Current and Future Profitability of Long-Duration Energy Storage Technologies

Johannes Grimm  
Technical University of Munich

Michiel Kenis  
University of Leuven

Magnus Schauf (✉ magnus.schauf@tum.de)  
Technical University of Munich  https://orcid.org/0000-0003-1728-679X

Article

Keywords:

Posted Date: May 25th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2952938/v1

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Additional Declarations: There is NO Competing Interest.
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May 2023

Abstract

Intermittent renewable electricity generation is increasing in many power systems. Long-duration electricity storage (LDES) could complement this development to decrease curtailment and improve system cost-effectiveness. We investigate levelized costs of storage (LCOS) and investment profitability for prospective LDES technologies. Using granular German power market data, we optimize each technologies’ bidding schedule. We find that under current costs, only pumped hydro is profitable while also achieving the lowest LCOS by far. Assuming technological progress to maturity and improved financing conditions, iron redox flow batteries outperform and gravity storage converges to the pumped hydro benchmark of 47-54 EUR/MWh LCOS and 7-15% return on equity. Yet, meeting investor expectations is sensitive to cost and price volatility assumptions. Furthermore, additional revenue from a higher duration generally does not compensate for associated higher costs. Subsidies of 73-83 EUR/kWh or mechanisms enabling further revenue streams might be necessary to mobilize private investment into promising LDES.
Electricity storage or power-to-power energy storage, that is the conversion of electrical energy with subsequent re-conversion to electricity [1], tends to become an important feature of decarbonized power markets characterized by high shares of intermittent generation from wind and solar energy [2, 3]. The need for storage entails both short-duration storage – seconds, minutes, or a few hours – and long-duration electricity storage (LDES) of multiple hours or days [1, 4]. Literature generally concludes that installed capacity of electricity storage must increase in future energy systems but it is yet unclear which technologies to which extent will contribute to this growth, especially for LDES [3, 6, 7, 8].

Two key technologies already participate in power markets around the globe. First, lithium-ion battery storage has primarily contributed to the growth of grid-scale battery storage from 0.3 GW in 2015 to 16 GW in 2021 [9], arguably due to its rapid technological progress [10, 11, 12, 13, 14, 15] and the variety of grid services it can provide [16]. Second, pumped hydro storage (PHS) currently has the largest installed capacity, around 160 GW worldwide in 2021 [9], and is a mature technology employed for decades [17, 18]. However, both technologies face technical, resource-related, and environmental sustainability limitations that open a window of opportunity for new technologies. In particular, topographic constraints limit future capacity investments in PHS in many power markets currently transitioning to intermittent renewable generation [6, 17]. Lithium-ion batteries will likely play a role as rather short duration storage assets with limited applicability for long-duration storage due to degradation, self-discharge, and challenging economics [19, 20, 21, 22]. Hence, future power markets require new technologies to provide LDES.

Previous literature has defined a “technology design space”, i.e. a set of parameters with weights and target values, for LDES as an energy asset class [23]: Promising candidates for LDES should be evaluated primarily by their energy storage cost and discharge efficiency. Additionally, less important parameters entail charge power capacity cost, discharge power capacity cost, and charge efficiency [23, 24]. Since many candidate technologies have not yet
been deployed on a commercial scale, such technology comparisons also require predictions of their future cost and performance. Corresponding methods include empirical models such as the prominent experience curve, bottom-up engineering models, and expert elicitation methods \cite{25, 26, 27, 28}. Resulting projections allow for estimating, i.a., future levelized cost of storage (LCOS) by technology \cite{29, 30, 31, 32}. A further literature stream qualitatively compares different storage technologies across the aforementioned design space criteria and additional dimensions like land footprint or reaction time as qualifier for certain business models \cite{33, 34}. Due to the multiple different sub-specifications of LDES and uncertainty around technological progress, optimal LDES likely comprises a portfolio of technologies as known from electricity generation \cite{4, 24, 35}.

Recent literature has investigated the potential role of LDES in future energy systems \cite{4, 6, 8, 20, 23, 24, 36}. The focal points are mostly technology parameter comparisons, such as costs and round-trip efficiency, or optimization of storage operations in macro-scale systems models. These models tend to primarily represent power markets in the US or UK where some form of capacity market is in place. Yet, few studies have investigated optimal operation of LDES technologies in a real market environment and the attractiveness of corresponding profitability scenarios for investors \cite{36}.

This study analyzes prospective technologies – iron redox flow battery (IRFB), vanadium redox flow battery (VRFB), liquid air energy storage (LAES), gravity storage (GRAV), and hydrogen (H2) – from an investor perspective, i.e. with explicit focus on profitably operating the storage asset in the electricity market. We assume that LDES assets can generate revenue from spot markets and the frequency reserve market. Such a power market is present in several European countries where, in contrast to the focal markets of previous studies (US, UK), a separate market for power capacity does not exist. This is important for storage assets since capacity markets tend to lower risks and increase bankability. To facilitate a transparent comparison and examine the role of energy storage capacity, we model four
variants of each technology. We scale the exemplary assets to a power capacity of 100 MW and an energy volume corresponding to delivering peak capacity for 10, 40, 70, and 100h, also called duration.

To assess financial profitability, we develop an optimization model with a mixed-integer linear programming solution to simulate an optimal bidding behavior for each technology. Based on granular, realized spot market and frequency reserve market results from Germany in 2019, the model maximizes the revenue generated by each system, assuming price-taking behavior in all markets. The resulting operation schedule yields a technology’s gross profit and full load hours in an exemplary year which we then extrapolate over the technology’s lifetime for calculation of its LCOS and internal rate of return (IRR).

We find that under base assumptions, hardly any technology is profitable except for the already mature PHS. At predicted maturity, when technological and financial learning effects have been exhausted, more technologies become attractive but sensitivity to investment costs and financing costs is high. Our results also show that profitability decreases with increasing duration.

Our analysis informs investors and regulators about optimal bidding behavior for LDES technologies, resulting operation cycles, and expected profitability. Our approach also provides a new angle on assessing the prospects of each technology to serve as an electric LDES.

Technology status quo and outlook

We focus explicitly on selected long-duration electricity storage technologies (PHS, LAES, GRAV, IRFB, VRFB, and H2). While the term “long-duration” is not used consistently in the literature, we follow recent suggestions that characterize a duration of 10-100h as long-duration [6, 20, 37]. Consequently, technologies with a typical duration of less than 10h like flywheels [38] or lithium-ion batteries [20, 21] are out of scope. Moreover, we exclude
compressed-air energy storage as this technology is currently neither operated on a stand-alone basis, nor compatible with a low-carbon future given its co-location with natural gas due to its heat demand [6, 39]. The modeled technologies all have relatively high technology readiness levels (≥8, i.e. “first of a kind commercial”) according to the International Energy Agency [40]. Overall, our technology set is comparable to other studies.

Table 1: Technology parameters

<table>
<thead>
<tr>
<th>Technology</th>
<th>Duration</th>
<th>Round-trip efficiency</th>
<th>CAPEX current</th>
<th>CAPEX mature</th>
<th>OPEX current</th>
<th>OPEX mature</th>
<th>Life-time</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHS</td>
<td>10h</td>
<td>0.74</td>
<td>55.0</td>
<td>57.6</td>
<td>0.5</td>
<td>0.5</td>
<td>60</td>
</tr>
<tr>
<td>PHS</td>
<td>100h</td>
<td>0.74</td>
<td>145.0</td>
<td>151.9</td>
<td>0.5</td>
<td>0.5</td>
<td>60</td>
</tr>
<tr>
<td>LAES</td>
<td>10h</td>
<td>0.60</td>
<td>69.9</td>
<td>69.9</td>
<td>1.4</td>
<td>1.4</td>
<td>40</td>
</tr>
<tr>
<td>LAES</td>
<td>100h</td>
<td>0.60</td>
<td>250.1</td>
<td>250.1</td>
<td>5.0</td>
<td>5.0</td>
<td>40</td>
</tr>
<tr>
<td>GRAV</td>
<td>10h</td>
<td>0.85</td>
<td>141.2</td>
<td>104.5</td>
<td>0.7</td>
<td>0.6</td>
<td>40</td>
</tr>
<tr>
<td>GRAV</td>
<td>100h</td>
<td>0.85</td>
<td>471.5</td>
<td>104.5</td>
<td>1.7</td>
<td>0.6</td>
<td>40</td>
</tr>
<tr>
<td>IRFB</td>
<td>10h</td>
<td>0.76</td>
<td>130.2</td>
<td>20.0</td>
<td>1.1</td>
<td>1.1</td>
<td>20</td>
</tr>
<tr>
<td>IRFB</td>
<td>100h</td>
<td>0.76</td>
<td>320.3</td>
<td>74.0</td>
<td>1.1</td>
<td>1.1</td>
<td>20</td>
</tr>
<tr>
<td>VRFB</td>
<td>10h</td>
<td>0.76</td>
<td>172.0</td>
<td>79.9</td>
<td>0.7</td>
<td>0.7</td>
<td>20</td>
</tr>
<tr>
<td>VRFB</td>
<td>100h</td>
<td>0.76</td>
<td>712.0</td>
<td>330.9</td>
<td>0.7</td>
<td>0.7</td>
<td>20</td>
</tr>
<tr>
<td>H2</td>
<td>10h</td>
<td>0.39</td>
<td>190.3</td>
<td>74.7</td>
<td>2.9</td>
<td>1.1</td>
<td>15</td>
</tr>
<tr>
<td>H2</td>
<td>100h</td>
<td>0.39</td>
<td>340.3</td>
<td>164.7</td>
<td>5.1</td>
<td>2.5</td>
<td>15</td>
</tr>
</tbody>
</table>

Notes: This table reports average technology parameters for the two extreme duration variants (10h and 100h). We omit the 40h and 70h parameters as they are in between the two extremes (CAPEX, OPEX) or the same (round-trip efficiency, lifetime). CAPEX and OPEX are denoted in million Euro, economic lifetime is denoted in years. In the model, the round-trip efficiency is an outcome obtained from charging and discharging efficiencies as well as self-discharge in the case of PHS (0.02% per day [34]).

a PHS is assumed to be mature, so that current values equal maturity values. Data is based on prior literature [41, 42, 29].
b LAES is also assumed to be mature as claimed by one of the pioneering companies [43]. Data is obtained from literature [44, 45, 34] and a company web page [43].
c Within the duration range of our model, CAPEX at maturity is independent of duration because of concrete recycling [46]. Data is based on literature [46, 47] and company web pages [48, 49].
d Data is based on literature [32, 50, 51, 52], magazine news [53, 54], and company web pages [55, 56, 57, 58].
e Data is based on literature [59] and company web pages [60].

Table 1 reports parameters of the technologies, differentiating current values from expected future values when maturity is reached. Maturity values are obtained from industry
reports and scientific literature. Since PHS is a mature technology without significant technological progress [11], there is no improvement over time for PHS. While LAES is less employed compared to PHS, it has reached technological maturity so that we do not assume future technological progress in terms of CAPEX or OPEX [43]. Nevertheless, given the low number of operating LAES systems, we consider LAES immature from a financing perspective. On the contrary, studies and industry reports predict significant potential for technological progress for gravity storage and flow batteries. Moreover, advancements and market scale-ups of H2 components are expected to decrease the cost of H2 LDES [31] [32].

**Optimal bidding and resulting schedule**

Using the technology parameters from Table 1, we run a two-step procedure to determine the optimal bidding strategy on each market – i.e. the day-ahead market (DAM), intraday market (IDM), and the automatic frequency restoration reserve market, a part of the frequency reserve market (FRM). In the first step, the model maximizes the profit receivable in all markets for the next day. We assume perfect foresight on prices in the DAM as well as IDM, and a set of scenarios for the price in the FRM. In the second step, we assume that the information on which bids in the FRM have been accepted is available. This information is used to re-optimize bids in the IDM as arbitrage opportunities might exist due to unrealized bids in the FRM.

In other words, the model selects for each quarter per hour per day the amount of power to be charged or discharged and the optimal amount of power capacity offered in each market. We assume price-taking behavior in all markets, perfect foresight in the two spot markets and a probabilistic functioning of the FRM [61]. As such, our results indicate maximum profitability from these markets and thus likely an upper limit to the real world. The Methods section and Supplementary Information contain details on the modeling, objective
function, and constraints.

Figure 1: Gross profit (GP) per market segment in [mEUR]. The underlying optimization problem is formally introduced in the Supplementary Information.

Figure 1 presents the corresponding results in terms of the gross profit obtained in each of the three markets in 2019. 100h GRAV storage reaches the highest gross profit with 7.1 mEUR per year, about 17% more than the 10h variant. On the lower end of the technologies, H2 generates a maximum gross profit of 2.5 mEUR per year. Strikingly, the total absolute contribution from the frequency reserve market is generally quite similar, whereas the gross profit from the two spot markets differs. Moreover, the largest share of gross profit across all storage assets comes from the IDM.

The gross profit is associated with technology performance characteristics as represented by the full load hours, i.e. the cycled energy divided by the 100 MW peak power. As shown in Figure 2, the technology with the largest gross profit – GRAV – also has the highest full load hours (2,603-2,891) and the highest round-trip efficiency of 85%. In contrast, H2 with its low round-trip efficiency of 39% only runs 323-349 hours on full load. Considering all technologies, there seems to be an approximately linear positive relationship between optimized full load hours and round-trip efficiency. Our operating schedule yields full load hours
for PHS that exceed the German average of ca. 1,100 by up to 1,000 [62]. This difference could arise for three reasons. First, we do not account for the now resolved regulatory issue of double grid charges (see Supplementary Information). Second, we disregard maintenance downtime which arguably affects operations of realized plants given their old average age. Third, older PHS systems were often scheduled consistently over several hours, while PHS can switch operation at each 15 minute slot in our model, based on a ramp-up ability of modern systems within seconds to minutes [32]. Finally, 100 MW storage assets can achieve up to 3,500 full load hours in other studies [63], which exceeds the full load hours of our most productive technology.

Figure 3 compares the state of charge (SOC) over the entire modeled year for all technologies and their duration variants. Most 10h systems quite frequently hit their energy storage capacity limit of 1,000 MWh. 40h systems are also fully charged from time to time, but 70h systems and 100h systems rarely store more than 5,000 MWh at a certain time and are never fully charged. Thus, these SOC profiles in combination with the relatively small
Figure 3: State of charge [%] simulation in optimal bidding schedule. The optimization is based on power market data from January 2019 to January 2020.
difference in gross profits and full load hours between 10h and 100h designs could indicate that “longer” LDES systems may not be economic.

**Levelized Cost of Storage and profitability**

To translate the optimal schedule and associated gross profits into holistic economic indicators, we draw on LCOS [29, 31] and IRR. These metrics facilitate cost and profitability comparisons of the assets considering all major cost components (see Methods).

![Figure 4: Current LDES technologies’ LCOS [EUR/MWh] and IRR [%]. Per technology variant, the upper bar shows the range of values for both indicators when the current CAPEX is 20% lower or higher than in the base assumption. The lower bar replicates this sensitivity check for OPEX.](image)

Figure 4 shows current LCOS (left part) and IRR (right part) for systems with a duration of 10h and 100h. As a sensitivity test, we depict LCOS and IRR when capital expenditures (CAPEX) or operating expenditures (OPEX) are 20% lower or higher. For the sake of clarity, we omit systems with 40h and 70h as they are in between the two extreme duration cases (see Supplementary Information).
As can be seen, PHS, the mature technology, reaches the lowest LCOS values with about 47-54 EUR/MWh. LCOS generally correlates with gross profit within the 10h duration. However, when comparing the different duration scales, the 100h systems tend to have much higher LCOS as additional revenue from higher full load hours cannot offset higher CAPEX and OPEX. In terms of IRR, no technology except PHS would currently earn its cost of equity. While 10h LAES and 10h GRAV at least come relatively close in favourable CAPEX assumptions (i.e. 20% lower than the base), other systems are currently vastly not providing a positive return. Moreover, some technologies (H2, 100h VRFB, and 100h LAES) cannot cover annual expenses (OPEX, interest, debt repayment) in any year under current technology parameters so that it is impossible to compute an IRR.

Technological progress is expected for all storage technologies but PHS and LAES [11, 31, 32]. Since LDES will gain particular importance in the future with a projected increase in the share of intermittent renewable power generation, a forward-looking scenario should complement the status quo analysis. As such, we rerun our financial analysis using projected technology and financing parameters at maturity.

Figure 5 shows LCOS and IRR at maturity, again as a range determined by -20% to +20% CAPEX (upper bar) or OPEX (lower bar). According to our results, several technologies could become competitive with PHS at maturity. In particular, 10h IFRB reaches the lowest LCOS, marginally below the range of PHS. In addition, the LCOS of GRAV and – under favorable CAPEX assumptions – of 10h VRFB also intersects with the 10h PHS interval. Given our specific assumption of recycled concrete making GRAV CAPEX independent of energy capacity, 10h and 100h GRAV have similar LCOS ranges. However, for all other technologies, the 100h systems again strongly underperform 10h systems. H2 still is the most expensive LDES, with LCOS of about 200 €/MWh under optimistic assumptions. In other words, H2 is unlikely to play a major role in electricity storage in the foreseeable future [64].

While we exclusively focus on revenue streams from power markets, H2 could have additional
Figure 5: LCOS [EUR/MWh] and IRR [%] of LDES technologies at maturity. Per technology variant, the upper bar shows the range of values for both indicators when the future CAPEX at maturity is 20% lower or higher than in the base assumption. The lower bar replicates this sensitivity check for OPEX.

<table>
<thead>
<tr>
<th>Technology</th>
<th>LCOS (€/MWh)</th>
<th>IRR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHS - 10h</td>
<td>47 - 66</td>
<td>3% - 11%</td>
</tr>
<tr>
<td>PHS - 100h</td>
<td>51 - 55</td>
<td>2% - 4%</td>
</tr>
<tr>
<td>LAES - 10h</td>
<td>50 - 73</td>
<td>2% - 6%</td>
</tr>
<tr>
<td>LAES - 100h</td>
<td>66 - 74</td>
<td>1% - 4%</td>
</tr>
<tr>
<td>GRAV - 10h</td>
<td>51 - 55</td>
<td>4% - 11%</td>
</tr>
<tr>
<td>GRAV - 100h</td>
<td>55 - 57</td>
<td>6% - 9%</td>
</tr>
<tr>
<td>IRFB - 10h</td>
<td>43 - 54</td>
<td>0% - 3%</td>
</tr>
<tr>
<td>IRFB - 100h</td>
<td>44 - 52</td>
<td>2% - 5%</td>
</tr>
<tr>
<td>VRFB - 10h</td>
<td>46 - 62</td>
<td>6% - 10%</td>
</tr>
<tr>
<td>VRFB - 100h</td>
<td>56 - 69</td>
<td>9% - 13%</td>
</tr>
<tr>
<td>H2 - 10h</td>
<td>61 - 67</td>
<td>17% - 39%</td>
</tr>
<tr>
<td>H2 - 100h</td>
<td>67 - 68</td>
<td>28% - 30%</td>
</tr>
</tbody>
</table>

Impact of price volatility

A limitation to our analysis is that future market prices are unknown but affect investments decided on today. In light of ambitious wind and solar capacity expansion targets, future market outcomes may fundamentally differ from observed historic realizations. For instance, a frequent hypothesis is an increase in price volatility with an increasing share of intermittent
renewable generation, albeit empirical evidence is mixed so far [66, 67, 68]. On the contrary, volatility in future power markets with substantial storage capacity or other flexibility mechanisms might also decrease [69]. Consequently, we investigate the sensitivity of profitability against such potential changes in price volatility. To this end, we modify average exploited spreads, i.e. the difference between discharge and charge prices, as a proxy for volatility.

![Figure 6: LCOS and IRR sensitivity to changes in price spread.](image)

Figure 6 shows LCOS and IRR if the average spread changes by -20% to +20%. The resulting IRR range is almost as big as in the mature CAPEX sensitivity analysis. For some technologies, changes in the average exploited spread determine whether investors return expectations, represented by the cost of equity, will be met or not. However, even a 20% spread increase does not allow for calculating an IRR for 100h LAES, 100h VRFB, and H2 for the same reason as before. Overall, while we show that potentially increasing volatility could result in more attractive investment returns, the increase in volatility needs to translate into spread increases of at least 20% to make a difference for the majority of LDES technologies.
Disentangling technological and financial maturity

In the previous sections, we model improvements in the LCOS and IRR as a combined effect of technological progress and “financial learning” materializing in a lower weighted average cost of capital (WACC) \( [70] \). Subsequently, we aim to disentangle both these cost-decreasing
channels and their contribution to profitability.

Figure 7 shows that cost-decreasing technological progress is key to lower LCOS and convergence of IRR and cost of equity. The contribution of the WACC is generally lower, but also non-negligible. For instance, financial learning reduces LCOS by less than 10% for 10h IFRB, but by about the same as technological progress for the CAPEX-intensive 10h GRAV.

**Discussion**

Our analysis, based on optimal bidding in the German electricity market, shows that of all LDES technologies, only PHS can currently cover costs of capital. Assuming technological progress and financial learning, further LDES technologies become interesting, in particular iron redox flow batteries and gravity storage. However, whether a technology will reach maturity depends on the previous construction and operation of some more expensive units to facilitate technological and financial learning. Thus, financial support, whose magnitude can be derived from our analysis, might be warranted so that investors’ costs of capital are covered. Such subsidies should arguably apply to upfront investment because feed-in-tariff-like subsidies could imply unwanted effects on day-to-day power market operations. For the 10h systems, we calculate subsidies of EUR 39 (LAES), 73 (GRAV), 82 (IRFB), and 115 (VRFB) per kWh energy storage capacity. Importantly, these values of 10h duration systems generally exceed the corresponding values of systems with 100h duration. As such, comparisons of upfront subsidy levels per kWh energy capacity can be misleading and should thus be put into perspective to system size. Transformed into EUR/MWh of discounted discharged electricity, corresponding subsidy values range from 34 EUR (GRAV) to 80 EUR (VRFB) per MWh discharged. While policymakers might be tempted to support the currently most attractive option, our analysis shows that technological progress could make some technologies
significantly more attractive in the future. Consequently, adequately tailoring support policies to each technology while avoiding technological lock-in is important due to uncertainty of technological progress and sensitivity financial measures.

Furthermore, our analysis points to potential problems in bringing LDES with a long duration of up to 100h to markets. Even under favourable CAPEX or volatility assumptions, these larger LDES assets are less profitable than smaller LDES, and usually unprofitable – except for GRAV due to the special assumption of using low-cost recycled concrete. Therefore, regulators and policymakers might need to consider additional compensation mechanisms to attract investment in 100h LDES, when security of decarbonized supply constitutes the objective. A possible instrument could be upfront subsidies around 150 EUR/MWh discharged that suffice for the most promising technologies (IFRB and GRAV). Policymakers should phase out subsidies if technological progress realizes as predicted.

Finally, our results emphasize the value of de-risking storage investments in light of the notable impact of financing costs.

Methods

Electricity market participation

We project the revenues of LDES by simulating their market participation. Specifically, we develop a two-stage optimization problem to determine the bids in the day-ahead (DAM), intraday (IDM) and frequency reserve market (FRM) in the next day [71]. The first stage refers to one day ahead of delivery of electricity. In reality, the day-ahead market and frequency reserve capacity market are settled during this stage. The second stage refers to the day of delivery. In reality, the intraday market is open during this stage.

We determine the yearly revenue by iterating over the two-stage optimization problem using a rolling horizon as the two-stage optimization problem only optimizes the bids during
the next day. In the first stage, we optimize the quantity bids in the DAM, IDM, and FRM assuming we have complete information about the day-ahead and intraday prices during the next day and a set of scenarios on the prices in the FRM during the next day. We do not assume perfect foresight in the FRM because its market outcomes are much more difficult to predict. Instead, we calculate the mean and standard deviation of the marginal prices of the previous two weeks by FRM product category [61]. Based on the assumed normal distribution, we next derive the set of scenarios on the prices in the FRM. The bid in the FRM might not be successful as opposed to fully informed bids in the DAM and IDM.

In the second stage, we optimize the quantity bids in the IDM assuming we have complete information on which bids in the FRM were successful. The bids in the DAM were all successful because we assume complete foresight on the day-ahead prices. Opportunities for arbitrage could exist in case some bids in the FRM were not successful. We refer to the Supplementary Information for a mathematical description of the optimization problems.

**Financial modeling approach**

Similar to technological progress, studies have highlighted the presence of financial learning.[70] Further de-risking LDES assets, e.g. by granting access to green bond financing, could boost financial learning and lower costs of debt and equity.[72] To account for these cost-decreasing channels, we also assume changes in the financing structure and weighted average cost of capital when the LDES assets progress from the current state to maturity. Our financing assumptions are based on current industry reports for the only “entirely mature” technology, PHS [73]. Specifically, leverage increases from 20% to 50% while cost of equity (debt) falls from 12% (8%) to 8% (3%). Consequently, the weighted average cost of capital decreases from 10.7% to 5.5% at maturity, comparable to assumptions in other studies [63]. Debt is repaid as an annuity over a maximum of 30 years, i.e. we do not assume a specific debt structuring. Further assumptions include a 30% tax rate, and a 2.37% percentage increase in OPEX each year to account for average inflation between 1950 and 2021 [74].
Financial performance is measured with two key metrics widely adopted in literature and industry. First, the levelized cost of storage indicates the compensation per discharged unit of electricity required for an investor to break even [29, 31]. Formally, the LCOS is defined as

$$LCOS = \sum_{t=0}^{T} \frac{CAPEX_t + OPEX_t + cc_t}{(1 + WACC)^t} \times \frac{1}{Fullloadhours_t}$$

(1)

, where $CAPEX$ and $OPEX$ are defined as before, and $cc_t$ indicates charging expenses, i.e. electricity costs when loading the storage asset. $WACC$ is the weighted average cost of capital.

Second, the internal rate of return represents the discount rate that implies a zero net present value of the storage investment. The IRR indicates expected profitability for an investor’s equity share [63]. We used the build-in IRR function of Microsoft Excel to calculate the IRRs.

**Data availability statement**

Some of the data used for optimization are proprietary. In particular, we have licensed the electricity spot market data from EPEX Spot. FRM data are publicly available at [www.regelleistung.net](http://www.regelleistung.net). Key technology parameters and underlying sources are shown in Table I.

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Supplementary Information

German electricity market

Our analysis focuses on optimized bidding of long-duration energy storage (LDES) systems in the German electricity market. This section provides some background on the three markets – Day-Ahead, Intraday, and frequency reserve market – where the systems can place bids.

The German Day-Ahead market (DAM) follows the procedures of the mutual European DAM design. Verified participants place physical buy and sell bids about specific amounts of electricity for one-hour blocks. The bids must be allocated until 12 pm for the day after. Calculation of the market clearing price is based on the merit order – or marginal pricing principle – with uniform pricing. In 2019, 226.4 TWh of electricity were traded on the German DAM, i.e. 25.8 GWh per hour on average [75]. Compared to this amount of traded electricity, the 100 MW storage systems in our analysis are relatively small, achieving a market share of less than 0.4% under full load.

Similar to the DAM, the German Intraday market (IDM) is managed by the EEX. Traded products in the IDM are to be delivered over a 15-min period. At first, IDM products are auctioned until 3 pm the day before delivery. However, this is a pay-as-bid procedure implying that not the latest bid below the demand threshold sets the price for all called bids, but actually, all bids below the demand curve receive their respective offer at delivery. Furthermore, to ensure flexible pricing, the IDM allows continuous after-market trading of the auctioned products until shortly before delivery. The traded volume on the IDM, 53.7 TWh, is about four times smaller compared to the DAM volume in 2019 [75]. Nevertheless, a single asset as modelled in our analysis still has a small market share even under full load (ca. 1.6%).

To avoid blackouts and other incidents, a transmission system operator (TSO) must
ensure frequency- or, respectively, supply-demand stability of their controlled grid area. Consequently, TSOs ask for flexible loads to in- or decrease the grid’s total load profile, which is traded in the secondary FRM in the form of positive and negative frequency reserve energy. Market participants tender a belonging offering price for capacity and potentially called energy. The defined product length is four hours, during which the successful market participants must be able to provide demanded reserve energy. There are three main types of frequency reserve energy. The first one, frequency containment reserve (or primary reserve), must react within 30 seconds to the TSO demand. Here, most systems that are fast to respond participate in that area, e.g., high-voltage capacitors or other magnetic storage systems. Then, within 5 minutes, the TSO can use automatic frequency restoration reserve (aFRR or secondary reserve). If there is still need for balancing, the third stage, manual frequency restoration reserve (mFRR, or tertiary/minute reserve) can be activated.

Supplementary Figure 1: Reserve energy tenders in Germany, in MW, as tendered by the four German TSOs.

As shown in Supplementary Figure 1, the aFRR market is the biggest market in terms of tendered and called volumes, and hence the best market opportunity for LDES. Primarily, most LDES systems can react within minutes, some even seconds, making them suitable market participants.
Looking at the size of capacity or energy offers to the FRM, 84% of all bids are in the size of 5 MW and over 90% below the threshold of 10 MW in 2019 (see Supplementary Figure 2).

The German FRM markets have seen frequent changes in the past years. Most recently, capacity and energy tenders in the aFRR and mFRR were decoupled in order to increase market efficiency and liquidity. Further changes are to some extent driven by European efforts for market harmonization under PICASSO and MARI regulation. One major issue energy storage systems faced until 2021 was double taxation. Since standalone storage systems buy electricity from and sell to the grid, they had to pay grid charges twice – for each unit of electricity purchased and sold. However, a regulatory change of German EnWG,
§ 118 No. 6, now enables electrical energy storage systems to buy and sell electricity without additional grid charges. Hence, we ignore this issue of double taxation as we expect it to be irrelevant in the future.

**Mathematical formulation of optimization problems**

**First stage**

The decision variables are:

1. Quantity bids in the day-ahead market $y_{t}^{dc,DA}$ and $y_{t}^{ch,DA}$ for each hourly block in the next week $\mathcal{T}_{\text{week}}$. However, only the optimal values for each hourly block in the next day $\mathcal{T}_{\text{day}}$ are retained. The capacity bid is with certainty accepted by the market because the price bid equals the DAM price, which is a given parameter.

2. Quantity bids in the intraday market $y_{t}^{dc,ID}$ and $y_{t}^{ch,ID}$ for each 4-hourly block in the next day $\mathcal{T}_{\text{day}}$. The capacity bid is with certainty accepted by the market because the price bid equals the IDM price, which is a given parameter.

3. Quantity bids in the frequency reserve market $y_{t}^{dc,+}$ and $y_{t}^{ch,-}$ for each quarter hour in the next day $\mathcal{T}_{\text{day}}$.

4. The state of charge $\text{SoC}_t$ during each quarter hour $t \in \mathcal{T}_{\text{week}}$.

The parameters are:

1. Prices in the day-ahead market $p_{t}^{DA}$, the intraday market $p_{t}^{ID}$ as well as in the frequency reserve market for capacity $p_{t}^{C,+}$ and $p_{t}^{C,-}$ and for energy $p_{t}^{E,+}$ and $p_{t}^{E,-}$.

2. The probability that a quantity bid in the frequency reserve market for capacity is accepted $\pi_{t}^{dc,C,+}$ and $\pi_{t}^{ch,C,-}$. 
3. The probability that a quantity bid in the frequency reserve market for energy is accepted \( p_t^{dc,E} \) and \( p_t^{ch,E} \).

4. The maximal charging and discharging capacity \( \bar{y}^{ch} \) and \( \bar{y}^{dc} \) as well as the maximal state of charge \( \bar{SoC} \).

5. The self-discharge rate \( \eta^{sd} \), the charging efficiency \( \eta^{ch} \) and discharging capacity \( \eta^{dc} \).

6. The initial \( \bar{SoC}^0 \) which equals the optimal value of \( SoC_t \) with \( t = |\mathcal{T}^{day}| \) from the second stage optimization problem in the previous iteration.

Equations (2a)-(2u) present the optimization problem in the first stage. \( \mathcal{T}_{i}^{DA\text{ block}} \) and \( \mathcal{T}_{i}^{FRM\text{ block}} \) are the sets of quarter hours \( t \) in an hourly block and 4-hour block respectively, with \( \mathcal{T}^{DA} \) and \( \mathcal{T}^{FRM} \) the set of hourly blocks and 4-hour blocks respectively in the next week \( \mathcal{T}^{week} \).

\[
\max_{t \in \mathcal{T}^{week}} \left[ R_{t}^{DA} + R_{t}^{ID} + R_{t}^{C+} + R_{t}^{C-} + R_{t}^{E+} + R_{t}^{E-} \right] \times \frac{1}{4} \quad (2a)
\]

subject to

Definition of revenues:

\[
R_{t}^{DA} = p_{t}^{DA} \times \left[ y_{t}^{dc,DA} - y_{t}^{ch,DA} \right], \quad \forall t \in \mathcal{T}^{week} \quad (2b)
\]

\[
R_{t}^{ID} = p_{t}^{ID} \times \left[ y_{t}^{dc,ID} - y_{t}^{ch,ID} \right], \quad \forall t \in \mathcal{T}^{week} \quad (2c)
\]

\[
R_{t}^{C+} = p_{t}^{C+} \times y_{t}^{dc,+} \times \pi_{t}^{dc,C+}, \quad \forall t \in \mathcal{T}^{week} \quad (2d)
\]

\[
R_{t}^{C-} = p_{t}^{C-} \times y_{t}^{ch,-} \times \pi_{t}^{ch,C-}, \quad \forall t \in \mathcal{T}^{week} \quad (2e)
\]

\[
R_{t}^{E+} = p_{t}^{E+} \times y_{t}^{dc,+} \times \pi_{t}^{dc,E+}, \quad \forall t \in \mathcal{T}^{week} \quad (2f)
\]

\[
R_{t}^{E-} = p_{t}^{E-} \times y_{t}^{ch,-} \times \pi_{t}^{ch,E-}, \quad \forall t \in \mathcal{T}^{week} \quad (2g)
\]

Definition of charging and discharging capacities:
\[y_{t}^{ch} = y_{t}^{ch,DA} + y_{t}^{ch,ID} + y_{t}^{dc,+}, \quad \forall t \in T^{week} (2h)\]
\[y_{t}^{dc} = y_{t}^{dc,DA} + y_{t}^{dc,ID} + y_{t}^{ch,-}, \quad \forall t \in T^{week} (2i)\]

Limits to the charging and discharging capacities:
\[0 \leq y_{t}^{ch} \leq \bar{y}^{ch}, \quad \forall t \in T^{week} (2j)\]
\[0 \leq y_{t}^{dc} \leq \bar{y}^{dc}, \quad \forall t \in T^{week} (2k)\]
\[y_{t}^{ch,DA}, y_{t}^{ch,ID}, y_{t}^{ch,-}, y_{t}^{dc,DA}, y_{t}^{dc,ID}, y_{t}^{dc,+} \in \mathbb{R}_{0+}, \quad \forall t \in T^{week} (2l)\]

Definition of state of charge:
\[SoC_{t} = SoC_{t-1} \times [1 - \eta^{sd}] + \left[ y_{t}^{ch} \times \eta^{ch} - \frac{y_{t}^{dc}}{\eta^{dc}} \right] \times \frac{1}{4}, \quad \forall t \in T^{week \setminus \{1\}} (2m)\]
\[SoC_{t} = SoC^{0} \times [1 - \eta^{sd}] + \left[ y_{t}^{ch} \times \eta^{ch} - \frac{y_{t}^{dc}}{\eta^{dc}} \right] \times \frac{1}{4}, \quad \forall t \in \{1\} (2n)\]

Limits to the state of charge:
\[0 \leq SoC_{t} \leq \bar{SoC}, \quad \forall t \in T^{week} (2o)\]

Limits to simultaneous charging and discharging:
\[y_{t}^{ch} \times y_{t}^{dc} = 0, \quad \forall t \in T^{week} (2p)\]

Limits to the time horizon of IDM and FRM:
\[y_{t}^{ch,ID} = y_{t}^{dc,ID} = y_{t}^{dc,+} = y_{t}^{ch,-} = 0, \quad \forall t \in T^{week \setminus T^{day}} (2q)\]

Limits to the temporal granularity in DAM and FRM:
\[y_{t}^{dc,DA} = y_{t-1}^{dc,DA}, \quad \forall t \in T^{DAblock}, \forall i \in \mathcal{I}^{DA} (2r)\]
\[y_{t}^{ch,DA} = y_{t-1}^{ch,DA}, \quad \forall t \in T^{DAblock}, \forall i \in \mathcal{I}^{DA} (2s)\]
\[y_{t}^{dc,+} = y_{t-1}^{dc,+}, \quad \forall t \in T^{FRMblock}, \forall i \in \mathcal{I}^{FRM} (2t)\]
\[y_{t}^{ch,-} = y_{t-1}^{ch,-}, \quad \forall t \in T^{FRMblock}, \forall i \in \mathcal{I}^{FRM} (2u)\]

Objective (2a) maximizes the expected revenue from the DAM, IDM, and FRM during the next week. Constraints (2b-2g) define the revenue of each product and market and
constraints \((2h-2i)\) define the total charging and discharging capacity assuming that the bids in the FRM for capacity and energy will be successful in order to be reliable in delivery. Note that this leads to unused storage capacity in case not all bids in the FRM are successful. The second optimization fills this gap using information on which bids in the FRM are cleared one day ahead of delivery. Next, constraints \((2j-2l)\) pose limits to the charging and discharging capacities. While constraints \((2m-2n)\) define the state of charge (SOC) for each quarter hour, constraint \((2o)\) limits the SOC. Furthermore, constraint \((2p)\) prohibits simultaneous charging and discharging and constraint \((2q)\) prohibits participation in the IDM or FRM for later quarter hours than during the next day. Finally, constraints \((2r-2u)\) impose a temporal granularity of the bids in the DAM (1-hour blocks) and the FRM (4-hour blocks).

The optimal values for the quantity bids in the day-ahead market \(y_{t}^{*,dc,DA}\) and \(y_{t}^{*,ch,DA}\) \((\forall t \in T_{day})\) as well as the quantity bids in the frequency reserve market \(y_{t}^{*,dc,+}\) and \(y_{t}^{*,ch,-}\) \((\forall t \in T_{day})\) are inputs to the second stage optimization problem.

**Second stage**

In the second stage, we optimize the quantity bids in the IDM assuming we have complete information on which bids in the FRM were successful. The bids in the DAM were all successful because we assume complete foresight on the day-ahead prices. Opportunities for arbitrage could exist in case some bids in the FRM were not successful. Specifically, the only decision variables are the quantity bids in the intraday market \(y_{t}^{*,dc,ID}\) and \(y_{t}^{*,ch,ID}\) for each 4-hourly block in the next day \(T_{day}\). The capacity bid is with certainty accepted by the market because the price bid equals the intraday market price, which is a given parameter.

The parameters are, among others:

1. The optimal quantity bids in the day-ahead market \(y_{t}^{*,dc,DA}\) and \(y_{t}^{*,ch,DA}\) for each hourly block in the next day \(T_{day}\) as determined in the first stage optimization problem.
2. Prices in the intraday market \(p_{t}^{ID}\) as well as in the frequency reserve market for capacity
\[ p_t^C^+ \text{ and } p_t^C^- \text{ and for energy } p_t^{E^+} \text{ and } p_t^{E^-}. \]

3. A boolean that indicates whether a quantity bid in the frequency reserve market for capacity is accepted \( b_t^{dc,C^+} \) and \( b_t^{ch,C^-} \), based on the quantity bids in the frequency reserve markets \( y_t^{dc,+} \) and \( y_t^{ch,-} \) that was determined in the first stage optimization problem.

4. The fraction of the quantity bids in the frequency reserve market for energy that is accepted \( v_t^{dc,E^+} \) and \( v_t^{ch,E^-} \), based on the quantity bids in the frequency reserve markets \( y_t^{dc,+} \) and \( y_t^{ch,-} \) that was determined in the first stage optimization problem.

\[
\max \sum_{t \in T^{day}} p_t^{ID} \times [y_t^{dc, ID} - y_t^{ch, ID}] \times \frac{1}{4} \quad (3a)
\]

subject to

Definition of charging and discharging capacities:

\[
y_t^{ch} = y_t^{sch, DA} + y_t^{ch, ID} + y_t^{sch, +} \times v_t^{dc, E^+}, \quad \forall t \in T^{day} \quad (3b)
\]

\[
y_t^{dc} = y_t^{sch, DA} + y_t^{dc, ID} + y_t^{sch, -} \times v_t^{ch, E^-}, \quad \forall t \in T^{day} \quad (3c)
\]

Limits to the charging and discharging capacities:

\[
0 \leq y_t^{ch} \leq \bar{y}^{ch}, \quad \forall t \in T^{day} \quad (3d)
\]

\[
0 \leq y_t^{dc} \leq \bar{y}^{dc}, \quad \forall t \in T^{day} \quad (3e)
\]

\[
y_t^{ch, ID}, y_t^{dc, ID} \in \mathbb{R}^{0+}, \quad \forall t \in T^{day} \quad (3f)
\]

Definition of state of charge:

\[
SoC_t = SoC_{t-1} \times \left[1 - \eta^{sd}\right] + \left[ y_t^{ch} \times \eta^{ch} - \frac{y_t^{dc}}{\eta^{dc}} \right] \times \frac{1}{4}, \quad \forall t \in T^{day} \setminus \{1\} \quad (3g)
\]

\[
SoC_t = SoC^0 \times \left[1 - \eta^{sd}\right] + \left[ y_t^{ch} \times \eta^{ch} - \frac{y_t^{dc}}{\eta^{dc}} \right] \times \frac{1}{4}, \quad \forall t \in \{1\} \quad (3h)
\]

Limits to the state of charge:
\begin{align*}
0 \leq & \text{SoC}_t \leq S\text{SoC}, \quad \forall t \in T^{day} \quad (3i) \\
\text{Limits to simultaneous charging and discharging:} \\
y_t^{ch} \times y_t^{dc} = 0, \quad \forall t \in T^{day} \quad (3j)
\end{align*}

Objective (3a) maximises the revenue from the IDM during the next day. Constraints (3b-3c) define the total charging and discharging capacity. Next, constraints (3d-3f) pose limits to the charging and discharging capacities. While constraints (3g,3h) define the SOC for each quarter hour, constraint (3i) limits the SOC. Finally, constraint (3j) prohibits simultaneous charging and discharging.

As a result, the revenue of the storage system during the next day is \[ \sum_{t \in T^{day}} \left[ R_t^{DA} + R_t^{ID} + R_t^{C^+} + R_t^{C^-} + R_t^{E^+} + R_t^{E^-} \right] \times \frac{1}{4} \] with:

- \[ R_t^{DA} = p_t^{DA} \times [y_t^{dc,DA} - y_t^{ch,DA}] \]
- \[ R_t^{ID} = p_t^{ID} \times [y_t^{dc,ID} - y_t^{ch,ID}] \]
- \[ R_t^{C^+} = p_t^{C^+} \times y_t^{dc,+} \times b_t^{dc,C^+} \]
- \[ R_t^{C^-} = p_t^{C^-} \times y_t^{ch,-} \times b_t^{ch,C^-} \]
- \[ R_t^{E^+} = p_t^{E^+} \times y_t^{dc,+} \times v_t^{dc,E^+} \]
- \[ R_t^{E^-} = p_t^{E^-} \times y_t^{ch,-} \times v_t^{ch,E^-} \]
Supplementary Figure 3: Current LDES technologies’ LCOS [EUR/MWh] and IRR [%]. Per technology variant, the upper bar shows the range of values for both indicators when the current CAPEX is 20% lower or higher than in the base assumption. The lower bar replicates this sensitivity check for OPEX. Results for the 10h and 100h variants are discussed in the main part.
Supplementary Figure 4: LCOS [EUR/MWh] and IRR [%] of LDES technologies at maturity. Per technology variant, the upper bar shows the range of values for both indicators when the future CAPEX at maturity is 20% lower or higher than in the base assumption. The lower bar replicates this sensitivity check for OPEX. Results for the 10h and 100h variants are discussed in the main part.

Supplementary Figure 5: LCOS and IRR sensitivity to changes in price spread. Changes in average price spread of ± 20% under given dispatch proxy for changes in market volatility. Results for the 10h and 100h variants are discussed in the main part.
Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- LDESFMsubmission.xlsx