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Storage requirements in a 100% renewable electricity system: Extreme events and inter-annual variability

Storage requirements in a 100% renewable electricity system: Extreme events and inter-annual variability

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Abstract. In the context of 100% renewable electricity systems, prolonged periods with persistently scarce supply from wind and solar resources have received increasing academic and political attention. This article explores how such scarcity periods relate to energy storage requirements. To this end, we contrast results from a time series analysis with those from a system cost optimization model, based on a German 100% renewable case study using 35 years of hourly time series data. While our time series analysis supports previous findings that periods with persistently scarce supply last no longer than two weeks, we find that the maximum energy deficit occurs over a much longer period of nine weeks. This is because multiple scarce periods can closely follow each other. When considering storage losses and charging limitations, the period defining storage requirements extends over as much as 12 weeks. For this longer period, the cost-optimal storage capacity is about three times larger compared to the energy deficit of the scarcest two weeks. Adding other sources of flexibility for the example of bioenergy, the duration of period that defines storage requirements lengthens to more than one year. When optimizing system costs based on single years rather than a multi-year time series, we find substantial inter-annual variation in storage requirements with the most extreme year needing more than twice as much storage as the average year. We conclude that focusing on short-duration extreme events or single years can lead to an underestimation of storage requirements and costs of a 100 % renewable system.

Keywords. Renewable energy, wind and solar power, inter-annual variability, low-wind events, Dunkelflaute, electricity system, energy storage, hydrogen, batteries.

1 Introduction

Background. The viability of 100% renewable electricity supply continues to be a controversial topic (Jacobson et al., 2015; Clack et al., 2017; Heard et al., 2017; Brown et al., 2018; Bogdanov et al., 2019; Tröndle et al., 2020). Because a fully renewable electricity system must heavily rely on wind and solar energy in most countries, one frequently discussed aspect is the system reliability during events with low availability of these variable energy sources. For the example of Germany, such extreme events have also received public and political attention (German Federal Government, 2021; Wetzel, 2019), and the German term for dark doldrums, *Dunkelflaute*, has made it to the international debate (de Vries and Doorman, 2021; Li et al., 2021, 2020; Ohlendorf and Schill, 2020).

Time series analyses on low-wind-speed events. Previous studies on renewable scarcity periods mostly focused on wind power (Cannon et al., 2015; Patlakas et al., 2017; Ohlendorf and Schill, 2020). These studies are similar in their approaches and results (Table 1). They define a threshold below which wind power or wind speed is considered "low". On this basis, they characterize the frequency and duration of low-wind periods based on decades-long, national time series. The maximum duration of low-wind events identified in these studies is 4–10 days.

Table 1: Previous studies on low-wind events

	Cannon et al. (2015)	Patlakas et al. (2017)	Ohlendorf and Schill (2020)
Definition	Capacity factor below 10%	Wind speed below 3 m/s	Mean capacity factor below 10%
Regional scope	Great Britain	North Sea	Germany
Temporal scope	33 years	10 years	40 years
Maximum duration	< 4 days	Near shore: 10 days Open sea: 4-5 days	8 days

Further time series analyses. Further time series analyses found that, due to geographical smoothing, low-wind events are more pronounced when focusing on single locations (Leahy and McKeogh, 2013) and become less extreme when extending the geographical scope to the continental scale (Grams et al., 2017; Handschy et al., 2017; Kaspar et al., 2019). Finally, Raynaud et al. (2018) extended the scope to solar, hydro, and load to examine “energy droughts”, defined as periods when renewables supply less than 20% of demand. They found that a mix of renewables reduces the duration of energy droughts by a factor of two or more when compared to single energy sources, and that the duration of energy droughts will not exceed two days in 100% renewable scenarios. While several studies claimed that the identified scarcity periods will define storage requirements in renewable electricity systems, it remains unclear whether and how storage requirements can be inferred from the results.

Existing optimization studies. Meanwhile, many studies have analyzed the cost-optimal configuration of 100% renewable electricity systems (see Hansen et al. (2019) for a review). These studies employ optimization models to decide on the investment in renewable generators and energy storage, solving the trade-off between storage and renewable curtailment (Zerrahn et al., 2018). Besides storage, the models usually consider other flexibility options such as flexible supply from bioenergy, demand response, and international electricity trade. The results of five German and European studies are summarized in Table 2. The reported optimal storage energy capacities are large enough to supply 12–32 days of the average load within the considered region, which is about 2–3 times longer than what time series analyses found as the duration of low-wind events.

Table 2: Storage requirements in cost optimization studies

	Region	Optimization period	Maximum storage discharge per average load[a]
Bussar et al. (2014)	Europe	3 years	15 days
Schill and Zerrahn (2018)	Germany	1 year	12 days
Child et al. (2019)	Europe	1 year	32 days
Tröndle et al. (2020)	Europe	1 year	12 days
Neumann and Brown (2021)	Europe	1 year	23 days

[a] Including hydro reservoirs.

Research gap. Contrasting the results from time series analyses and optimization models seems interesting for three reasons. First, the larger storage volumes in the optimization studies suggest that storage requirements may not directly be inferred from the length of the worst *Dunkelflaute* as identified by time series analyses. Second, the larger storage volumes in the optimization studies seem counter-intuitive given that these studies include flexibility options beyond storage, which are not considered in the times series analyses. Third, the above optimization models are based on 1-3 weather years, and it remains unclear whether these years include the worst *Dunkelflaute* as identified by the time series analyses based on multiple-decades-long datasets. While previous studies analyzed the inter-annual variability of renewables and implications for system planning in general (Collins et al., 2018; Kumler et al., 2019; Pfenninger, 2017; Schlachtberger et al., 2018; Zeyringer et al., 2018), the implications for storage energy requirements in particular remain unclear. A notable exception is a study by Dowling et al. (2020), which relates long-term storage requirements to the inter-annual variability of renewables but without analyzing the role of extreme events.

This study. This study bridges the gap between time series analyses of extreme events and optimization models. On the one hand, we analyze 35 years of renewable and load time series to characterize the *Dunkelflaute* in terms of the maximum energy deficit accumulating over a certain period. We also calculate the required storage energy capacity with a stylized cost optimization model using the same input time series. The role of other flexibility options on storage requirements is analyzed using the example of flexible bioenergy. Finally, we contrast the optimization results based on single versus multiple years of data.

Contribution. Our work contributes to the understanding of how the variability of renewable sources defines storage requirements in a 100% renewable electricity system. Our findings suggest that both time series analyses and optimization models often come with simplifications that may lead to an underestimation of storage requirements. Regarding time series analyses, it appears insufficient to look at short periods with extreme scarcity because these can be surrounded by other scarcity periods, which jointly define storage needs. Regarding optimization models, analyzing single years seems insufficient because these do not necessarily include extreme events. Furthermore, with an increase in other flexibility options, the role of long-term storage transitions from bridging extreme events to smoothening the inter-annual variability of renewables.

Outline. The remainder of this paper is structured as follows. Section 2 describes the applied methods and utilized data, Section 3 presents the results, Section 4 discusses the findings, and Section 5 draws conclusions.

2 Methods and data

Outline. This section describes the time series analysis (Subsection 2.1), the optimization model (Subsection 2.2), and the joint input data (Subsection 2.3). To highlight methodical similarities and differences, we use rather stylized assumptions—the limitations of which are discussed in Section 4.

2.1 Time series analysis

Capacity and energy deficit. Based on the time series data described in Subsection 2.3, we define the maximum energy deficit as follows:

$$E_{def,max} = max_{t_0,t_1} \int_{t_0}^{t_1} P_{load}(t) - P_{RE}(t)\, dt, \tag{1}$$

where $P_{load}(t)$ is the hourly load data and $P_{RE}(t)$ is the sum of wind and solar generation profiles scaled with the capacity resulting from the cost optimization model plus hydro power input time series and a constant profile for bioenergy. Such a perfectly inflexible bioenergy generation is a hypothetical and conservative assumption, which was chosen to make the results of the different methods comparable, and which is relaxed in Subsection 3.4. In addition to the overall maximum energy deficit, we compute the maximum energy deficit for different durations $T = t_0 - t_1$.

2.2 Cost optimization model

Optimization model. We use an optimization model to find the least-cost 100% renewable electricity system for the example of Germany. The model decides on investment in variable renewable generators and electricity storage in batteries and via hydrogen. Simultaneously, the dispatch of storage is optimized, while considering existing bioenergy and hydro power (including pumped hydro storage). The optimization problem extends over a 35-year-long horizon with an hourly resolution of dispatch. For perspective, the results of the multi-year optimization are contrasted with those based on single years.

Investment. The investment variables for variable renewables include three distinct technologies: solar photovoltaic (PV), onshore wind, and offshore wind. The investment in batteries is distinguished into an energy-specific component (the battery packs) and a power-specific component (the inverters). For hydrogen storage, three investment dimensions are considered: energy (salt caverns), charging power (electrolyzers), and discharging power (combined cycle gas turbines, CCGT). The annualized investment costs and the fixed operation and maintenance costs for all these technologies are included in the objective function of the optimization model.

Dispatch. The hourly dispatch optimization is based on the time series data described in Subsection 2.3. Load time series are used as is, and the generation profiles for wind and solar energy are scaled according to the corresponding investment variables. Fixed generation time series are applied to hydro run-of-river (Hydro ROR), while reservoir and pumped hydro are modeled as one generic dispatchable hydro technology (Hydro DIS), which is constrained by existing capacity. For comparability with the time series analysis, bioenergy is conservatively assumed to produce at constant load in the base case, and a more flexible operation is considered in a sensitivity analysis.

More details. Further assumptions used in the cost optimization model are described in the Appendix.

2.3 Time series data

Time series data. Both methods use 35-year-long time series data form ENTSO-E (2020) as an input. These time series reflect a scenario for 2030 based on weather reanalysis data from 1982-2016. This dataset is used by European system operators for adequacy calculations and, more generally, reanalysis data have frequently been used in the literature on renewable electricity systems (Cannon et al., 2015; Neumann and Brown, 2021; Ohlendorf and Schill, 2020; Tröndle et al., 2020). The dataset includes hourly load data and hourly generation profiles for wind and solar energy. Furthermore, daily generation time series are provided for hydro run-of-river, as well as weekly time series for the natural inflow to hydro reservoirs and to pumped hydro storage.

3 Results

Outline. This section starts with an overview of the multi-year cost optimization results (Subsection 3.1). We then present the output from the time series analysis (Subsection 3.2) and compare it with the cost-optimal storage requirements (Subsection 3.3). Furthermore, we analyze the impact of flexibility on storage requirements for the example of bioenergy (Subsection 3.4) and contrast the results of the multi-year optimization with those of single years (Subsection 3.5).

3.1 Cost-optimal system configuration and storage requirements

Installed capacity. The characteristics of the multi-year cost-optimal 100% renewable German electricity system are summarized in Figure 1. On the supply side, almost 300 GW of variable renewable generators are installed: 92 GW solar PV, 94 GW onshore wind, and 98 GW offshore wind (Figure 1a). For solar PV and onshore wind power, this is nearly twice as much as the installed capacity in 2020; for offshore wind power, this means more than a tenfold increase (Agora Energiewende, 2021). These variable generators are complemented with about 81 GW of storage discharging capacity, including mostly hydrogen-fired CCGT (62 GW). For perspective, the installed capacity of CCGT almost equals the average load, while the overall discharging capacity can supply 77% of the peak load (105 GW). The storage charging capacity is about 72 GW, which is somewhat lower than the discharging capacity. Up to 161 GW of renewable surplus generation is curtailed because this is more economical than building more storage.

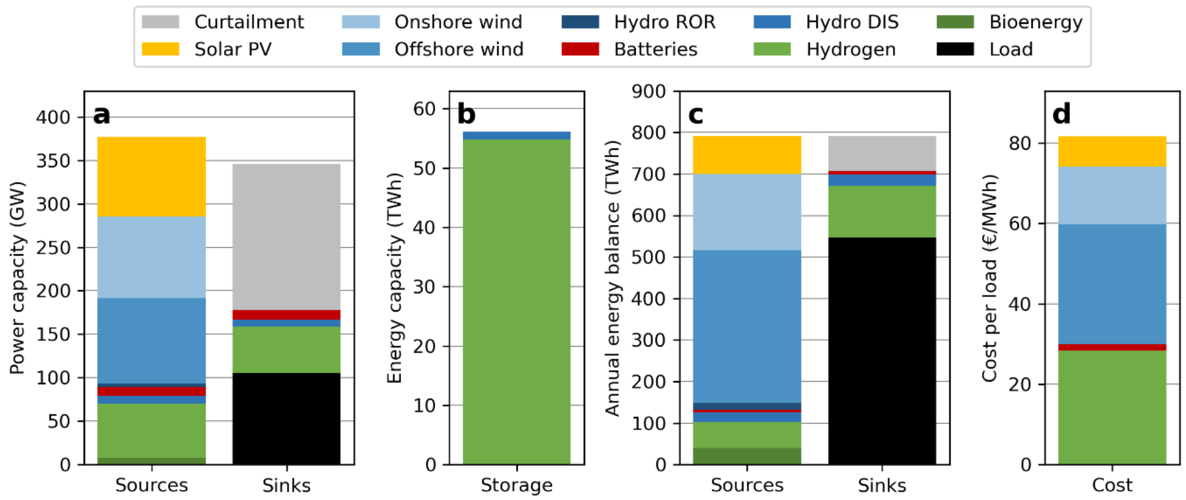

Figure 1: Cost-optimal power capacity (a), storage energy capacity (b), annual energy balance (c) and cost breakdown (d)

Storage volume. The storage energy capacity, which is the focus of the present paper, is 56 TWh (Figure 1b). Most of this is hydrogen storage (54.8 TWh), while existing pumped hydro storage contributes 1.3 TWh and batteries just 59 GWh (0.059 TWh). Accounting for discharging efficiency, the storage volume translates into a maximum supply of 36 TWh electricity.[1] This is about 7% of the annual load or 24 days of average load—much longer than what previous time series analyses find based on their definition of a *Dunkelflaute*. The storage duration is 23 days for hydrogen, 6 days for pumped hydro, and 6 hours for batteries.[2]

Energy balance. The total primary supply from renewable sources is about 700 TWh, which is roughly 130% of the annual load (Figure 1c). The largest contribution comes from offshore wind (53%), onshore wind (26%), and solar PV (13%). Only 65% of the primary energy supply directly serve load (455 TWh),

[1] 34.5 TWh from hydrogen, 1.1 TWh from hydro power, and 56 GWh from electricity.
[2] Here, we define this as the storage volume in electricity terms divided by storage discharge capacity (also referred to as energy-to-power ratio).

while 23% are charged into storage (160 TWh) and 12% are curtailed (84 TWh). Storage discharge accounts for 92 TWh (17% of load).

Cost. Although not in the focus, Figure 1d reports the cost for storage (about €30 per MWh of load) and variable renewables (€50 per MWh of load). Note that these costs include neither the cost of existing hydro and bioenergy, nor grid cost. Nevertheless, even the reported fraction of total system costs is relatively high compared to previous studies. For example, Tröndle et al. (2020) report total system costs of €50–60 per MWh, depending on the distribution of renewables. On the one hand, the fact that we model Germany as an island may lead to an overestimation of cost. On the other hand, as opposed to previous studies, we consider multiple years of data, which means that our estimate includes the cost related to the inter-annual variability of renewables (see Subsection 3.5).

3.2 Maximum energy deficit based on time series analysis

Intro. Using the multi-year cost-optimal wind and solar capacity as an input, we analyze renewable and load times series to find the maximum energy deficit.

Maximum 10-day energy deficit. Because previous time series analyses identified scarcity events with a duration of up to 10 days (Table 1), we first focus on the scarcest 10-day period. We find that this period occurs in December 2007. with a maximum energy deficit of 12.4 TWh (8 days of average load). Figure 2 reveals that there is very low supply form all renewable sources throughout this entire period, which is in line with the intuition behind the concept of *Dunkelflaute*. However, it can be seen from Figure 2 that the two days before and the first day after the worst ten-day period are also short on energy, even though supply is not as scarce as during the ten days. As a result, storage requirements can be expected to be defined by a period longer than ten days.

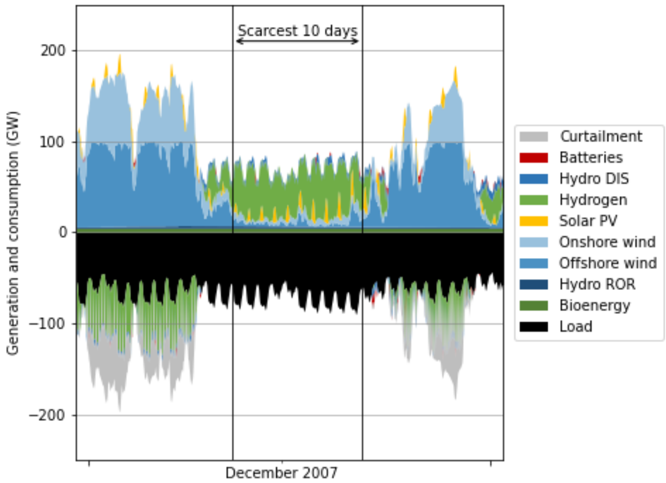

Figure 2: Hourly generation and consumption patterns for the maximum 10-day energy deficit

Maximum energy deficit as a function of duration. This expectation is confirmed in Figure 3a, which displays the maximum energy deficit as a function of duration. In fact, the maximum energy deficit increases monotonously with duration for up to 14 days and starts oscillating for longer durations. Intuitively, this means that, for every increase in duration up to 14 days, another day with renewable scarcity is included in the calculation of the energy deficit; for longer durations, the period with the maximum energy deficit may also include single days with energy surplus. It should be noted however, that scarcity periods of different duration do not necessarily coincide (Figure 3b).

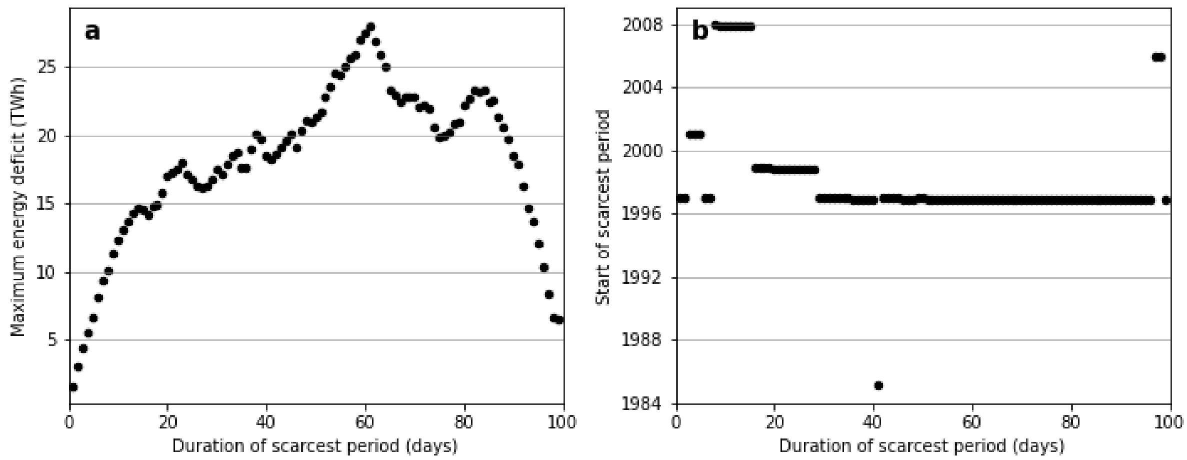

Figure 3: Maximum energy deficit (a) and start of the corresponding period (b) as a function of the duration of the scarcest period.

Max. overall energy deficit. The overall maximum energy deficit is 27 TWh (18 days of average load) and accumulates over 61 days (almost 9 weeks). Rather than one period with constantly low supply, these 61 days include several scarce periods in a row, interrupted by short periods with energy surplus (Figure 4). This finding will be compared to the results from the cost optimization in the following.

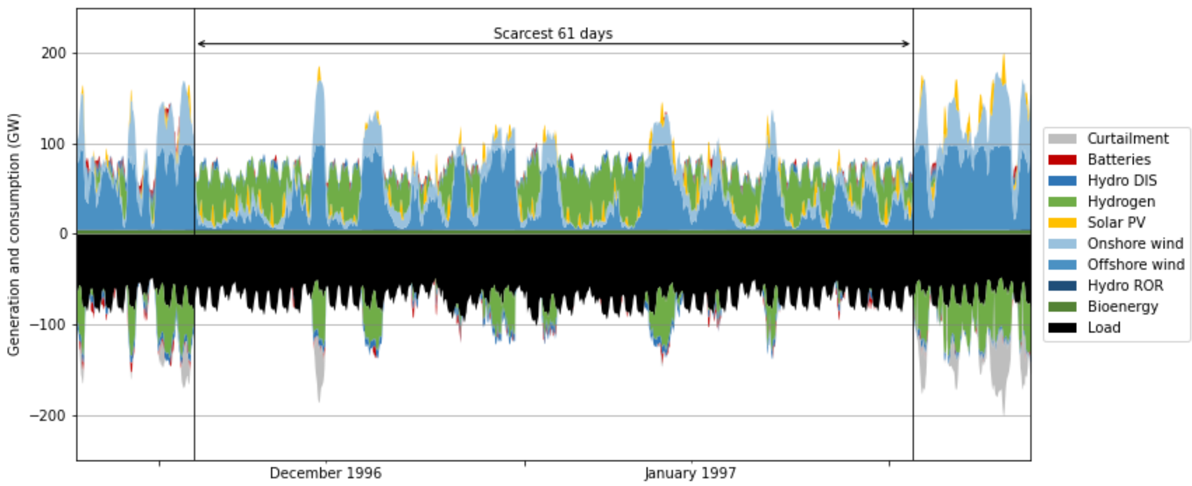

Figure 4: Hourly generation and consumption patterns for the maximum 61-day energy deficit (the overall maximum in the 35-year dataset)

3.3 Bridging the gap between cost optimization and time series analysis

Gap. The electricity-equivalent storage energy capacity in the cost optimization model (36 TWh) is considerably higher than the maximum energy deficit identified in the time series analysis (27 TWh). This may be for two reasons. First, the cost optimization model considers storage losses, which means that one unit of excess energy during the worst period reduces the storage requirement only by one unit of energy times the storage cycle efficiency (50.4% for hydrogen). By contrast, the time series analysis ignores storage losses, as one unit of excess energy reduces the energy deficit by exactly one unit. Second, the cost optimization model accounts for curtailment when excess energy exceeds the storage charging capacity. As it can be seen in Figure 4, such curtailment occurs even during the worst 61-day period.

Sensitivity runs. To test these potential reasons, we conduct two sensitivity runs with the cost optimization model, fixing renewable capacities. One run ignores storage losses ("No losses") and, in addition to this, the other also ignores charging capacity limitations ("Unlimited charging"). Figure 5 reports the resulting storage volumes. As expected, both assumptions reduce storage requirements, and the results in the "Unlimited charging" scenario coincide with the maximum energy deficit calculated in the time series analysis. Put differently, to derive realistic storage requirements from time series analyses, one needs to consider charging limitations and storage losses.[3]

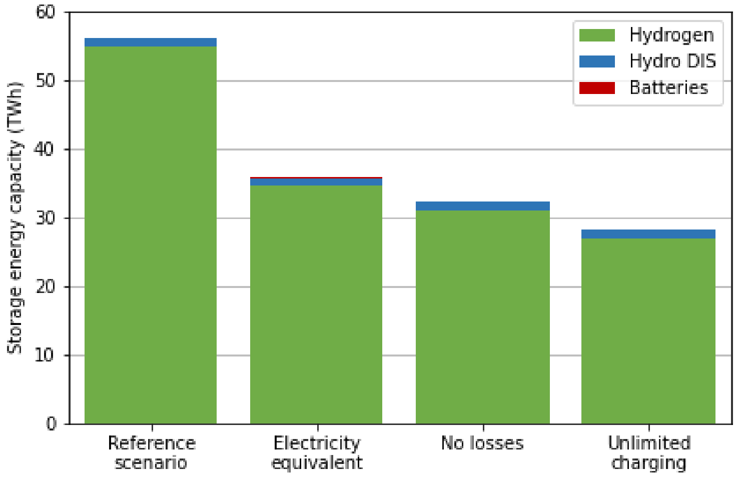

Figure 5: Storage energy capacity in the reference scenario and for the hypothetical cases of loss-free storage and, in addition, unlimited charging capacity

Periods when storage is fully used. Finally, we identify the periods when the overall storage volume is fully used in the optimization model, that is, periods starting when all types of storage are fully charged and ending when the state-of-charge initially reaches zero. In the sensitivity runs without storage losses and with unlimited charging, the identified periods perfectly coincide with the worst 61 days identified with the time series analysis. Accounting for storage losses, however, prolongs the worst period from 61 to 84 days (12 weeks, almost 3 months). Figure 6 reveals that this period includes the 61 days identified with the time series analysis but also about 3 weeks before this period.

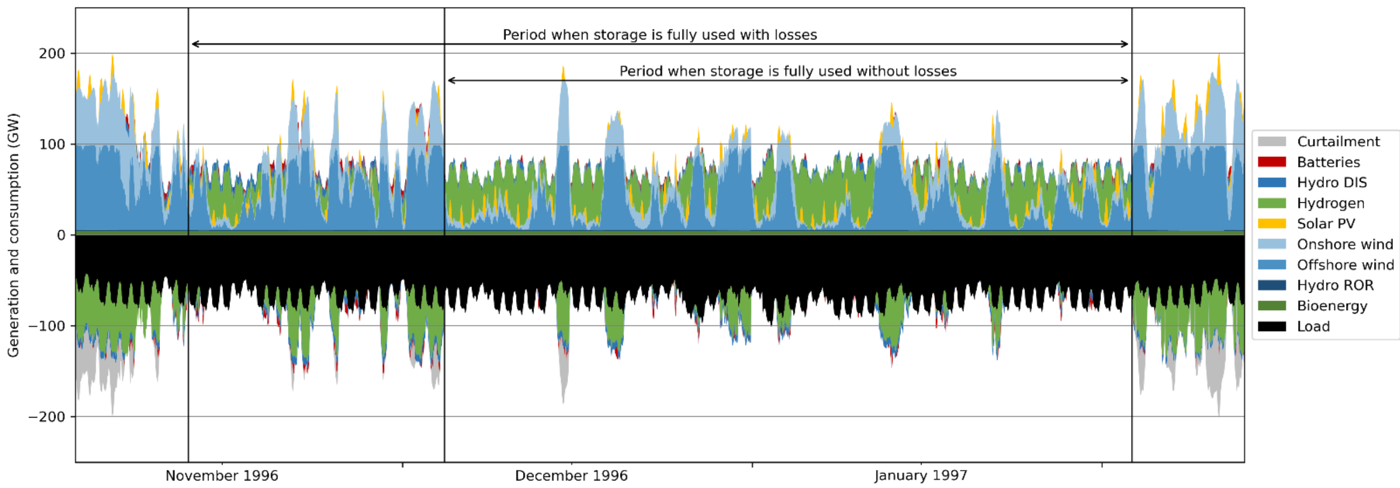

Figure 6: Hourly generation and consumption patterns for the period when storage is fully used

[3] For example, Heide et al. (2011) and Rasmussen et al. (2012) employ a more elaborated time series analysis, which accounts for storage losses but not for charging limitations.

3.4 Flexibility as a substitute for storage: the example of bioenergy

Flexibility assumptions. To enhance the comparability of the cost optimization and the time series analysis, we have so far assumed that bioenergy runs as baseload. In fact, German bioenergy-based electricity generation historically runs almost baseload at around 4.6 GW despite a much higher installed capacity of 8 GW. However, this is mostly due to inadequate regulatory incentives and market price signals and can be expected to change in a future 100% renewable electricity system (Thrän et al., 2015). Against this background, we now relax this assumption, allowing for bioenergy to reduce and increase its output by ±100% (4.6 GW). As a sensitivity, we increase the maximum amount of bioenergy that can be shifted in steps of 2 TWh up to 10 TWh in electricity terms. For comparison, the assumed annual electricity production from bioenergy is 40 TWh. This means that 3 months of production can be stored, which is longer than the previously identified period when storage was fully used. Note that we use bioenergy as an example of flexibility. Similar effects may be observed with demand-side flexibility or international trade.

Results. The impact of flexible bioenergy on the need for other storage technologies is ambiguous: the electricity-equivalent volume of other storage decreases less than proportionately with increasing bioenergy flexibility (Figure 7a), the decrease in discharging capacity equals exactly the capacity by which flexible bioenergy can increase production (Figure 7b), and the charging capacity initially decreases by much more than the capacity by which flexible bioenergy can decrease production but then increases at larger bioenergy flexibility (Figure 7c). These partly counter-intuitive results can be explained by the fact that flexible bioenergy not only substitutes for storage but also for part of the renewable overcapacity (Figure 7d). Interestingly, the decrease in renewable overcapacity in parallel to the increase in overall storage volume means that the period when storage is fully used is prolonged to more than one year (10 October 1995 to 3 February 1996).

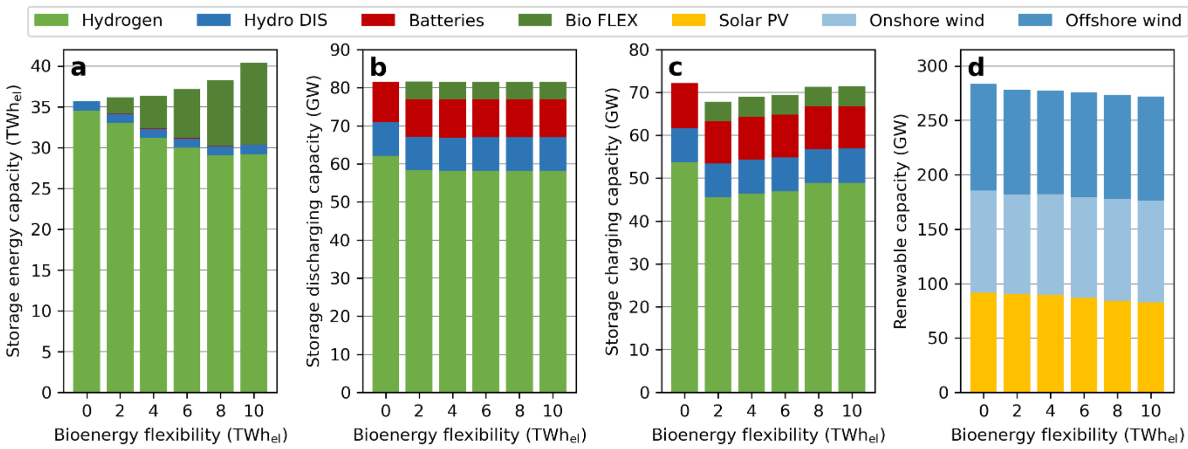

Figure 7: Impact of flexible bioenergy on storage energy capacity (a), storage charging capacity (b), storage discharging capacity (c), and renewable capacity (d)

3.5 Comparing multi- and single-year optimization

Single-year optimization. This section contrasts the results from the multi-year optimization to those based on single years. In the multi-year optimization, we found that storage requirements are defined by a winter period crossing the turn of the calendar year. To capture this period in one of the single-year optimizations, we now consider 12-month periods from July to June of the next year instead of calendar years. For comparability, bioenergy is assumed to be inflexible again.

Results. Figure 8 presents the distribution of the single-year results relative to the multi-year results. The investment in variable renewables varies by a lot (Figure 8a). This can be linked to the inter-annual variability of wind energy: for years with relatively high wind yields, the optimization model decides to build more wind power and less solar, and vice versa. Furthermore, we find a tendency toward more solar and less wind power in single-year optimizations. There is also a tendency toward more batteries (Figure 8b-d), which is correlated with solar deployment. For hydrogen storage, which is decisive to bridge the largest energy deficit, the relative variation is less pronounced, but it should be noted that that the absolute hydrogen storage volume is in the TWh scale while batteries are deployed in the GWh scale. Remarkably, the single-year optimization systematically underestimates long term storage volume (by 50% on average). The one single year that almost matches the multi-year storage requirements is the 12-month period from July 1996 to June 1997—which includes the previously identified scarcest period. The fact that the required storage volume does not match exactly can be explained by a slightly different mix of renewables when this 12-month period is optimized in isolation. The single-year optimization also tends to underestimate cost, with 1996–1997 being closest to the multi-year estimate (Figure 8d).[4]

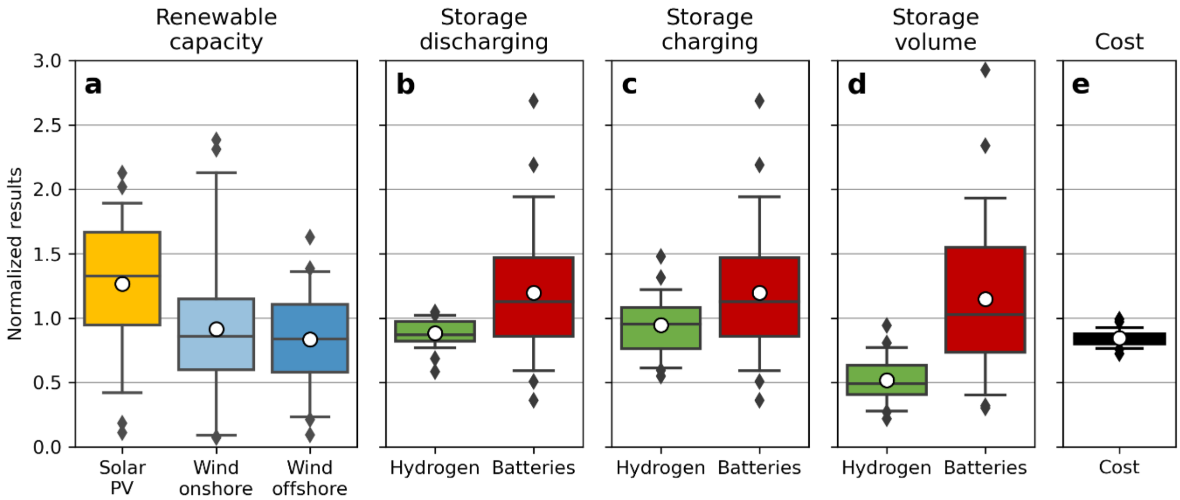

Figure 8: Single-year results divided by the results from multi-year optimization. The black lines in the middle of the boxes indicate the median, the boxes extend from the first to the third quartile (inter-quartile range), and the whiskers include the 5-95% confidence interval of the observations. Observations outside of this confidence interval are depicted as black dots and the white points represent the mean of the distribution.

4 Discussion

Comparison with time series analyses. The results of this study can be compared to the literature. First, our results support the finding from previous time series analyses that the Dunkelflaute—a period with constantly high load and low renewables—does not exceed two weeks (Table 1). However, we demonstrate for the example of Germany that storage requirements are defined by a much longer period of about 12 weeks, including multiple periods with low renewable supply but also some surplus. With increased flexibility from bioenergy, the defining period may even be longer.

[4] Note that the key result that single-year optimization underestimates storage volume and cost holds true also for calendar years, but the worst single year is then different from the worst period in the multi-year optimization.

Comparison with optimizations models. Second, our finding that single-year optimization generally underestimates the required storage volume when compared to multi-year optimization is in line with Dowling et al. (2020). However, while we find that the multi-year storage need is almost equal to that of the worst single year, that study reports that multi-year storage is even larger than that. This may be explained by the larger geographical scope analyzed by Dowling et al. (2020) compared to the present study. Like the above-discussed effect of bioenergy flexibility, geographical smoothing may reduce variability on shorter time scales such that the remaining variability, which needs to be addressed by long-term storage, spans multiple years. Note that both single- and multi-year results on storage energy capacity lie within the wide range of results from previous cost-optimization studies (Table 2).

Geographical scope. Some limitations of the present study and possibilities for further research may be highlighted. First, for simplicity and comparability this study narrowly focuses on Germany, ignoring both international trade and intra-national grid constraints. While geographical smoothing within Europe will certainly reduce challenges and costs related to wind and solar variability, the effect on optimal storage deployment is not trivial due to the trade-off with renewable overcapacity. In this regard, it should be mentioned that during the period of the largest energy deficit in Germany—winter 1996–1997—neighboring countries were suffering severe deficits as well. This included the Swedish and Norwegian hydroelectric system, which usually exports electricity to central Europe but experienced its historically highest energy deficit during 1996. It is therefore unlikely that including modelling of international electricity trade would fundamentally impact our general results on storage requirements in 100% renewable electricity systems. Finally, sub-national grid constraints within countries may increase the requirement for storage and/or renewable overcapacity.

Demand side. Furthermore, this study has a limited view on changes on the demand side of the electricity system. The decarbonization of other energy sectors may require additional electricity for electric heat pumps, electric vehicles, and the production of synthetic fuels (Ruhnau et al., 2019). Our input load time series already consider part of this for the horizon of 2030, but a fully decarbonized system may require additional changes in the demand profile and the related flexibility. Furthermore, we ignore load shedding, which may substitute for part of the storage requirements.

Changing climate. Finally, future load and renewable profiles may change due to climate change, which has been neglected in the current analysis. While the impact of climate change on wind and solar output is subject to large uncertainty (Bloomfield, 2021), extreme events are likely to increase (Bennett et al., 2021). Hence, storage requirements may be even higher than our estimates.

Comparison with existing natural gas storage. Despite these limitations, our quantitative results on storage requirements may be compared with the size of existing energy storage. The estimated 59 GWh of required battery storage in our reference scenario mean a 40-fold increases versus the 1.5 GWh installed capacity of small- and large-scale batteries in Germany 2018 (Figgener et al., 2020). As underground hydrogen storage is currently limited to pilot systems in Germany, the currently 250 TWh of German natural gas storage, which is mostly underground storage in salt caverns, may serve as a reference (Sterner et al., 2015). After accounting for the 70% lower volumetric energy density of hydrogen and an about 20% lower feasible peak pressure,[5] this is in the same order of magnitude as the estimated 56 TWh of required hydrogen storage in our reference scenario.

[5] 250 TWh * 0.3 * 0.8 = 57.6 TWh

5 Conclusions

Conclusions. Based on our results, we conclude that focusing on short extreme events or single years can be misleading when estimating the amount of storage needed in 100% renewable electricity systems. Instead, for the example of Germany, storage requirements are defined by a 12-week or longer period of intermittent scarcity, and system planning based on average years significantly underestimates storage requirements and system costs. Despite these economic challenges and remaining technological uncertainty with a large-scale deployment of hydrogen infrastructure, the estimated necessary storage energy capacity seems feasible when compared to the current German natural gas storage capacity.

Acknowledgements

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Data Availability Statement

No new data were created or analyzed in this study.

Appendix: Assumptions used for the cost optimization

The cost assumptions are summarized in Table 3. They are based on the 2050 estimates in De Vita et al. (2018), except for the assumptions on hydrogen storage and electrolyzers, which we take from Element Energy (2018) and Ruhnau (2021), respectively. A discount rate of 6% is applied to the investment cost.

Table 3: Cost assumptions.

Technology	**Unit**	**Investment cost (unit)**	**Lifetime (years)**	**Fixed O&M (unit p.a.)**
Solar PV	€/kW	450	25	10
Wind onshore	€/kW	900	25	13
Wind offshore	€/kW	1800	25	26
Hydrogen CCGT	€/kW	750	25	15
Hydrogen electrolyzer	€/kW	450	25	9
Hydrogen storage	€/kWh	2	25	-
Battery inverter	€/kW	100	15	-
Battery pack	€/kWh	125	15	-

The natural inflow to the dispatchable hydro technology is set to the sum of the weekly timeseries on natural inflow to reservoirs and to pumped hydro storage. The reservoir size is set to the sum of reservoirs (0.26 TWh) and pumped hydro (1.02 TWh), and the aggregated turbine and pump capacities are set to 8.85 and 7.96 GW, respectively. Bioenergy is assumed to constantly produce 4.6 GW, which is the average value of 2016-2020.

The cycle efficiency for pumped hydro storage and batteries is assumed to be 80% and 90%, respectively (https://www.eesi.org/papers/view/energy-storage-2019). The conversion efficiency of hydrogen electrolyzers and combined cycle turbines is set to 80% (IEA, 2019) and 63% (De Vita et al., 2018), respectively. As a constraint, the storage levels at the end of one year must be equal to the levels at the beginning of the next year, and the storage levels at the end of the last year must be equal to the levels at the beginning of the first year. To avoid arbitrary results related to unintended storage cycling, a penalty term in the objective function ensures that electricity is only stored when needed and curtailed otherwise (Kittel and Schill, 2021).

The model is implemented in the modeling software GAMS and solved on an individual computer within less than two hours using the solver CPLEX.

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