ESTIMATION OF STORAGE PARAMETERS FROM WEATHER DATA AND ENERGY SYSTEMS MODELS

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ABSTRACT

Thermo-mechanical energy storage systems, such as Carnot batteries and pumped thermal energy storage currently operate at a low technology readiness level and are subject to ongoing research. While the engineering community focuses on efficiency improvements, other essential storage parameters like the levelized cost of storage (LCOS) are often over-simplified or neglected. For instance, a very optimistic daily charging and discharging cycle is assumed throughout the entire year, which may lead to underestimated LCOS. This paper questions the realism of such assumptions and explores alternative approaches for estimating needs and use cases of storages in decarbonised future power systems. First, we utilize weather data from a single weather station in Cuxhaven (Germany) for wind and solar irradiation and simplified load profiles to estimate residual load profiles. Second, we use residual load profiles directly obtained from an energy system model (ESM) for Germany. Third, we analyse subsequent periods of excess generation and excess demand regarding both their length and energy intensity for both data sources. Finally, we include a simplified storage model to analyse storage use cases and the level of autonomy, both under varying storage sizes. We find that the analysis of weather data already provides good orientation for storage use, while differences to ESM data may be due to spatial and technological aggregation. Analysing storage use only based on subsequent periods provides a lower limit for full cycles, but the assumption of 365 cycles per annum seems unrealistic in any case. For solar-dominated systems, a storage size of around four times the PV peak power should not be exceeded as larger sizing does neither increase the total energy cycled, nor the level of autonomy. Overall, there is no one-fits-all assumption on storage needs and use cases, as both strongly depend on the power system under study.

1 INTRODUCTION

Energy storage is an unsolved issue and gains importance with the share of fluctuating renewable energy sources in the energy system. Thus, many engineers and scientists develop new storage technologies or try to improve existing ones, for example Carnot batteries or pumped thermal energy storage (PTES). The most obvious parameter for assessment is the round-trip or overall efficiency Ψ, defined as the ratio of electrical energy discharged over the electrical energy used for charging.

$$\Psi = \frac{E_{\mathrm{dis}}}{E_{\mathrm{ch}}} \tag{1}$$

Optimistic cycle calculations for PTES with very efficient machines, as they are available for large mass flow rates at their rated conditions, come up with round-trip efficiencies around 70% (McTigue et al., 2015). For smaller machines and smaller devices, it is more realistic to reach 60 - 70% of the thermodynamically limiting efficiencies for charging or discharging alone. Neglecting further losses, this would lead to upper limits for round-trip efficiencies between 36 and 49% (McTigue et al., 2022). This also follows from fundamental studies for moderate storage temperatures (Atakan, 2024; Roskosch et al., 2020). Using more realistic calculations, Yu et al. (2023) calculated round-trip efficiencies below 30%, putting the benefits and use cases of such storages into question.

But beyond that, most engineers are aware that the overall efficiency is only one parameter to assess a new technology. Costs are generally as important, if not even more important. This poses difficulties for engineers who are not familiar with cost estimations and thus use simplified methods and parameters from the literature. Cost relations are quite uncertain, but nevertheless single values for costs per energy or cost per power are often calculated and presented, e.g. the levelized costs of storage ($LCOS$), which is given by

$$\mathrm{LCOS} = \frac{C_{\mathrm{tot}} + \sum_{i=1}^{\mathrm{LT}} \frac{C_{\mathrm{an}}}{(1+r)^i}}{\sum_{i=1}^{\mathrm{LT}} \frac{E_{\mathrm{dis}}}{(1+r)^i}} \tag{2}$$

with the total capital costs C_{tot}, the lifetime LT, the annual costs C_{an}, the interest rate r and the total energy discharged per year E_{dis} (Jülch, 2016). Although there are many uncertainties in estimating LCOS, we will only concentrate on E_{dis}. In many publications, the value is calculated as

$$E_{\mathrm{dis}} = n_{\mathrm{dis}} \cdot P_{\mathrm{dis}} \cdot t_{\mathrm{dis}} \tag{3}$$

with the number of (full) discharging events n_{dis}, the nominal discharging power P_{dis}, and the nominal discharging time t_{dis}. Often, the number of full discharging events is assumed to be 365 per year, referring to daily net full charging and discharging (Jülch, 2016; Li et al., 2024; McTigue et al., 2022; Yu et al., 2023). Overall, this number seems quite optimistic, even for very sun-rich countries relying solely on solar energy. Moreover, it neglects the specific use case: on the one hand, one might evaluate storage specifications for large areas or entire countries; on the other hand, one could consider a local combination with a wind or solar park. The latter corresponds more closely to the size of a single storage device, whereas the former would require many distributed, likely large-scaled storage systems.

Therefore, more reliable insights on future requirements and use cases of storage technologies are desired. Especially for the large-scale application, results from energy system models (ESMs) for future low-CO_2 energy scenarios can be consulted to obtain more realistic assumptions on the storage use. Such results are available for whole continents, countries, or different smaller regions (e.g. Bistline et al., 2020; Mutke et al., 2023). They yield optimized capacities and operational time-series for (renewable) electrical energy generation and energy storage in different scenarios. Moreover, residual loads[1] and the total amount of energy discharged along a year can be obtained from such ESMs and it can be analysed how these change with storage parameters or across scenarios. Although ESMs can be valuable tools to obtain such insights into future storage requirements and use, most engineers do not have the required expertise in this field and lack access to sophisticated ESMs. Therefore, this paper presents a simplified approach to provide the desired insights and compares it to the use of an ESM.

In a power system that mainly relies on intermittent renewables, storage use is strongly linked to fluctuations of weather conditions and demand. Historic weather data is easily available for many places and long periods with high time resolution of 10 min to 1 h. Electricity demand (or load) in large systems with many consumers follows typical variations between seasons, days of the week and times of the day and can thus be simplified, to estimate residual load curves (Le et al., 2023). Such an approach was adopted by several studies, for instance to obtain ratios between wind and solar installations that reduce overall storage needs (Heide et al., 2010; Weitemeyer et al., 2015).

In this study, we follow a similar approach. We obtain residual load profiles using a simplified demand profile and power generation profiles from a single weather station in Germany. For brevity, the residual load profiles are also called residuals in this paper. We analyze these residuals regarding subsequent periods with negative and positive residuals. Finally, we add a simplified storage model to analyse the storage usage and the level of autonomy reached. Across all steps, we compare the results of the simplified approach to those from an ESM for a fully decarbonised German power system.

2 METHODS

In a first step, we obtain residual load curves in two ways, directly from an ESM and from weather data. Then, the time series are analyzed for periods with negative residuals directly followed by periods with positive residuals. For these periods, durations and energy integrals are calculated. Finally, a simple storage model with a fixed round-trip efficiency is applied, using the residuals as an input. It yields the amount of energy stored and (dis)charged along the year, subject to variations of the storage size. For the sake of generality and to compare different data types without many detailed assumptions, we analyse normalized time dependent energies. They are normalized either by their mean value, if all values of the time-series have the same sign as generation and demand, or by the mean of all negative values for residual loads.

[1] At the system level, residual load is defined as demand minus all variable renewables at each point in time.

2.1 Residual load estimation

Residual loads were taken from an ESM directly and derived from weather data and a simplified load profile. As for the ESM data, results from a European power system model by Mutke et al. (2023) were used. The model represents the year 2050 at hourly resolution and comprises 21 countries. A scenario with zero CO_2 emissions and significant storage use was selected. While the paper by Mutke et al. (2023) reports results that are spatially and temporally aggregated, we used hourly resolved model outcomes for Germany. As Germany is represented by multiple nodes in the model, we selected and compared aggregated results for the whole of Germany ("D tot") and an individual node in north-western Germany (D region 3).

As for the weather data, a single weather station in Cuxhaven, Germany, from Deutscher Wetterdienst (DWD) was selected, which has a time resolution of 10 minutes. The Global Solar Irradiance (GSI) (DWD, 2024a) data and wind velocity v_w data (DWD, 2024b) of the year 2020 were selected. The power output of a solar photovoltaic system was assumed to be proportial to GSI values and normalized by its yearly mean value. The power output of a wind turbine P_w was calculated as (Schaffarczyk, 2023)

$$P_\mathrm{w} \propto \begin{cases} 0 & \text{for } v_\mathrm{w} < 3{,}3 \text{ m/s or } v_\mathrm{w} > 25 \text{ m/s}, \\ v_\mathrm{w}^3 & \text{for } 3{,}3 \text{ m/s} \le v_\mathrm{w} \le 11 \text{ m/s}, \\ (11 \text{ m/s})^3 & \text{for } 11 \text{ m/s} < v_\mathrm{w} \le 25 \text{ m/s} \end{cases} \tag{4}$$

and normalized by its mean value. All power data was resampled to 1 h resolution, to ease the comparison with ESM data.

The energy demand estimation was simplified, taking into account seasonal changes with a cosine function, which yields demands 5% higher than the mean in January and 5% lower in July:

$$P_\mathrm{y} = 1 + 0.05\ \cos(2\pi \cdot d/365) \tag{5}$$

with d being the day of the year. Moreover there is a modulation differentiating between time of day as well as weekdays and weekends. It has a maximum of 1 between 7 a.m. and 7 p.m. on weekdays and a maximum of 0.85 between 7 a.m. and 10 p.m. on the weekend, falling linearly to 0.65 at midnight for all days and rising again at 6 a.m. The product of the seasonal P_y and daily factors P_w are taken for each point in the time-series and normalized to the mean value finally, giving the relative load curve P_d.

The yearly ratio γ of normalized energy generation E_i^n (i = w for wind and i = s for solar) and normalized energy demand $E_{d,n}$ is a measure of the expansion of the given type of renewables. A γ value of 1 means that on average (or in sum, which is equivalent here), the generated energy and the energy demand are equal. Here, $\gamma = 1.07$ was considered for both solar and wind, which corresponds to the value obtained by the ESM for Germany[2]. Residual loads are then calculated as

$$P_\mathrm{r,i}(t) = \gamma \cdot P_\mathrm{d,n}(t) - P_\mathrm{i,n}(t), \tag{6}$$

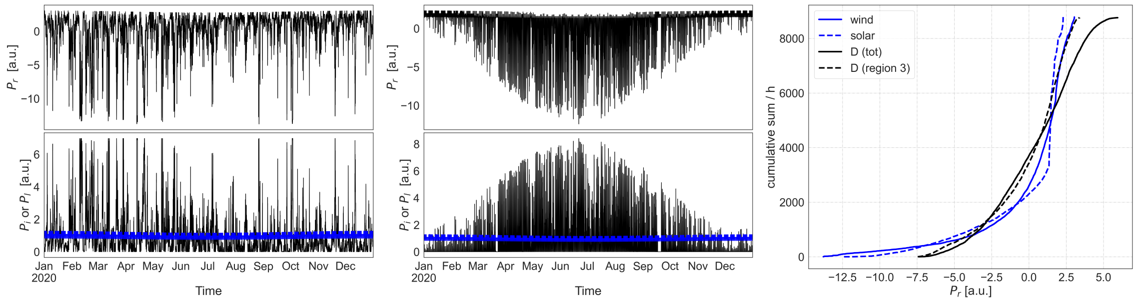
i.e. a positive residual indicates excess demand and a negative residual indicates excess generation. This is re-normalized using the absolute mean value of the negative residual power per year to facilitate comparison with ESM data:

$$P_\mathrm{r}(t) = \frac{P_\mathrm{r,i}(t)}{\bar{P}_\mathrm{neg}}, \quad \text{where} \quad \bar{P}_\mathrm{neg} = \left| \frac{\sum_{P_\mathrm{r,i}(t)<0} (P_\mathrm{r,i}(t) \cdot \Delta t)}{\sum_\mathrm{year} \Delta t} \right| \tag{7}$$

The resulting residuals $P_\mathrm{r}(t)$ are shown in Fig.1.

The difference in the power time-series and the resulting residual power is obvious, especially with respect to seasonal change and the day and night periodicity. The selected γ value leads to nearly equal mean values of the positive and the negative residuals, which would, however, not lead to an autonomous system, even for storages of 100% efficiency. In addition, the period lengths and the period integrals are influenced by the γ value. Comparing the residual loads (normalized to the negative mean values), it is seen that the minima are around -13 for the weather data and around -7.4 for the ESM data, while the positive residuals are below 3.05. This can be seen more easily from the cumulative sums in Fig. 1c. Here the ESM predictions are also included, showing that the curve has a lower slope for whole Germany, but also for the node representing north-western Germany (region 3). It is seen that for solar power many points have similar positive residuals, which are mainly values for the nights and the winter. Without storages, residuals of zero are very seldom. For a European ESM, national residuals of zero are not important and are not found here, because imports and exports are part of the economic optimization.

[2] The ESM yields a ratio of annual wind to solar energy generation of 545/73 and thus a strong dominance of wind energy (Mutke et al., 2023).



(a) Wind data (b) Solar data (c) Cumulative sum

Figure 1: In the lower two plots of (a) and (b), the power time-series derived from wind speed or solar radiation for Cuxhaven 2020 is shown in black and the load curve in blue. The upper plots shows the re-normalized residual, calculated from the difference of load (times γ =1.07) and power. Figure (c) shows the cumulative sum of each power for the two cases and the ESM results for whole Germany (D (tot)) and a node in the north near Cuxhaven (D (region 3)), both for 2050.

The residual curves from weather data and ESM data are analyzed in terms of the statistics related to both the duration and the integral energy of periods characterized by negative residuals, as well as the immediately following periods with positive residuals. This initial analysis represents a preliminary approach to understanding storage usage by examining the subsequent periods that exhibit surplus energy and energy demand. The statistics of both periods vary with different γ values. This is analysed using the pandas package (pandas development team, 2024) and the numpy package (Harris et al., 2020) within self-written python programs, which are publicly accessible (Atakan, 2025).

2.2 Storage integration and assessment

A more sophisticated approach to analyzing storage sizing requirements and utilization patterns combines a storage model with the calculated residuals. The proposed storage model is intentionally simplified, without power restrictions, where the capacity τ_{st} is defined as the ratio of maximum storage capacity to mean negative residual power, expressed in hours:

$$\tau_{st} = E_{\mathrm{st,max}}/|\bar{P}_{\mathrm{neg}}| \tag{8}$$

This ratio enables straightforward scaling across system sizes. For example, with τ_{st} = 1 h and $|\bar{P}_{\mathrm{neg}}|$ = 1 MW, the storage capacity would be 1 MWh. It should be noted that renewable energy systems are typically characterized by peak rather than mean power values. As shown in Fig. 1c, maximum absolute values can exceed the mean by a factor of up to 14 in this case (depending on γ).

The storage operation follows these principles: surplus power (negative residual) is stored unless the capacity limit is reached. The storage dynamics can be expressed through the following variables: P_{st} (charging/discharging power), E_{st} (currently stored energy), and $E_{st,max}$ (maximum capacity). The power flow to the storage P_{st} is determined by:

$$P_{st} = \begin{cases} \textbf{Storage full:} & \\ 0 & \text{if } P_\mathrm{r} \le 0 \text{ and } E_\mathrm{st} = E_\mathrm{st,max} \\ \textbf{Charging:} & \\ \frac{E_\mathrm{st,max} - E_\mathrm{st}}{\Delta t} & \text{if } P_\mathrm{r} \le 0 \text{ and } E_\mathrm{st,max} \ge E_\mathrm{st} \ge E_\mathrm{st,max} - P_\mathrm{r}\Delta t \\ P_\mathrm{r} & \text{if } P_\mathrm{r} \le 0 \text{ and } 0 < E_\mathrm{st} < E_\mathrm{st,max} - P_\mathrm{r}\Delta t \\ \textbf{Discharging:} & \\ \frac{|P_\mathrm{r}|}{\Psi_\mathrm{RT}} & \text{if } P_\mathrm{r} > 0 \text{ and } E_\mathrm{st} > |P_\mathrm{r}|\Delta t/\Psi_\mathrm{RT} \\ \frac{E_\mathrm{st}}{\Psi_\mathrm{RT}\Delta t} & \text{if } P_\mathrm{r} > 0 \text{ and } 0 < E_\mathrm{st} \le |P_\mathrm{r}|\Delta t/\Psi_\mathrm{RT} \\ \textbf{Storage empty:} & \\ 0 & \text{if } P_\mathrm{r} > 0 \text{ and } E_\mathrm{st} = 0 \end{cases} \tag{9}$$

The stored energy at each time step n is updated according to:

$$E_{\mathrm{st}}^{\mathrm{n}} = E_{\mathrm{st}}^{\mathrm{n}-1} - \Delta t \cdot P_{\mathrm{st}} \tag{10}$$

Storage performance is evaluated through two key metrics: total discharged energy E_{dis} and the number of full discharge cycles n_{dis}, which can be compared to the values discussed in the introduction:

$$E_{\mathrm{dis}} = \sum_{P_{\mathrm{st}}<0} |P_{\mathrm{st}}| \Delta t \tag{11}$$

$$n_{\mathrm{dis}} = E_{\mathrm{dis}} / E_{\mathrm{st,max}} \tag{12}$$

For microgrid and autonomous system applications, an additional performance metric is the Level of Autonomy (LA), which quantifies the fraction of time the system operates without power deficits when using storage (Luna-Rubio et al., 2012):

$$LA = 1 - \frac{\sum_{P_{\mathrm{r}}>0} \Delta t}{\sum_{\mathrm{all}} \Delta t} \tag{13}$$

3 RESULTS AND DISCUSSION

We first regard the time scales and integrals of periods with negative residuals followed by positive residuals, before including the storage model and showing the outcome for one storage size, before finally the storage size dependence is shown and discussed.

3.1 Negative load periods directly followed by positive load periods

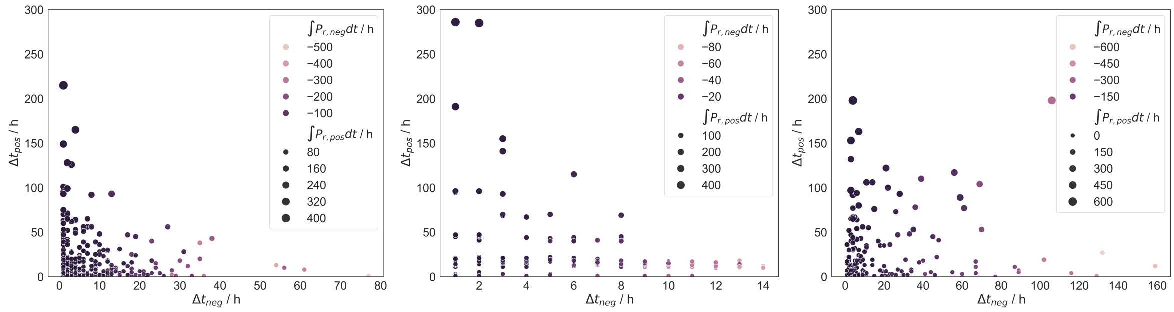
The period lengths of all positive residuals are plotted in Figure 2 as a function of the directly preceding period length with negative residuals for wind, solar and ESM outcomes (for Germany).

The distributions for wind and ESM data resemble each other more than the solar data. However, the ESM yields several longer periods with negative residuals and large integrals, followed by small integrals of positive residuals. Thus, for storage applications, the excess energy of the negative residual should be stored for longer times. For this purpose, rather large storages were needed, which would be used only a few times a year. Similarly, there are several occurrences of large positive residuals for long times preceded by short periods with little excess energy. If these positive residual loads were to be met with a storage, this would again require rarely used large storages.

For solar, the typical hours of sunshine are recognized in the negative residual period lengths that are at most 14 h. And while many periods with excess demand are within the length of 24 h, they can also stretch across multiple days. This trend that periods of negative residuals are often much shorter than periods of positive residuals may be most pronounced for solar, but holds for all three cases. It indicates that the charging times often need to be shorter than the discharging times. This may suggest that, regardless of energy integrals, storages with relatively higher charging power and lower discharging power may be more beneficial.

From the data of the scatter-plots, 2D histograms were constructed for subsequent negative-positive residual intensity pairs, i.e. energies instead of period lengths, as shown in Figure 3. They indicate the most frequently occurring load shifting requirements. From a system perspective, when striving for self-sufficiency and utilisation of available renewables, the diagonal from the bottom left to top right corner (note the different x- and y-scales) represents situations, where the excess energy of one period matches the excess demand of the subsequent period. In these situations, storages of the adequate size could run one full cycle to utilise all renewable generation and meet all demands. The top left corner, in contrast represents situations, where high excess generation is not needed in the subsequent period of positive residual load. Thus, this allows for shifting generation to an even later period with positive residual, if the storage is large enough. Finally, situations in the bottom right corner have a high excess demand but no excess generation in the preceding period. Here, larger storages that already contain energy from a previous top-left situation would be needed to meet demand.

From the perspective of a storage operator, every situation on the diagonal means that they can run a direct charging-discharging cycle. Whether or not it is a full cycle depends on the storage size. Situations on the bottom



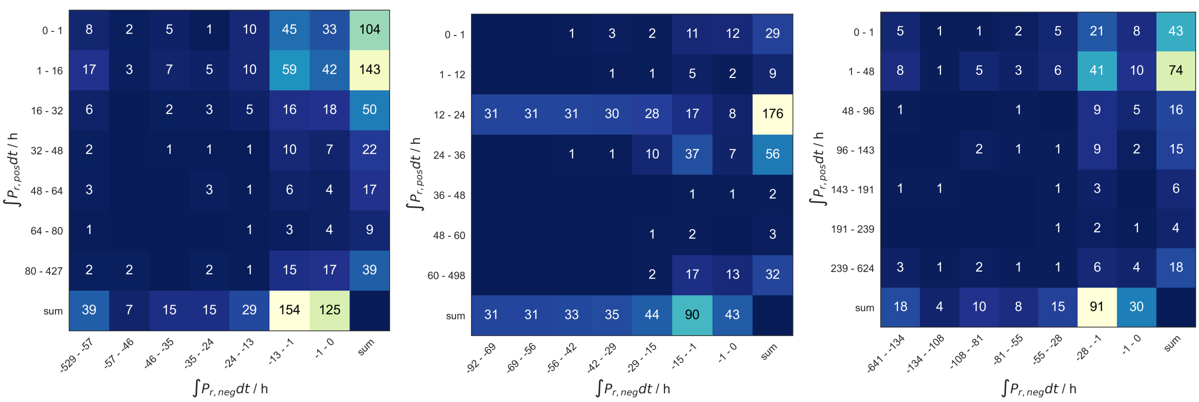
(a) Wind data (b) Solar data (c) ESM-Data

Figure 2: The period length of negative residuals is plotted vs the directly following positive residual length, while the integral energy of each point is indicated by its size for positive loads and its hue for the negative one. They are shown for the wind and solar cases with $\gamma = 1.07$ of Fig. 1 and the ESM outcome for Germany. Note that all three ordinates have the same scale, while the abscissa do not.

right mean that all energy just charged can be discharged immediately in the following period. However, much more energy could be discharged if it was available in the storage. The top left refers to situations, where large amounts of energy can be charged, but not discharged directly.

The three cases differ considerably. While the structure appears again similar for the wind data and the ESM data, the numbers differ. For the wind data, 59 times periods with excess power generation of around -13 to -1 h are followed by periods with excess demand of 1- 16 h, as the most often occurring sequence. For the ESM data, in 41 cases a negative integral between -28 and -1 h is followed by a positive residual between 1 and 48 h, as peak occurrence. Therefore, a storage sized accordingly would be larger for the ESM than for the wind data. However, both could only meet part of the demand in both cases, even with a round-trip efficiency of 1. To balance energy generation and demand, especially when considering lower storage efficiencies, other measures would thus be needed.

For solar, the histogram shows an accumulation of ca. 150 cases where excess generation exceeds the demand of 12 to 25 h of the following period. These cases allow for meeting demand with a storage, even with efficiencies below 1. Across all regarded histograms, there are at most ca. 150 periods with enough energy generation that a direct charging-discharging cycle could meet the demand, even with an infinitely large storage.



(a) Wind data (b) Solar data (c) ESM-Data

Figure 3: 2D histograms of the integrals of negative residuals directly followed by a positive residual, shown for the three cases of Fig. 2. Note that the scales of the x- and y-axes differ between all three subplots.

Determining the number of full cycles directly from 2D histograms is challenging. However, considering the occurrence of larger demand integrals following smaller surplus integrals, these would represent points where stored energy could be directly utilized in subsequent periods, provided that the storage capacity is at least equal to the magnitude of the negative integral.

For the wind case, many points appear in the upper left corner, indicating that a storage size of $\tau = 1$ h (assuming 100% efficiency) would result in at least 92 full discharging cycles. However, the total stored energy remains small

(92 × 1 h). In contrast, increasing the storage size to τ = 13 h leads to 50 direct cycles with a total of 650 h of transferred energy. This represents the largest amount of energy that can be cycled directly using only subsequent periods. For the solar case, this largest amount of cycles energy is achieved at a storage size of τ = 15 h, resulting in at least 57 full cycles and a total of 855 h of shifted energy. Similarly, in the ESM case, a storage size of τ = 28 h yields approximately 29 full cycles (assuming 100% efficiency), corresponding to 812 h of shifted energy. However, it must be noted that these calculations only consider full cycling at subsequent periods of negative / positive residual load. It neglects the potential role of long-term storages that may require more generous sizing and the fact that large storages can run partial cycles. Therefore it should be interpreted as a lower bound to storage sizes.

A key distinction between the solar case and the other two is that, for solar, large storage capacities do not appear to be utilized in subsequent periods. In contrast, for wind, the largest storage size of τ = 57 h would still be fully used at least twice, transferring 114 h of energy. Likewise, for ESM, a storage size of τ = 134 h would also be fully cycled twice, shifting 268 h of energy.

If efficiency were reduced to 50%, as would be expected in the best case for Carnot batteries, an interesting effect emerges in the solar case: the number of full discharging cycles increases, while the discharged energy per cycle decreases, resulting in a nonlinear relationship. Specifically, for solar, 74 full discharging cycles are observed with the 15 h storage, leading to a shifted energy of 555 h—significantly greater than half of 855 h. In contrast, for the other cases, the shifted energy is simply halved.

It should be noted that the storage sizes are given relative to the mean negative residual power over the entire year. Storage values often referenced relative to peak power can be estimated using the minimum values from Fig. 5b, which are approximately 13 for the weather data and 7.5 for the ESM. This corresponds to relative-to-peak power storage durations of 1 h and 4 h, respectively, for 100% efficiency.

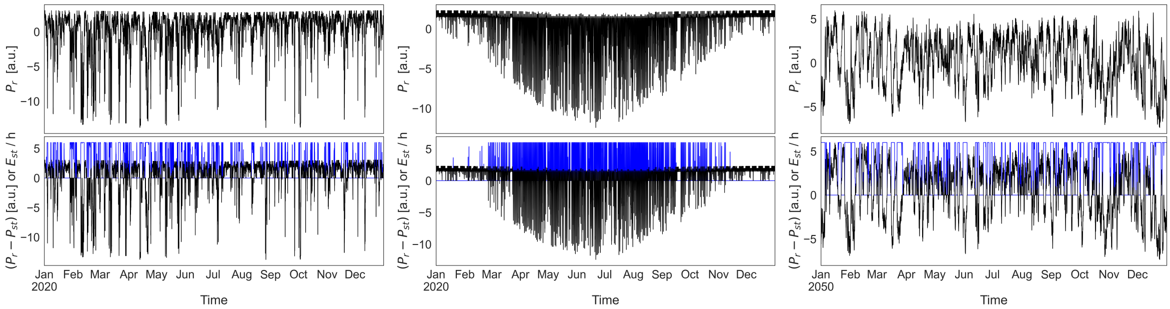
The γ value is one assumption driving these results. If this value is reduced (not shown), i.e., if the share of renewables increases while demand remains unchanged, the number of periods changes and the integral values are shifted significantly. As a result, negative residuals are more frequently sufficient to supply energy in subsequent periods with positive residuals. This implies that with a greater expansion of renewables, storage systems may be sufficient to establish energetically autonomous energy systems.

Since this analysis of subsequent periods may be overly simplistic, the following section introduces an additional level of complexity by incorporating a storage model without power constraints.

3.2 Storage and residuals

The three time series resulting for integrating a storage with a size of τ = 6 h and a round trip efficiency of Ψ_{RT} = 50% are shown in Fig. 4. The other parameters are as discussed above. The upper plots show the residuals for the three cases, while the lower ones show the resulting energy states of the storage (in blue) together with the remaining residuals. At first sight, it is obvious that the periods with positive states of charge are concentrated in the summer months for the solar case, while they are much more evenly distributed for the wind and ESM cases. Calculating the integral energy discharged along the year confirms that in the solar case, the storage is also utilised more than in the other two cases. For the solar case, 714 h of the mean negative residual power is discharged, 533 h for the wind case and only 290 h for the ESM case. This storage size would be most favourably used in combination with solar energy. Division by the storage capacity leads to 119.1, 88.8, and 48.4 times the full capacity equivalent discharging value, respectively. These numbers are significantly, up to a factor of 7.5, below the value of 365 used frequently in Equations 2 and 3 for LCOS estimations. Moreover, they differ from each other by a factor of up to 2.5 depending on renewable energy source. Both would lead to a substantial underestimation of LCOS and thus to an unrealistically favourable economic evaluation of the storage. Comparing these numbers with the evaluation without storage, the results are consistent, keeping in mind that here storage efficiencies of 50% were analysed exemplarily and that the previous numbers were given not for a single size for all scenarios, but for the size of the most often occurring integral residuals. The size dependence will be discussed below.

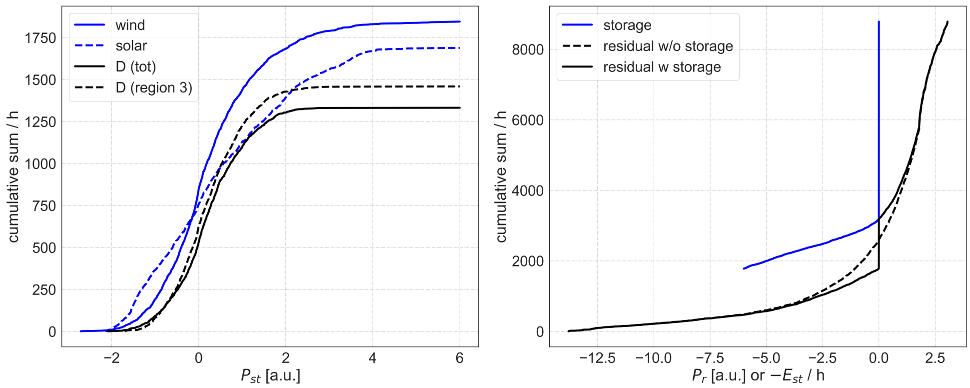
Regarding the statistics of charging and discharging events (see Fig. 5a), it is seen that most charging events take place for a relative power P_{st} below 3, meaning that the energy to maximum power ratio of the storage could be restricted to half the energy to mean power value (of 6 h in this example). The discharging power again is asymmetric due to the 50% efficiency, but for solar energy the asymmetry remains also for 100% efficiency (not shown). All final cumulative sums remain far below the 8740 h of the leap year 2020, so charging/discharging events take place ca. 14 - 20% of the year for the regarded scenarios. The storage would most often change its state of charge in the wind case and the least in the ESM case for whole Germany. In 5b the statistics of the energy



(a) Wind data (b) Solar data (c) ESM-Data

Figure 4: In the upper plots the residuals derived from wind, solar, and ESM data are shown (partly replicating Fig. 1), in the bottom the charging status of a storage with an energy-to-power ratio off $\tau = 6$ h for each case is shown in blue, together with the remaining residual energy in black. The storage efficiency is 50%, the weather data are all for Cuxhaven 2020, the ESM data for Germany in 2050.

stored in the battery is shown with the residual power statistics without and with the storage for the wind case. Here, it is recognized that the storage is empty most of the year and that the level of autonomy (the periods with residuals lower or equal zero) are only increased slightly from ca. 28 to 36% and the ratio of the integral negative to the positive residuals is changed from 86 to 80%. This metrics is now used to analyze the influence of storage size.



(a) Storage charging statistics (b) Cumulative sum, wind

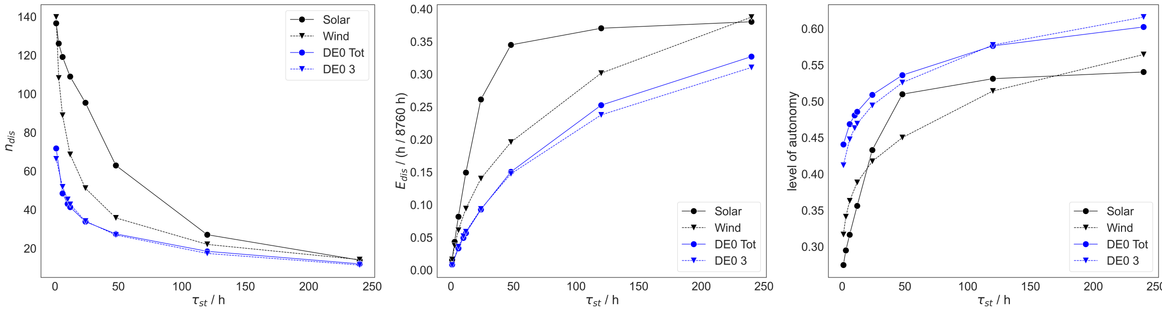
Figure 5: In 5a the cumulative sum of the storage charging and discharging power for the four indicated cases are shown, excluding all times without charging/discharging events. In 5b the cumulative sum for the storage charging state and the residual power without and with the storage.

3.3 Energy stored vs. storage size

Differences and similarities are again seen for the storage size dependent number of full capacity equivalent dischargings (see Fig.6a) and for the integral energy discharged over the year (per hours of the year) (see Fig.6b). Regarding the number of dischargings, the difference between ESM residuals and the two weather-derived residuals is large for small storage sizes, but approach each other for large storages, especially for wind. But the difference between the results from the local weather data to the nationwide averaged ESM data does not disappear, and is also important for local coupling applications. From the integral energy plot, it is obvious that the discharged energy in the solar case runs into saturation at storage capacities of ca. 48 h. Any larger storage will probably be not meaningful or economic. For the wind and ESM cases, the total discharged energy rises with storage size even at storage capacities of 240 h. Although the events are quite seldom, it may be worth (or necessary from a system's perspective) to increase storage size in these cases.

The level of autonomy is shown in Fig. 6c.[3] For the ESM residuals, the values are above 40%, and thus, relatively

[3] Note that the definition of the level of autonomy by Luna-Rubio et al. (2012) used in this paper (see eq. (13)) focuses on the temporal, not the energetic dimension. There are other definitions autonomy, also referring to self-sufficiency (e.g. Bertsch et al., 2017; Luthander et al.,



(a) Number of full discharging per year (b) Total energy discharged per year (c) Level of autonomy.

Figure 6: Storage size dependence of three parameters: the number of full discharging per year, energy discharged per year, and the level of autonomy.

high for small storage sizes and only increase slowly to values around 60%. This is probably due to the nationwide averaging and can also be recognized for the case without storage (see Fig. 1c). In total the averaging over both fluctuating energies and different parts of the country cannot be directly reproduced with data from a single weather station. It should be mentioned, that the same analysis was also carried out with weather data from 2021 (not shown here), it leads to very similar results.

For the case regarded here, with $\gamma = 1.07$, τ values of around 48 h would be most favourable from an energetic point of view for the solar case, leading to ca. 60 full cycle equivalent dischargings. A level of autonomy of 50% is reached, which can only be increased by adding more solar power (reducing γ). For the other three cases, storage sizes between 120 and 240 h of the mean negative residual power is energetically useful. If there is a power restriction of the storage, the values given above hold. For the weather systems the peak power to be stored is around 12.5 times the mean negative residual power, for the ESM data it is ca. 7 times the value. These numbers should help in the design of energy storages like Carnot batteries and to calculate their LCOS. Note, however, that the level of autonomy is primarily driven by the preferences and ambitions of decision makers at different levels for energy sovereignty. This means that autonomy is much more driven by energy policy and corresponding constraints than by the technical performance of storage technologies.

4 CONCLUSIONS

This work focused on comparing different approaches for estimating selected design and operating characteristics of thermo-mechanical energy storage systems such as Carnot batteries. While different round-trip efficiencies were considered as a fixed exogenous parameter, the design and operating characteristics of interest particularly included the number of charging and discharging cycles per year, which strongly impacts the levelized cost of storage (LCOS), the storage size, and the level of autonomy. From the present work, the following points are concluded, especially for the used γ value, representing a similar amount of renewables installed compared to the load:

- The analysis of (even local) weather data already provides useful guidance concerning the number of charging and discharging cycles to be expected and the energy to be stored.
- Differences between using weather data and residual load data from an energy system model (ESM) are likely driven by spatial and technological aggregation.
- Both the use of weather data and the use of ESM data come to the result that 365 full-cycle equivalent charging-discharging cycles for energy storages – a standard assumption in the literature – is highly unrealistic. As a result, LCOS are likely underestimated in the literature.
- The analysis of storage use based only on subsequent periods of excess generation and excess demand may lead to an underestimation of storage sizes, but can be regarded as a lower limit.
- Using a simple storage model to assess the storage use for weather data and ESM residual loads reveals that for – especially local – solar applications, storage sizes should not be larger than ca. $\tau = 48$ h since larger sizing does neither increase the total energy cycled, nor the level of autonomy. For wind applications, larger sizes are energetically useful, but the incremental use decreases with size.

Future investigations should especially analyse different γ values, averaging of weather data of several stations and

2015), which may lead to different findings.

weighting between different forms of variable renewables.

NOMENCLATURE

LCOS	Levelized Cost of Storage
ESM	Energy System Model

Latin Symbols

C	costs
d	day of the year
n	number, –
E	energy (relative to power), h
LA	level of autonomy (see eq. 13)
P	power (relative to yearly mean value), –
r	interest rate
t	time, h
v	velocity, m/s

Greek Symbols

Δ	difference, –
γ	scaling factor for load,–
Ψ	round-trip efficiency, –
τ	energy-to-power ratio, h

Superscripts and Subscripts

an	annual
dis	discharge
i	Energy source: wind or solar
l	Load
LT	lifetime
max	maximum
n	iteration index or normalized
neg	negative
r	residual
RT	round-trip
s	solar
st	storage
tot	total
u	un-normalized
w	wind
y	year

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the authors used OpenAI GPT-4o in order to improve grammar and spelling. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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ACKNOWLEDGEMENT

The authors gratefully acknowledge the financial support by the Deutsche Forschungsgemeinschaft (DFG), grant numbers 525971077 and 526062606 within the framework of the DFG priority programme SPP 2403 'Carnot-Batteries: Inverse Design from Markets to Molecules'.