto} STO_{n,sto,h}^{out} + \sum_{rsv} RSV_{n,rsv,h}^{out} \\
& + \sum_l i_{l,n} F_{l,h} \quad \forall n, h \quad (A.2)
\end{aligned}$$

The left-hand side is total electricity demand in hour h at node n plus charging of storage technologies; the right-hand side is the total generation, including storage discharging, plus net imports: $F_{l,h}$ represents the directed flow on line l . If $F_{l,n} > 0$, electricity flows from the source to the sink of the line and reversed for $F_{l,n} < 0$. With the incidence parameter $i_{l,n} \in \{-1, 0, 1\}$, source, and sink are exogenously defined.

SI.3. Background on factorization

To identify the importance of different factors that reduce optimal storage need through interconnection, we (1) define several counterfactual scenarios and (2) then attribute the overall change to different factors using a ‘‘factorization’’ method [6, 7].

To explain the principles of factorization, we borrow an example used in another paper [7]. Using a case study from the field of climate science, we aim to explain why oceans around 3 million years ago were warmer than today. Assuming that two important factors are atmospheric CO₂ concentration and the extent and volume of large ice sheets, we apply a climate model and run several counterfactual scenarios. Both factors can have two kinds of states: CO₂ concentration can be low or high, and ice sheets can be small or large. Comparing different model outcomes, we can identify a “sole” CO₂ and ice sheet effect, but also an interaction effect between CO₂ concentration and ice sheet extension on ocean temperature.

Following the notation introduced in previous research [8], we describe the different scenarios in the following way: in f_0 , ice sheets are small, and CO₂ is low. In the scenario f_1 , the ice sheets are large, but CO₂ concentration is low. In scenario f_2 , ice sheets are small, but CO₂ concentration is high. Finally, in scenario f_{12} , ice sheets are large, and CO₂ concentration is high.

The factorization method on which we rely [6] defines the impact of the different factors in the following way:

$$\hat{f}_1 = f_1 - f_0, \tag{A.3}$$

$$\hat{f}_2 = f_2 - f_0. \tag{A.4}$$

\hat{f}_1 is the sole contribution of ice sheets, \hat{f}_2 of CO₂ concentration to the change in ocean temperature. However, with this factorization approach, the sum of the individual effects does not (in general) add up to the overall effect:

$$\hat{f}_1 + \hat{f}_2 \neq f_{12} - f_0 \tag{A.5}$$

Thus, an “interaction effect” \hat{f}_{12} is introduced which captures the joint effect of ice sheets size and CO₂ concentration on ocean temperature [6], such that \hat{f}_1 , \hat{f}_2 , and \hat{f}_{12} add up to the total effect $f_{12} - f_0$:

$$\begin{aligned} f_{12} - f_0 &= \hat{f}_1 + \hat{f}_2 + \hat{f}_{12} \\ \Leftrightarrow \hat{f}_{12} &= f_{12} - f_0 - \hat{f}_1 - \hat{f}_2 \\ \Leftrightarrow \hat{f}_{12} &= f_{12} - f_0 - (f_1 - f_0) - (f_2 - f_0) \\ \Leftrightarrow \hat{f}_{12} &= f_{12} - f_1 - f_2 + f_0 \end{aligned} \tag{A.6}$$

If interested in the overall effect of CO₂ concentration and ice sheets on ocean temperatures and not in the interaction term, \hat{f}_{12} has to be “distributed” to the other factors \hat{f}_1 and \hat{f}_2 . This distribution can be done in different ways. One possibility is to share that interaction term equally between the two factors that are involved in that interaction term. Following that logic, the total effect of the two factors becomes:

$$\hat{f}_1^{total} = f_1 - f_0 + \frac{1}{2}\hat{f}_{12} = \frac{1}{2}((f_1 - f_0) + (f_{12} - f_2)) \quad (\text{A.7})$$

$$\hat{f}_2^{total} = f_2 - f_0 + \frac{1}{2}\hat{f}_{12} = \frac{1}{2}((f_2 - f_0) + (f_{12} - f_1)) \quad (\text{A.8})$$

and capture the overall effect of ice sheets (\hat{f}_1) and CO₂ concentration (\hat{f}_2) on ocean temperatures. For a complete decomposition of factors, 2^n runs have to be conducted where n is the number of factors.

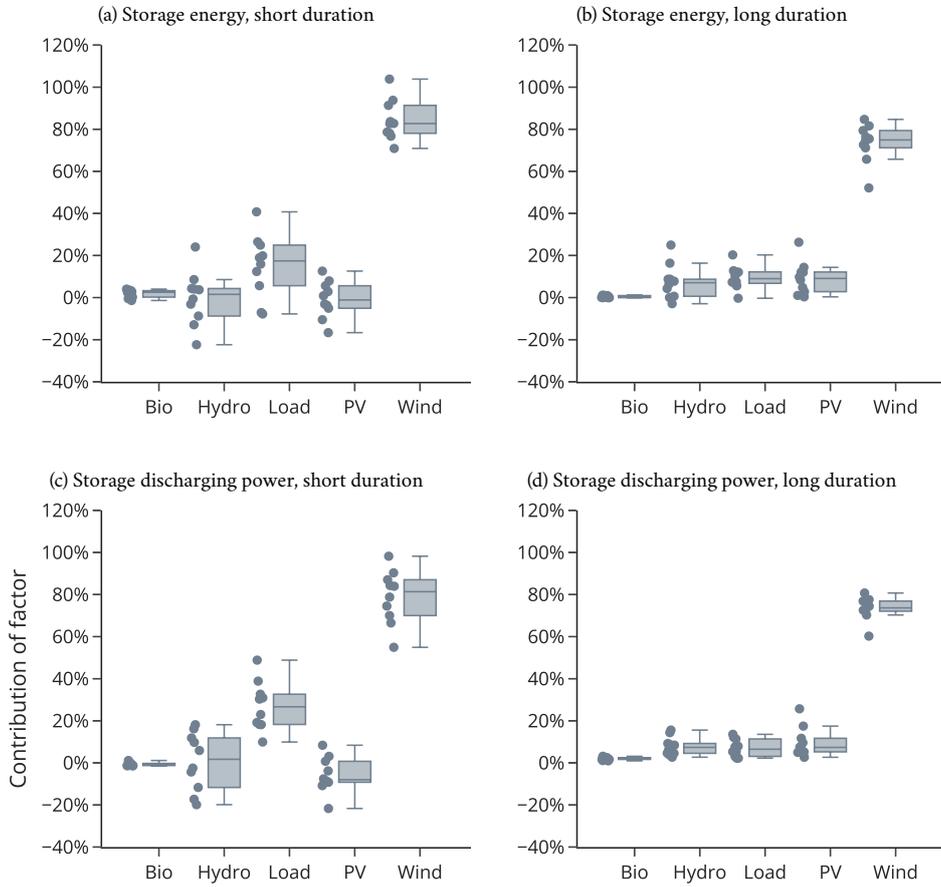
SI.4. Overview scenario runs

Run	Identifier	(1) Interconnection	(2) Wind	(3) PV	(4) Load	(5) Hydro	(6) Bio
1	f_0	no	harmonized	harmonized	harmonized	harmonized	harmonized
2	f_1	yes	harmonized	harmonized	harmonized	harmonized	harmonized
3	f_2	no	not harmonized	harmonized	harmonized	harmonized	harmonized
4	f_3	no	harmonized	not harmonized	harmonized	harmonized	harmonized
5	f_4	no	harmonized	harmonized	not harmonized	harmonized	harmonized
6	f_5	no	harmonized	harmonized	harmonized	not harmonized	harmonized
7	f_6	no	harmonized	harmonized	harmonized	harmonized	not harmonized
8	f_{12}	yes	not harmonized	harmonized	harmonized	harmonized	harmonized
9	f_{13}	yes	harmonized	not harmonized	harmonized	harmonized	harmonized
...
63	f_{23456}	no	not harmonized				
64	f_{123456}	yes	not harmonized				

Table SI.V: Overview scenario runs

Table SI.V provides an intuition of which scenario runs are performed and how they are defined. For every weather year, 64 runs are needed for a complete factorization.

SI.5. Further results



Notes: Every dot is the scenario result based on one weather year. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the 1st and 3rd quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the 1st quartile and above the 3rd quartile.

Figure SI.1: Relative contribution of different factors to the change in storage energy and discharging power capacity related to interconnection

Heterogeneity in wind power explains between 55% and 104% of short-duration storage energy and discharging power capacity reduction and 52% to 85% of long-duration storage capacity reductions, respectively. At the other end of the spectrum, country-specific differences in installed bioenergy hardly have an effect. Differences in hydropower, load time series, and PV profiles have varying contributions, especially for short-duration storage. The effect of hydropower ranges between -22% and +24% for storage energy and -20% and +18% for storage discharging power (Figure SI.1).

We find similar outcomes for PV. The effect of different PV capacity factors through interconnection on aggregate optimal short-duration storage energy or discharging capacity varies between -17% and +13%, or -22% and 8%, respectively. This contrasts with the results for wind power, which always decreases storage needs.

Negative percentage values indicate that the current heterogeneous mix of hydro capacities (run-of-river, reservoirs, and pumped hydro) may even increase optimal storage needs compared to a setting with equal relative shares, thus harmonized installations. Exploring this combined technology effects in detail merits further investigation.

Overall, the influence of different weather years on the composition of the factors is more pronounced for short-duration than for long-duration storage.

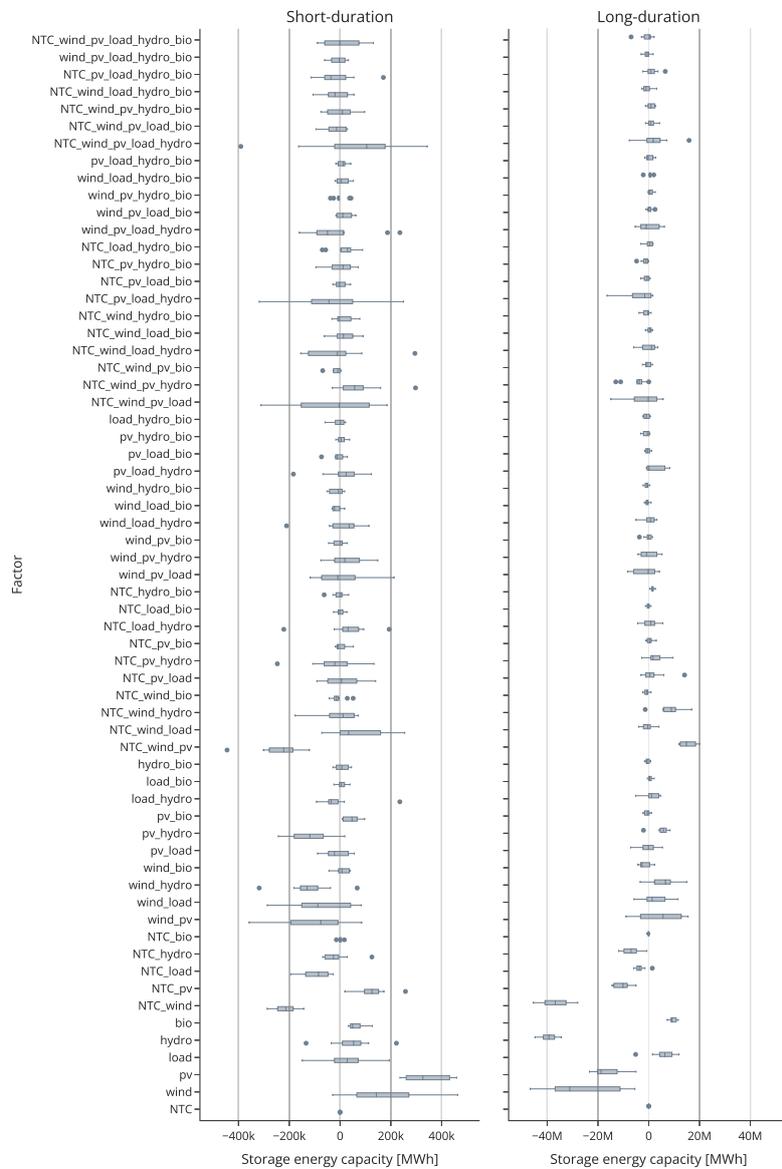


Figure SI.II: Impact of all factors on storage energy capacity in all years

Notes: Differentiated by short- and long-duration, the strength of each individual factor is depicted, covering all 10 weather years. If below zero, a factor negatively impacts aggregate optimal storage energy capacity. If above zero, a factor increases aggregate optimal storage energy capacity.

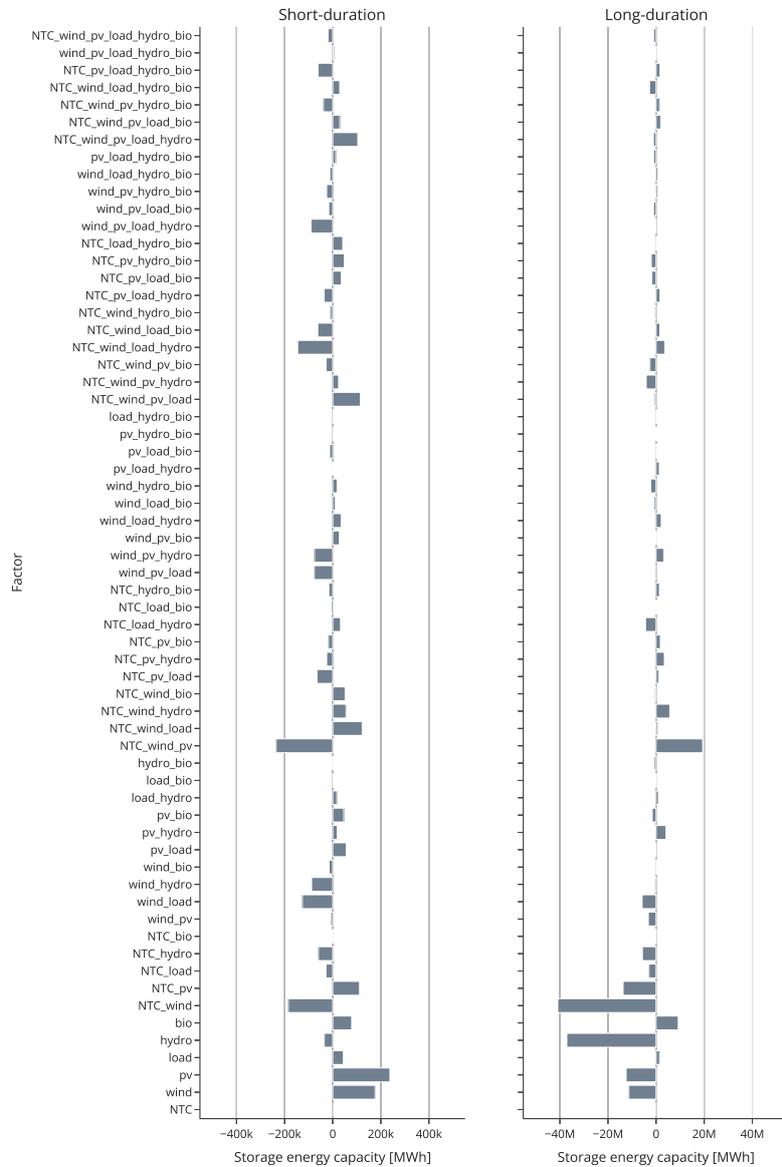


Figure SI.III: Impact of all factors on storage energy capacity in 2016

Notes: Differentiated by short- and long-duration, the strength of each individual factor is depicted for the weather year 2016. If below zero, a factor negatively impacts aggregate optimal storage energy capacity. If above zero, a factor increases aggregate optimal storage energy capacity.

SI.6. Further information

Code and data of this paper can be found in the Gitlab repository.

All figures were created with the “Plotly Open Source Graphing Library for Python” [9].

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