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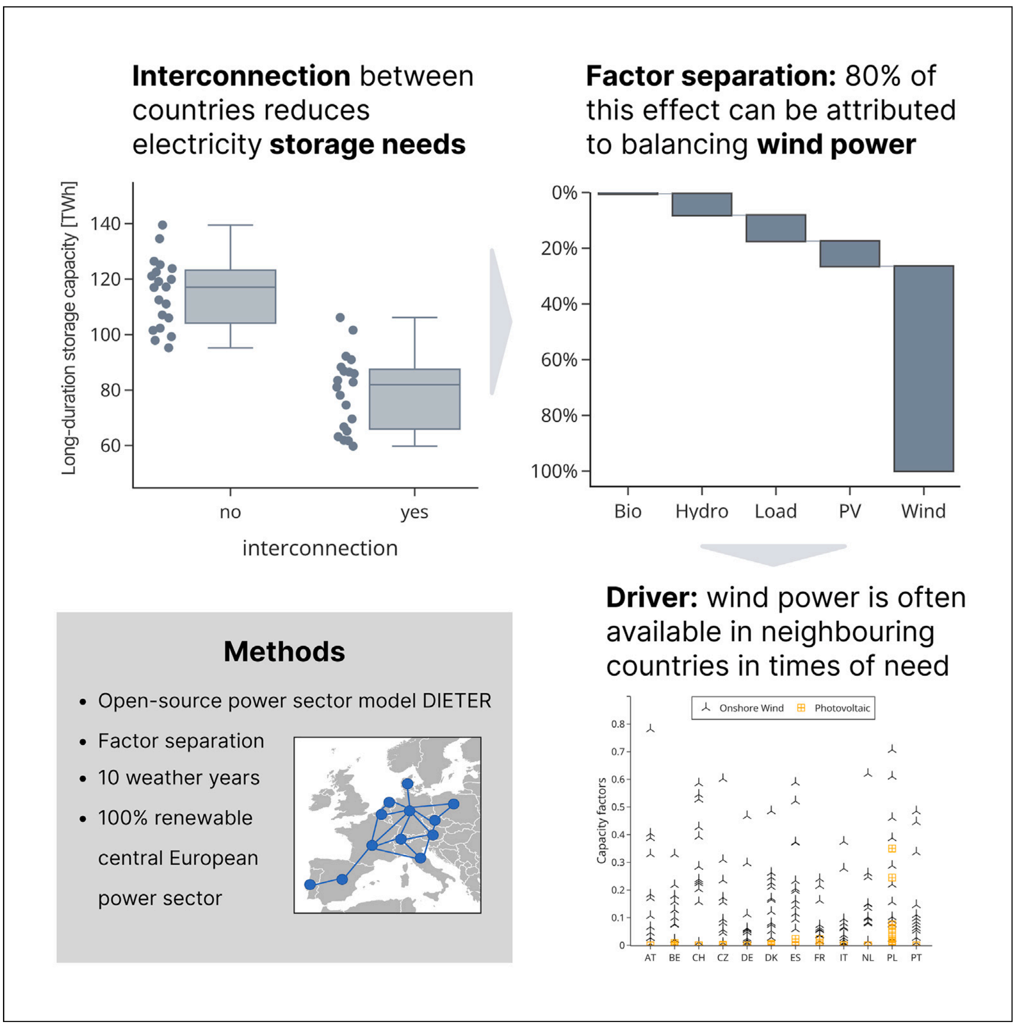

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Highlights

Interconnection lowers electricity storage needs by around 30%

We use a factorization method to disentangle the different factors at play

Wind power explains 80% of the decrease in storage needs

Open-source model analysis that uses ten weather years

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Geographical balancing of wind power decreases storage needs in a 100% renewable European power sector

Alexander Roth[1,2,*] and Wolf-Peter Schill[1]

SUMMARY

To reduce greenhouse gas emissions, many countries plan to massively expand wind power and solar photovoltaic capacities. These variable renewable energy sources require additional flexibility in the power sector. Both geographical balancing enabled by interconnection and electricity storage can provide such flexibility. In a 100% renewable energy scenario of 12 central European countries, we investigate how geographical balancing between countries reduces the need for electricity storage. Our principal contribution is to separate and quantify the different factors at play. Applying a capacity expansion model and a factorization method, we disentangle the effect of interconnection on optimal storage capacities through distinct factors: differences in countries' solar PV and wind power availability patterns, load profiles, as well as hydropower and bioenergy capacity portfolios. Results indicate that interconnection reduces storage needs by around 30% in contrast to a scenario without interconnection. Differences in wind power profiles between countries explain around 80% of that effect.

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 their power sectors.[2] For example, the G7 countries aim for "achieving a fully or predominantly decarbonized 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, e.g., 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] Geographical 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 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 surplus renewable generation and to meet residual load that could not be supplied by variable renewable sources at a particular location.

From a techno-economic perspective, geographical balancing, using the electricity grid, and temporal balancing, using electricity storage, are substitutes for one another 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 partly uncorrelated weather and demand patterns. In an application to twelve central European countries, we investigate the interactions between geographical and temporal balancing, enabled by electricity storage, in a future 100% renewable energy scenario. We do not aim to estimate the optimal amount of interconnection to be built; instead, we are interested in identifying and quantifying the drivers of why interconnection with neighboring countries mitigates electricity storage requirements. In terms of storage, we differentiate between "short-duration" storage, parameterized as lithium-ion batteries, and "long-duration" storage, parameterized as power-to-gas-to-power storage. We analyze the effects on both storage types separately. First, we measure the substitution effect between interconnection and storage by comparing the optimal storage capacities of two stylized least-cost power sector scenarios: in one

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electricity interconnection between countries is allowed; in the other, it is not. Then, we define several factors that can explain the reduced need for storage capacities in an interconnected electricity sector compared to one without interconnection. Finally, we quantify the magnitude of the different factors.

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 because of geographic or historical factors. A capacity factor determines how much electricity a power plant can produce in a given hour compared to its installed capacity. E.g., a capacity factor of 50% in a given hour means that a wind power plant with a power rating of 10 MW produces 5 MWh in that hour.

To determine the importance of each factor for storage capacity, we employ a factor separation method,[9,10] which attributes model outcomes to different model inputs. This can be achieved by systematically varying only specific model inputs and comparing the outcomes of selected model runs. At the core of the analysis lies a comparison between an interconnected central European energy system with interconnection capacities foreseen by regulators[11] and a counterfactual system without any interconnection. The difference in optimal storage deployed by the model can be explained with the factor separation method.

To generate these model outcomes, we use an open-source model of the European electricity system that minimizes total system costs given an hourly exogenous electricity demand in each county. The model determines endogenously optimal investment and hourly usage of different generation and storage technologies for each country to meet the energy demand as well as other policy-related constraints, such as minimum-renewable requirements. Thus, market clearing is achieved every hour. The solution of a cost-minimizing model represents a long-run equilibrium in which, under idealized assumptions, all generators and storage assets exactly cover their fixed and variable costs with their revenues. The model comprises twelve central European countries that are connected in a "net transfer capacity model" with fixed interconnection capacities. For increased robustness, our analysis considers 10 weather years from a 30-year 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.[12,13] Focusing on single countries, such as Germany, various analyses find that storage needs depend on the model scope, e.g., on the number of sector coupling technologies included and on how detailed these are modeled, as well as on the availability of other flexibility options.[14–17] Other studies investigate how much storage is needed in the wider European power sector. Although 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.[4,18–20] Other analyses investigate the need for electricity storage in the US.[21–23] For instance, long-duration storage requirements in Texas increase with growing penetration of variable renewable energy sources.[24] Related studies derive similar findings and also conclude that interconnection decreases storage needs, focusing on other parts of the US[25] or the whole of the US.[26–29] Similarly, geographical balancing and electricity storage are identified as partial substitutes in a model analysis of the North-East Asian region.[30] This substitution is considered to be particularly relevant for long-duration storage technologies.[31] Various papers have analyzed wind and/or solar power variability and its impacts on the future energy system, partly focusing on extreme energy drought events.[32–36] Yet, none of these studies focus primarily on quantifying the effect of interconnection on storage needs or on systematically isolating individual drivers of this effect.

Hence, we contribute to the literature by illustrating how spatial flexibility influences the need for temporal flexibility in an application to 12 central European countries. Our principal contribution is to quantify how different factors contribute to the reduction in storage capacity caused by geographical balancing. To identify the importance of these different factors, we use an adapted "factor separation" method.[9,10] As there is so far no established method to attribute outcomes of power market models to changing model inputs, we propose a modified procedure that builds on counterfactual scenarios and factor separation, which could also be used in other energy modeling applications. We are the first to employ factor separation in the context of energy modeling, using it to quantify the importance of which factors drive down storage needs in an interconnected central European energy system.

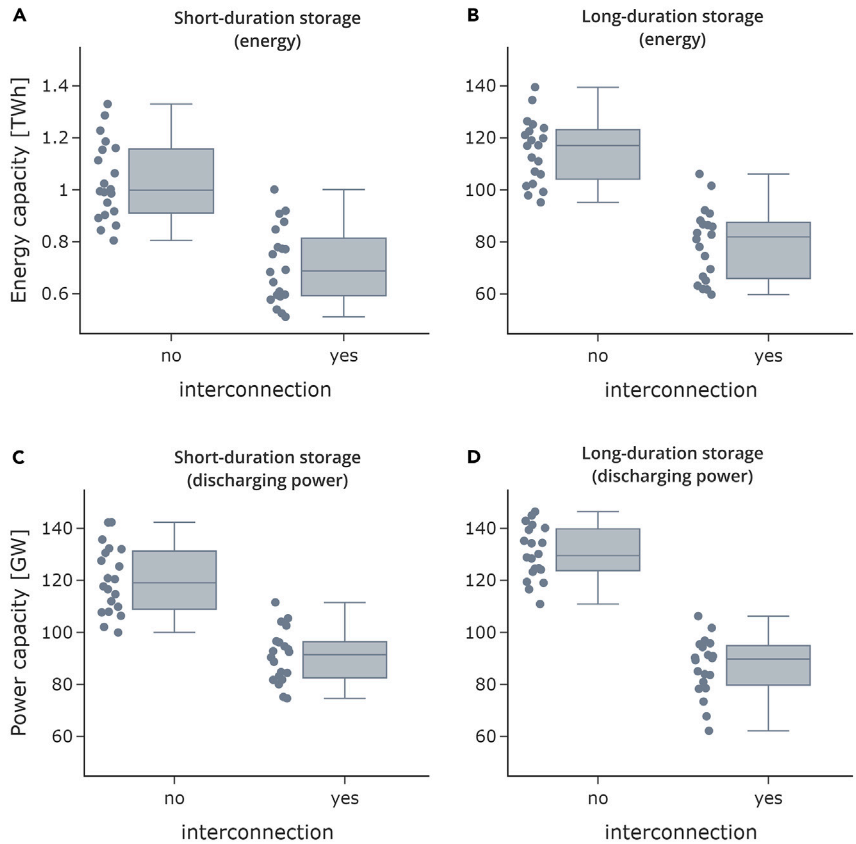

Figure 1. Aggregate installed storage energy and discharging power capacity

The figure shows energy (A and B) and discharging power (C and D) capacities of short- and long-duration storage 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 first and third quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the first quartile and above the third quartile.

RESULTS

Employing a factor separation approach in combination with a numerical energy sector model, we determine by how much interconnection between countries decreases the overall optimal storage energy and power capacity of the energy system (see Geographical balancing reduces optimal storage power and energy capacity). Afterward, we attribute the change in storage capacity to different drivers (see Wind power is the largest driver for mitigating storage needs) and explain the key mechanisms (see An explanation of key mechanisms).

Geographical balancing reduces optimal storage power and energy capacity

We find that aggregated optimal storage capacity is substantially lower in an interconnected 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 the 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 geographical balancing of variable renewable

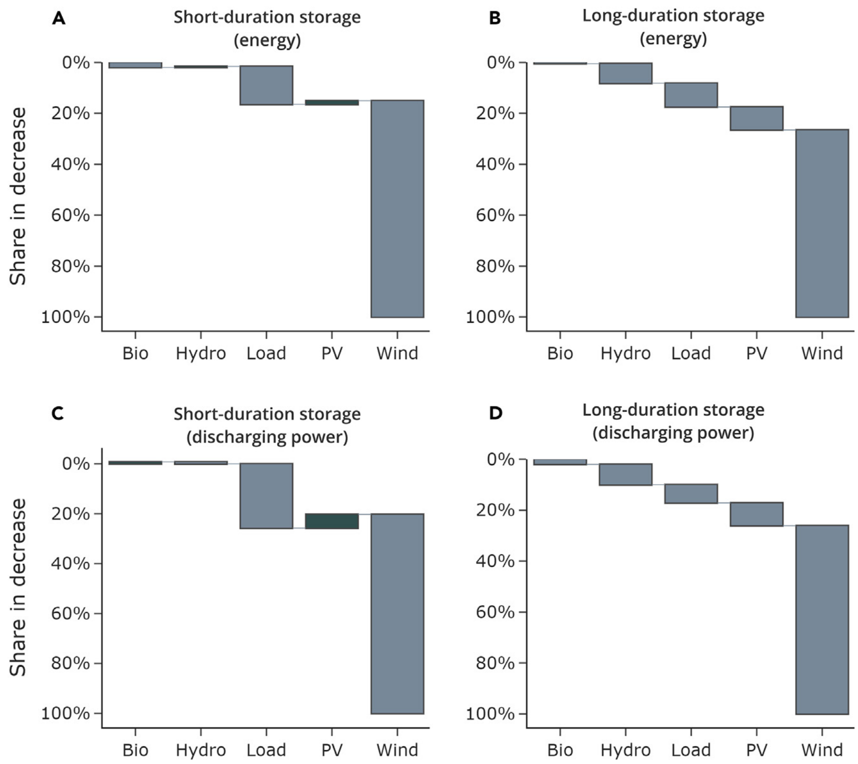

Figure 2. Relative factor contribution to storage mitigation

The figure shows the average relative contributions of different factors to the reduction in storage energy (A and B) and discharging power (C and D) capacity due to interconnection. The average is taken over all ten weather years included in the analysis.

electricity generation across countries mitigates storage needs. We show that this also holds in a scenario with 100% renewable energy. The variation of results between weather years is substantial, as optimal long-duration storage energy varies between 95 TWh and 140 TWh depending on the weather year. However, our results indicate that the storage-reducing effect of interconnection is robust to different weather years.

Wind power is the largest driver for mitigating storage needs

Using counterfactual scenarios and a factorization method (more information in the section Factorisation method), 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 have, on average, a small increasing effect on short-duration storage energy and discharging power. However, this effect is strongly heterogeneous, depending on the weather year. For instance, solar PV can explain in some years up to 13% of the drop-in storage energy and 8% of the drop in discharging capacity, yet in turn, has even a storage-increasing effect in other years (Figure S2). 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. Although wind power is again clearly dominating, differences in hydropower capacity, load curves, and PV time series almost equally contribute to reducing storage needs.

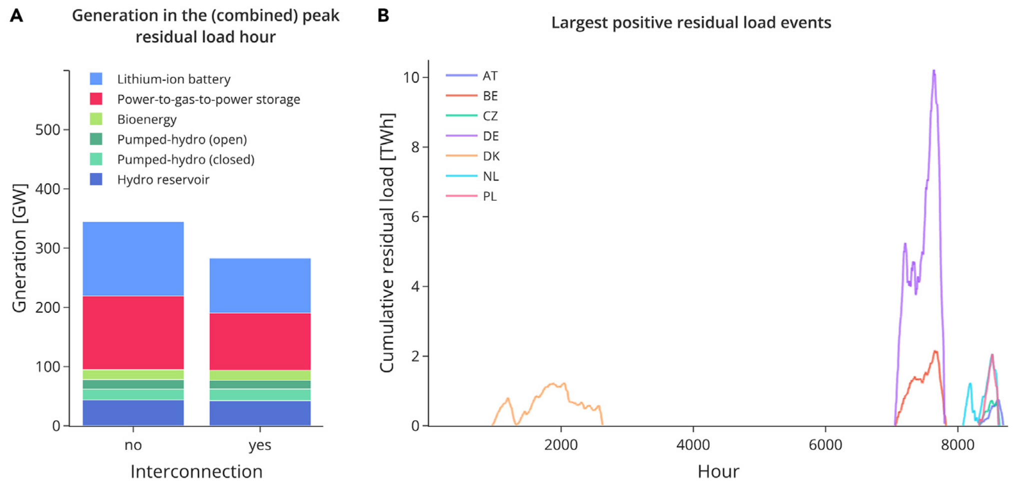

Figure 3. The drivers of reduced storage need: peak residual load hours and positive residual events

(A) The left bar 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. Both bars depict the aggregate values of all countries.

(B) Each country's largest positive residual load event is depicted. Countries with large hydro reservoirs are excluded as they have fundamentally different residual load events. Owing to the existence of reservoirs, they accumulate large positive residual load events over the year.

Both panels show data for the weather year 2016.

Although Figure 2 depicts average values, using ten weather years, results for individual years vary (see Figure S2 for more details). 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 show the already aggregated factors. In the Supplemental information, we provide further information on the magnitude of all factors of the factorization in all the weather years (Figure S3) and in weather year 2016 (Figure S4).

An explanation of key mechanisms

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.

When we compare an energy system without and with interconnection, the following thinking applies. In a system without interconnection, every country has to satisfy its own peak residual hourly load. Therefore, the overall (sum of all countries) storage discharging power needed in this system is simply the sum of all the countries' individual peak residual loads minus other existing generation options, such as bioenergy or hydro reservoirs. This simple addition is not true for an interconnected system if the countries' peak residual load hours do not coincide temporarily. Then, peak residual load hours in individual countries can potentially be compensated by geographical balancing, i.e., imports. Therefore, the overall storage discharging power needed in an interconnected system is most likely smaller than the sum of the countries' peak residual loads.

The left bar of Figure 3A, shows the sum of electricity generation in the different countries' peak residual load hours, whereas 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

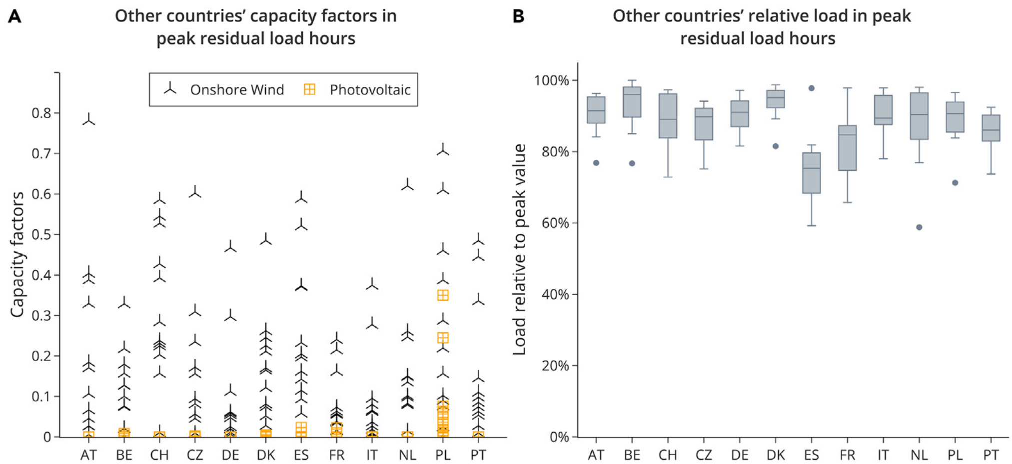

Figure 4. Illustration of main drivers: wind power, PV, and load

(A) Shows hourly capacity factors of all other countries in the peak residual load hour of the country shown on the horizontal axis.

(B) Shows the range of relative loads of all other countries in the peak residual load hour of the country shown on the horizontal axis. The middle bar shows the median value. The box shows the interquartile range (IQR), which are all values between the first and third quartile. The whiskers show the range of values beyond the IQR, with a maximum of 1,5 x IQR below the first quartile and above the third quartile.

Both panels show data of the weather year 2016.

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.

To explain the reduced need for storage energy, a similar reasoning applies. The size of needed storage energy is correlated with 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. On the contrary, in a system without interconnection, all these events have to be covered in and by each country individually; hence the aggregate storage energy needs 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, interconnection helps reduce the need for storage energy capacity.

As shown in the previous section, wind power is the principal factor that drives down storage needs when interconnection between countries is possible. Peak residual load and the largest positive residual load event largely determine storage needs. Therefore, the decrease in peak residual load and also in the largest residual load events are largely driven by the heterogeneity of wind power between countries. This can be confirmed in the data. 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).

Table 1. Factors and states		
Factor	State A	State B
(1) Interconnection	not allowed	allowed
(2) Wind	harmonized	not harmonized
(3) Solar PV	harmonized	not harmonized
(4) Load	harmonized	not harmonized
(5) Hydropower	harmonized	not harmonized
(6) Bioenergy	harmonized	not harmonized

Most countries have to cover their own load and have limited space to provide electricity for export. Most values range above 80%. Therefore, differences in load profiles provide 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 S3). This result may change under the assumption that the capacity of hydropower could be extended far beyond current levels. Then, the factor hydropower could play a bigger role in geographic balancing. This is also true for bioenergy, which we do not discuss here explicitly because of its minor effect.

DISCUSSION

Interconnection decreases storage needs

Identifying future electricity storage needs is highly relevant for planning deeply decarbonized, 100% renewable power systems.[37] Using an open-source numerical model, our results show that optimal electricity storage capacity in an application to 12 central European countries 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 scenario with 100% renewable energy. 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 employ a factorization approach used, for instance, in climate modeling.[10] To the best of our knowledge, this is the first time such an approach is adapted to a quantitative power sector model analysis.

Wind power is the most important factor

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.

Conclusions on geographical balancing and modeling

Our analysis fosters the grasp 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 long-duration 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.

Limitations of the study

As with any numerical analysis, our investigation comes with some limitations. First, we may underestimate storage needs because of averaging over specific weather years. In real-world systems, 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 an 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. The interaction of sector coupling with storage mitigation via geographical balancing appears to be a promising area for future research. Third, optimization model results depend on input parameter assumptions. In particular, we assume fixed interconnection capacities (Table S4) and do not aim to determine the optimal amount of interconnection capacity investments. For such an analysis, a more detailed network model that considers optimal power flows over individual lines should be used. Larger interconnection capacities than assumed here could increase the storage-mitigating effect of interconnection as additional flexibility from other countries would become available. We show average utilization rates of interconnections in the Supplemental information. 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.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Factorisation method
  - Definition of factors
  - Model

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2023.107074.

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AUTHOR CONTRIBUTIONS

A.R.: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. W-P.S.: Conceptualization, Methodology, Investigation, Writing – Original Draft, Funding acquisition.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Model and data	Gitlab	https://gitlab.com/diw-evu/projects/storage_interconnection
Software and algorithms		
Python 3.8.16	Python Software Foundation	https://www.python.org/downloads/
GAMS 36.1.0	GAMS Development Corp	https://www.gams.com/
DIETERpy 1.6.1	Gaete-Morales (2021)[38]	https://gitlab.com/diw-evu/dieter_public/dieterpy/-/tags/v1.6.1

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Alexander Roth (aroth@diw.de).

Materials availability

Not applicable.

Data and code availability

- Data: The data used in this paper can be accessed here: https://gitlab.com/diw-evu/projects/storage_interconnection.
- Code: The code used in this paper can be accessed here: https://gitlab.com/diw-evu/projects/storage_interconnection.

METHOD DETAILS

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.[10]

There are several factorization methods, and our analysis builds on the factorization method by "Stein and Alpert"[9] and its extension, the "shared-interactions factorization".[10] 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 and to a recent paper[10] providing an excellent introduction and overview.

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, which, to ease explanations, we call A and B. Table 1 provides an overview of all factors and their possible states.

To determine the magnitude of the different factors, we compare model outcomes of different scenario runs. We compare a default "real-world" setting to a counterfactual setting. In the counterfactual setting, corresponding to state A, all factors are *harmonized* which means that their respective cross-country variation is eliminated. In contrast, in the state B, *not harmonized*, all countries exhibit their own solar PV capacity factors. The same logic generally applies to the other factors as well. A more detailed definition and explanation of the factors is provided in the next section Definition of factors.

In contrast to other applications of factor separations, 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 instead 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. The notation to define the different factors is as follows. Whenever a factor is in state B, hence *allowed* or *not harmonized*, a subscript with the respective number is added. If the factor is in state A, no subscript 1–6 is added. The scenario in which all factors are in state A is called f_0, hence all factors are *harmonized*, and no interconnection is allowed. In this scenario, all modeled countries are very similar, i.e., they have the same capacity factors, load patterns, and equal relative installed hydropower and bioenergy capacities. The scenario f_1 is nearly identical, with the expectation that interconnection is allowed as it is indicated by subscript 1, pointing to the factor interconnection. Following that logic, scenario f_2 resembles f_0, except that factor (2), i.e., wind, is not harmonized. Following that structure, we can define and name all relevant scenarios. For instance, f_{12} denotes the scenario in which interconnection is allowed, and wind capacity factors are not harmonized, yet all the other factors are in their state A, hence *harmonized*.

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 one, 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 installed between these two scenarios f_{123456} and f_{23456}, and to attribute the difference to the various factors (2)-(6). To quantify the importance of the different factors, we calculate the size of interaction factors between factor *interconnection (1)* and the other factors (2)-(6).

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

$$\widehat{f}_1 = f_1 - f_0. \qquad \text{(Equation 1)}$$

As described above, we rely on the interaction effects of factors for our attribution. The definition of interaction effects is more complicated and requires the results of several scenarios. For instance, the combined effect of the factors (1), (2), and (3), denoted $\widehat{f}_{123}$, is defined as:

$$\widehat{f}_{123} = f_{123} - (f_{12} + f_{13} + f_{23}) + (f_1 + f_2 + f_3) - f_0 \qquad \text{(Equation 2)}$$

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

To quantify the importance of different factors of interconnection on storage, we first define the "difference of interest" (INT), which we define as:

$$INT = f_{123456} - f_{23456} \qquad \text{(Equation 3)}$$

Then, we quantify which factors explain most of this difference. INT can be written as the sum of all interaction factors between the different factors (2)-(6) and the interconnection factor (1). Hence, every element of that sum has to comprise at least factor (1). It can be shown that the difference *INT* is the sum of all the interaction factors where interconnection is involved, therefore

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

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 the respective 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 $\widehat{f}_{12}$ is part of it, but, e.g., also the interaction effects between interconnection, wind, and PV: $\widehat{f}_{123}$. To avoid double-counting, we have to distribute these shared interaction effects between - in this case - the factors wind and PV. There are different ways to distribute these effects. We use the "shared-interactions factorization"[10] that distributes the interaction effects equally between the different factors. Hence, the total interaction effect between the factors interconnection and wind can be defined as follows:

$$\widehat{f}_{12}^{total} = \widehat{f}_{12} + \frac{1}{2}\widehat{f}_{123} + \frac{1}{2}\widehat{f}_{124} + \ldots + \frac{1}{3}\widehat{f}_{1234} + \ldots + \frac{1}{5}\widehat{f}_{123456} \qquad \text{(Equation 5)}$$

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

All these interaction terms $\widehat{f}_{1i}^{total}$ add up to our difference of interest:

$$\mathrm{INT} = \widehat{f}_{12}^{total} + \widehat{f}_{13}^{total} + \widehat{f}_{14}^{total} + \widehat{f}_{15}^{total} + \widehat{f}_{16}^{total}. \qquad \text{(Equation 6)}$$

To determine the contribution of each factor (wind, PV, load, etc.) to the change in optimal storage capacities facilitated through interconnection, we calculate their share *s*. For instance, for the factor wind, this share reads as

$$s_{wind} = \widehat{f}_{12}^{total} \Big/ INT. \qquad \text{(Equation 7)}$$

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 different weather years, we run 640 different scenarios (see Table S5 for an illustrative overview).

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. For all our factors, we define two states in which they can exist. For most of the factors, these states are *not harmonized* and *harmonized*, in which, in the latter, all countries are made equal to eliminate the variation between countries. By "making equal", we refer to a counterfactual scenario in which differences between countries, such as different renewable energy availability time series or hydropower availabilities, are eliminated.

We define five factors we consider to be most relevant. The two factors "wind" and "PV", covering most of the energy supply, are associated with the variable capacity factors of these technologies. Another factor is "load" which covers energy demand. The two factors "hydropower" and "bioenergy" relate to different inherited power plant portfolios in different countries. Finally, the factor "interconnection" is defined only to make the analysis operational, not to explain reduced storage needs.

Wind

The factor that captures the impact of wind patterns is operationalized with the help of capacity factors and takes two different states: *not harmonized* or *harmonized*. In the state *not harmonized*, every country has its own capacity factor time series, as provided by the database used[39] (more information in the Supplemental information) given the specific weather year. On the contrary, in the state *harmonized*, capacity factors are equal in all countries using the capacity factors of our reference country Germany. Hence, all variation between countries in wind power capacity factors is taken away.

On top, we also have to account for geographic differences in offshore wind power, which cannot be deployed in all countries because of differences in access to the sea. In contrast to onshore wind power and solar PV which could be, in principle, deployed everywhere, wind offshore, like hydropower, cannot. In the state *harmonized*, not only do the capacity factors have to be the same across all countries, but also all countries have to operate as if they are the reference country (Germany in our case). Therefore, in the state *harmonized*, all countries exhibit the same share of offshore wind power plants. 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 have the incentive to change the total power plant fleet, which we have to avoid. This share is determined based on a scenario run of our reference country Germany in isolation.

Using this approach implies, given the share is larger than zero, that also countries without sea access, e.g., Austria or Switzerland, have offshore wind power plants in the state *harmonized*. Although this is clearly not realistic, this harmonization step - including the application of the share - is necessary to take away all the cross-country variation of capacity factors, and also geographic differences such as access to the sea. In the state *harmonized*, all countries act as if they were the reference country in isolation.

Solar PV

The factor *solar PV*, like wind power, takes two states. The state *not harmonized* corresponds to the default with solar PV capacity factors as provided by our data source. In *harmonized* case, PV capacity factors are equal in all countries using those of our reference country. Hence, all variation between countries in solar PV capacity factors is taken away.

Load

The definition of the factor "load" is similar to factors "wind power" and "solar PV". 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.

Hydropower

In addition to differences in wind, solar PV, and load patterns, we also 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 expansion potentials. Hydropower, comprising reservoirs, pumped-hydro, and run-of-river, can be considered to be exogenous. Some countries happen to have them while others do not. Also their installed generation capacities are considered to be exogenous.

In the state *harmonized*, all countries have the same share of installed power plant capacities of the respective technologies. We treat all countries as if they had a power plant portfolio like the reference country in isolation. In the case of hydropower, we also assume the German hydro times series for the other countries. 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*, this share is applied to all countries. For a detailed explanation regarding the shares, we refer to paragraph *Wind* above.

Bioenergy

The definition of the factor *bioenergy* closely follows the one of hydropower described above. In the state *harmonized*, all countries have the same share of installed bioenergy power plant capacities. We consider all countries as if they had a power plant portfolio like the reference country in isolation.

Interconnection

The factor interconnection is needed to make the factor separation operational. Like the other factors, it has only two states. In contrast to the other factors, they are called *not allowed* and *allowed* and determine whether electricity flows between countries is possible. In the state *allowed*, interconnection is allowed and the interconnection capacities between countries are fixed, as given in Table S4. If interconnection is *not allowed*, electricity flows between countries are not possible.

Model

To obtain the model results needed for the factor separation, we use the open-source capacity expansion model DIETER,[38,40] which has previously been used for detailed long-term electricity sector planning analyses[17,41–44] and for more stylized illustrations.[8,45,46] 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. In this application, the model comprises 12 central European countries: Austria, Belgium, Czechia, Denmark, France, Germany, Italy, Netherlands, Poland, Portugal, Spain, and Switzerland (Figure S1). In scenarios in which electricity exchange between countries is allowed, countries are connected with a transport model based on Net Transfer Capacities (NTC). These are fixed according to an ENTSO-E scenario (Table S4); an expansion or reduction of these cross-border interconnection capacities is not possible. The model does not consider transmission or distribution bottlenecks within a country.

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-duration 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 generation capacity of bioenergy to be exogenous, without any possibility of additional investments. Accordingly, there is no need to additionally cap the yearly electricity generation of bioenergy. Only a subset of countries can install offshore wind power. In the Supplemental information, we provide more details on assumptions and the input data.

Model results can be interpreted as the outcomes of an idealized, frictionless central European electricity market in which all generators maximize their profits. Real-world market outcomes may differ from this benchmark because of various frictions, i.e., limited information of market actors or barriers to market entry. Note that single countries do not possess individual objective functions, but costs are minimized for the overall interconnected power sector.

For robustness, we do not perform our analysis only for a single weather year only, but for ten different ones covering nearly three decades, 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.