The future cost of electrical energy storage based on experience rates

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Electrical energy storage could play a pivotal role in future low-carbon electricity systems, balancing inflexible or intermittent supply with demand. Cost projections are important for understanding this role, but data are scarce and uncertain. Here, we construct experience curves to project future prices for 11 electrical energy storage technologies. We find that, regardless of technology, capital costs are on a trajectory towards US$340±60/kWh for installed stationary systems and US$175±25/kWh for battery packs once 1 TWh of capacity is installed for each technology. Bottom-up assessment of material and production costs indicates this price range is not infeasible. Cumulative investments of $175–510bn would be needed for any technology to reach 1 TWh deployment, which could be achieved by 2027–2040 based on market growth projections. We then explore how the derived rates of future cost reduction influence when storage becomes economically competitive in transport and residential applications. Thus, our experience curve dataset removes a barrier for further study by industry, policymakers and academics.

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An informed understanding of the potential future costs of electricity storage technologies is essential to quantify their uptake as well as the uptake of low-carbon technologies reliant on storage[1–3]. This can increase investor confidence and enable policymakers to design suitable deployment strategies[4]. A lack of open data to project storage costs currently necessitates incorporating wide cost ranges[1], using cost projections of electric vehicle (EV) battery packs for stationary applications[4,5] or excluding storage from studies of future electricity systems[3].

Learning curves depict the development of production cost as a function of increased cumulative production and have been described as the most objective method to project future costs of technologies[6]. Instead of production cost, experience curves depict product price development to account for all cost factors (R&D, sales, depreciation, etc.) and, while more uncertain than learning curves, are also suitable to explore future costs[7,8]. The rate at which product prices change is termed the experience rate (ER). Cumulative production has been identified as the predictor of technology cost that performs best compared to other variables[9].

Although many studies refer to cost reduction potentials along experience curves of single storage technologies[2,10–14], there is no holistic overview covering multiple technologies within a consistent scope and methodology. Such an overview, as presented here, helps to identify overarching trends in cost reduction, compare investment levels required to achieve competitive price levels[15] and evaluate the technology-specific value added to renewable power systems[1].

In this paper, we construct a comparative appraisal of experience curves for promising electrical energy storage (EES) technologies. We then project future prices based on increased cumulative capacity and test their feasibility against possible cost floors set by material and production costs. Using market growth models, we define feasible timescales for realising these prices and we determine the required investments in deployment. Finally, we discuss the key implications of our analysis and use two stylized examples to show how derived experience rates can be used to assess the uncertainty around future competitiveness of storage.

Experience curves for electrical energy storage technologies

We derive experience curves following Wright's law[16] using historic product prices and cumulative installed capacities based on data from peer reviewed literature, research and industry reports, news items, energy storage databases and interviews with manufacturers. If available, already published experience curves are used directly or updated. We focus on using actual price data and avoid theoretical estimates (see Methods and Supplementary Table 1).

Prices for storage technologies differ by scope, application and size[17]. We differentiate along two main dimensions, application category and technology scope. Application category covers portable (electronics), transport (hybrid electric vehicle - HEV, and electric vehicle - EV) and stationary (residential, utility); technology scope covers cell, battery, module, pack, ex-works system and system (see Methods, Supplementary Figure 1 and Supplementary Table 2).

Figure 1 shows decreasing product prices with increasing cumulative installed capacities for most EES technologies. Pumped hydro (system), lead-acid (module), alkaline electrolysis (pack) and lithium-ion (Li-ion) for consumer electronics (battery) exhibit current prices below 300 US$/kWh above 100 GWh installed. The relatively low ERs below 5% of the first two are contrasted by 18% for electrolysis (pack) and 30% for Li-ion (battery). Technologies with between 1 and 100 GWh cumulative installed capacity, such as Li-ion for EVs (pack), nickel-metal hydride (pack) or sodium-sulphur (system) show current prices below 500 US$/kWh and ERs of 11% and 16%. Those below 1 GWh like stationary Li-ion (system), lead-acid (system), redox-flow (system) and fuel cells (pack) cost more than 1,000 US$/kWh with ERs between 11% and 18%.

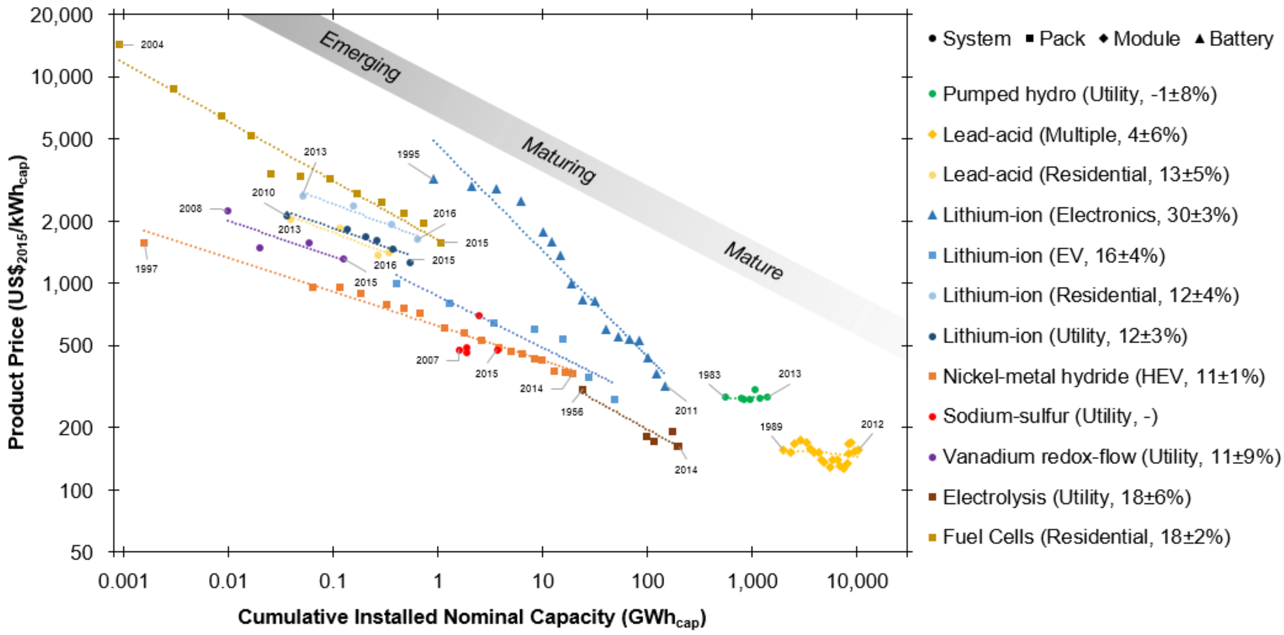

__Figure 1 – Experience curves for EES technologies.__ Results shown for product prices per nominal energy capacity (see Supplementary Figure 2 for power capacity). Dotted lines represent the resulting experience curves based on linear regression of the data. Top legend indicates technology scope and bottom legend denotes technology (including application and experience rate with uncertainty). Experience rate uncertainty is quantified as its 95% standard error confidence interval. Grey bars indicate overarching trend in cost reduction for EES relative to technology maturity. We use maturity level assessments in the literature[18,19] to categorise the technologies relative to their cumulative installed capacity as: Emerging (<1 GWh), Maturing (<100 GWh) and Mature (>100 GWh) (see Methods). According to this simplified categorisation, emerging technologies cost above 600 US$/kWh, maturing ones between 300 and 3,000 US$/kWh and mature technologies below 500 US$/kWh. Fuel cell and electrolysis must be considered in combination to form an EES technology (electrolysis converts electricity to storable hydrogen gas, fuel cells reconvert hydrogen to electricity). Data for

lead-acid (module) refer to multiple applications, including uninterruptable power supply or heavy duty transportation. kWh_{cap} - nominal energy storage capacity.

In addition, we observe that ERs for Li-ion technologies decrease with increasing technology scope. This implies that cost reductions are likely to be driven by experience in cell manufacturing rather than other components (see Supplementary Figure 3). Possible drivers for the negative ER of pumped hydro are explored in Supplementary Figures 4 and 5 by analysing hydropower plant price developments.

We determine ER uncertainty using the 95% standard error based confidence interval (CI) (see Methods and Supplementary Figure 6 and Note 1). This is relatively small (<±5%) for most emerging and maturing technologies, however most mature technologies (pumped hydro, lead-acid modules, alkaline electrolysis) exhibit high ER uncertainty (>±5%) and are not significantly different from zero ($p>0.05$).

We exclude other EES technologies for which there were not enough data, but these may still hold promise in the future. For sodium-sulphur, no feasible experience rate could be determined from the compiled data (displayed in Fig. 1 for reference).

Future costs of electrical energy storage

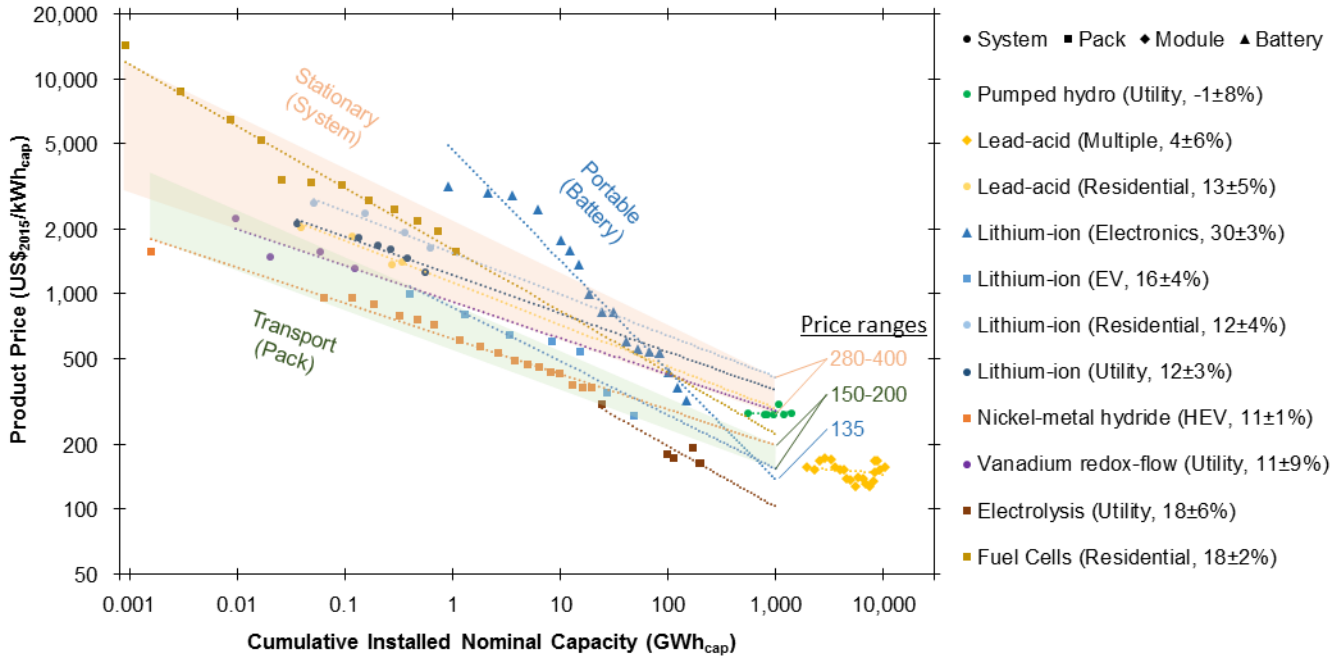

Figure 2 – Future cost of EES technologies at 1 TWh cumulative capacity. *Experience curves (dotted lines) are projected forwards to analyse product prices at future amounts of cumulative capacity. Top legend indicates technology scope and bottom legend denotes technology (including application and experience rate with uncertainty). Shaded regions are visual guides indicating the cost reduction trajectory for each application category (at a particular technology scope). These narrow to the price ranges given on the right of the figure; Systems used for stationary applications: 280-400 US$/kWh; Packs used for transport applications: 150-200 US$/kWh; Batteries used for portable applications: 135 US$/kWh. The experience curves outside of these ranges refer to technologies where product prices are reported for a different technology scope (stationary fuel cells and electrolysis: pack-level, and lead-acid: module-level). A fuel cell - electrolysis combination that could be used for stationary electrical energy storage would cost 325 US$/kWh at pack-level (electrolysis: 100 US$/kWh, fuel cell: 225 US$/kWh). kWh_{cap} - nominal energy storage capacity.*

Using the derived experience curves, we project future prices for EES based on increased cumulative capacity (Fig. 2) and test the feasibility of these projections against indicative cost floors defined by raw material and production costs.

When projecting the experience curves forwards to 1 TWh cumulative capacity, the categorisation of EES technologies along product prices versus cumulative installed capacities (see Fig. 1) can be refined into cost reduction trajectories for the three application categories. Prices for stationary systems reduce to a narrow range between 280 and 400 US$/kWh, and for battery packs to between 150 and 200 US$/kWh, regardless of technology. This implies that the one technology that manages to bring most capacity to market is likely to be the most cost-competitive. Prices for portable batteries reduce to 135 US$/kWh.

Due to the empirical rather than analytical nature of experience curves, extrapolations are subject to uncertainty of the derived ERs and uncertainty associated with unforeseeable future changes (technology breakthroughs, knowledge spill-overs, commodity price shifts)[8,20]. When accounting for uncertainty of the underlying price and capacity data, the resulting price range at 1 TWh is 75 – 1,130 US$/kWh (systems), 130 – 210 US$/kWh (packs) and 120 – 155 US$/kWh (batteries) (see Supplementary Table 5). The wide range for stationary systems is set by redox-flow systems where the high ER uncertainty means prices could stay at current levels (low ER) or reduce down to raw material costs (high ER).

The literature cautions that experience curve studies should include cost floors in extrapolated forecasts to avoid excessively low cost estimates[8,20]. We calculate raw material costs for each technology by multiplying material inventories from the literature with commodity prices of the past 10 years (see Methods and Supplementary Figure 7).

The average raw material cost across all technologies is below 110 US$/kWh, which is below the lowest price projection of 135 US$/kWh (Li-ion, Battery). Production and other costs are typically below 20%[21,22] of final system price for electrochemical, or between 50 and 80%[23] for mechanical storage technologies, confirming that the identified cost reduction potentials to 135 – 400 US$/kWh are feasible. Regarding resource availability, all active materials of the investigated EES technologies have a reserve base sufficient for the production beyond 10 TWh of storage capacity with current technology[24].

While experience rates can be useful to project future product prices, a high-level comparison of EES technologies can only be made based on application-specific levelised cost[25]. This would account for additional technical and economic parameters, for example technology lifetime, which are not reflected in this analysis.

Timeframe of potential cost reductions

To map future cost reductions onto time, we model the market diffusion process of EES technologies with the archetypal sigmoid function (S-curve) that has been observed for the deployment of several technologies[26] (see Methods).

We find that 1 TWh cumulative capacity could be installed for most technology types within 10 to 23 years (Fig. 3). By 2030 stationary systems cost between 290 and 520 US$/kWh with pumped hydro and residential Li-ion as minimum and maximum value respectively. When accounting for ER uncertainty, the price range expands to 120 – 1,160 US$/kWh (set by redox-flow systems, see Supplementary Figure 9). The price range for transport applications is 120 – 250 US$/kWh. Despite a moderate ER of 16%, Li-ion EV pack prices reduce to 120 US$/kWh by 2030 due to the high demand if 15m EVs are sold annually by 2030[27]. This equals more than 700 GWh annual capacity, compared to 50 GWh for utility storage. Demand in energy capacity for HEV packs is less pronounced, reducing prices to 250 $US/kWh. Li-ion batteries for consumer electronics would be at 130 US$/kWh by 2030.

Note that Figure 3 shows the impact of ER uncertainty on future cost projections (shaded area). Supplementary Figure 9 depicts this impact separately for each EES technology as well as the additional impact of market growth uncertainty.

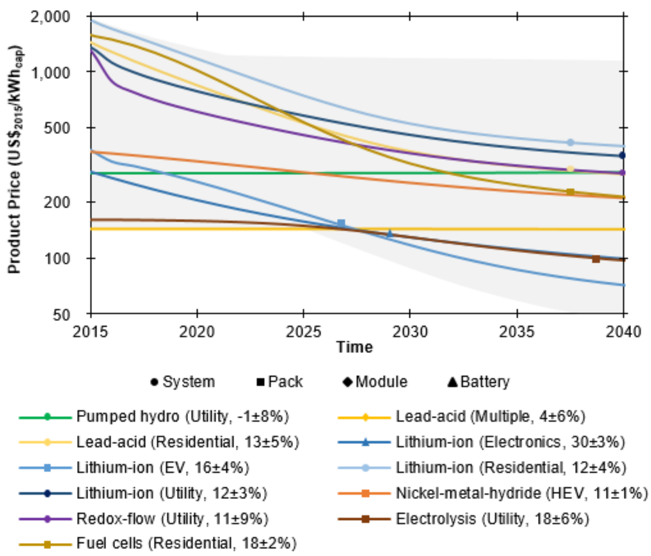

Figure 3 – Future cost of EES technologies relative to time. *Cost projections based on experience rates and S-curve type market growth assumptions for consumer electronics, hybrid electric vehicles, electric vehicles, residential storage and utility-scale storage. Market growth in different applications is mutually exclusive, but technology penetration is not, i.e. 100% market share assumed for each technology. Symbols indicate when 1 TWh cumulative installed capacity could be achieved for each technology under this condition. No symbol means 1 TWh cumulative capacity is not achieved within the given timeframe (pumped hydro: 2000, lead-acid - modules: 1970, NiMH: 2046). Shaded area marks impact of ER uncertainty. See Supplementary Figure 9 for the impact of ER and additional market growth uncertainty on each EES technology separately. Legend denotes technology (including application and experience rate with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology. kWh_{cap} - nominal storage capacity. Symbols: circle – system, square – pack, diamond – module, triangle – battery.*

The identified price range of 290 – 520 US$/kWh for stationary systems by 2030 lies within other projections (140 – 620 US$/kWh, see Supplementary Table 6). However, the recently announced Li-ion based *Tesla Powerwall 2* at an estimated price of 500 US$/kWh would be within that range already by 2017[28]. A possible explanation could be synergistic learning effects for an EES technology across applications due to shared components, cross-over techniques or knowledge spill-overs, leading to cost reductions not considered in this analysis[29]. In contrast, our cost projections are based on the assumption of 100% market share for each technology in their respective application, which yields optimistic trajectories, and would support the projections at the upper end of the literature.

The range of 120 – 250 US$/kWh for transport packs is at the lower end of similar projections (70 – 750 US$/kWh, see Supplementary Table 6), but supported by recent industry announcements of Li-ion cells reaching 100 US$/kWh as early as 2022[30]. Since higher estimates come from expert interviews versus lower from ER projections, the difference could be based on the latter placing more emphasis on future capacity additions, which would be significant if transportation is electrified. Conversely, increasingly competitive markets have driven strong price reductions since 2014, which could overestimate the underlying production cost reductions and distort the ERs we derive[7]. Studies which consider only recent years find more aggressive ERs of 19% and suggest pack costs of 73 US$/kWh by 2030[31], affirming this hypothesis.

Cumulative investment to achieve cost reductions

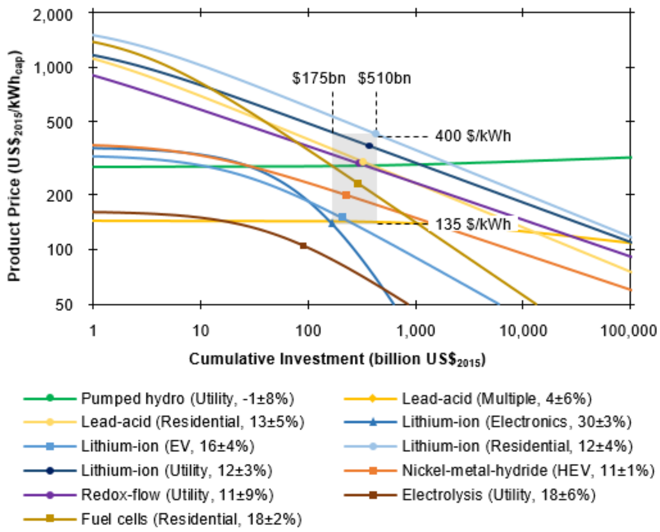

Figure 4 – Impact of cumulative investment in EES deployment on future cost of EES. *Graph shows investment in storage deployment required to "pull" technologies along individual experience curves. This investment could be consumer capital, industry capital, government subsidy or a mix of all. Shaded rectangle indicates investment required to reach prices of 135 – 400 US$/kWh. Symbols mark the amount of investment required to deploy 1 TWh cumulative capacity for each technology. No symbol means 1 TWh cumulative capacity is already deployed (pumped hydro, lead-acid modules). Legend denotes technology (including application and experience rate with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology. kWh_{cap} - nominal storage capacity. Symbols: circle – system, square – pack, diamond – module, triangle – battery.*

The cumulative investment required to deploy EES is of interest to academics, industry and policy[4,19]. By linking product prices to cumulative capacity, experience curves offer the possibility to quantify this[8,20,32].

Global investment in clean energy had a compound annual growth rate (CAGR) of 15.5% (2004 – 2015) and was US$349 billion (bn) in 2015, of which 78% were spent on wind and solar generators and 3% on electricity storage projects (US$10bn)[32–34]. Figure 4 shows that investments worth US$175bn (Li-ion, battery) to US$510bn (Li-ion, residential system) would be required for the deployment of each EES technology to reach the identified price range at 1 TWh cumulative installed capacity. This means 0.9 – 2.5% of annual clean energy investments must be spent on each technology if this price range were to be reached by 2030 at a CAGR of 15.5%. Accounting for experience rate uncertainty, the investment range could be US$30bn - US$100bn in the high ER or US$230bn - US$12,300bn in the low ER case (Supplementary Figure 10).

If end-users were willing to pay 400 $US/kWh for residential Li-ion systems already today, then US$110bn of the US$510bn total investment would be required to subsidise deployment until this price level is reached.

This can inform policymakers and industry on appropriate deployment policies and investment requirements. In light of the largest country-specific investments in renewable energy ranging from US$9bn (Germany) to US$103bn (China) in 2015[32], global cumulative investment of US$175 - US$510bn for individual EES technologies by 2027 - 2040 appear reasonable.

Discussion

Our analysis comes with three key implications for industry, policymakers and academics.

First, the common cost trajectory identified for EES technologies enables practitioners to assess proposed technologies against existing ones; with cost trajectories lying above or below signalling that the technology may remain uncompetitive or become disruptive. But, such conclusions are limited to capital costs, and a complete assessment of competitiveness must include additional factors (such as lifetime and efficiency) that affect application-specific levelised costs[25].

Second, the future projections made for EES technology prices enable simple assessment of price targets and investment requirements established for the competitiveness of EES. For example, it is suggested that benefit-stacking, the provision of multiple services simultaneously, can make EES competitive at 650 US$/kWh[4]. Our analysis indicates this price threshold could be achieved once 7 GWh of redox-flow or 33 GWh of utility-scale Li-ion systems have been deployed (central ER), which according to market growth assumptions could be by 2019 and 2023. This would correspond to US$4bn or US$94bn invested in the deployment of the respective technology. Such quantification enables an informed discussion about the scale of, and split between, private and public sector investments[4]. Note that such analyses are incomplete without considering alternatives to EES, such as network expansion, demand-side management and flexible low-carbon generation. Also, some manufacturers already propose installed system prices below 500 $/kWh[28]. If these prices prove sustainable, this represents a step-change in cost improvement which is not captured in this experience curve analysis.

The third and main implication of our analysis is that the provision of the experience curve dataset will, in our view, remove a significant barrier to analysing the future competitiveness of EES in distinct applications, and its associated uncertainty. Fig. 5 shows two stylised examples for EV transportation and residential storage, which are deliberately simplified to showcase the potential insights that can be gained from such data. The myriad of applications, technologies and location-specific contexts that are absent from this cursory analysis can now be more readily explored in future studies.

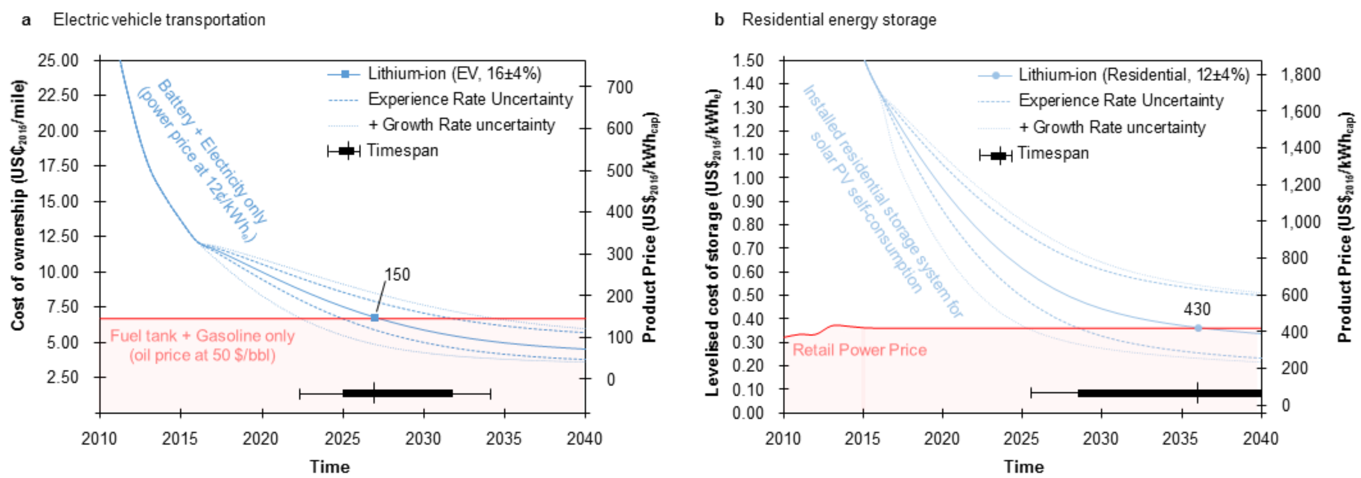

Figure 5 - Applicability of experience curve based cost projections to application-specific levelised cost analyses. *Experience curve based capital cost projections are included in levelised cost calculations for two stylised examples. (a) Cost of ownership for personal transport in the US, comparing Li-ion battery pack plus cost of electricity (blue) and a fuel tank plus cost of gasoline at US$50 per barrel oil price (red). (b): Levelised cost of storage (LCOS) in Germany for solar PV coupled residential Li-ion system (blue) compared to retail power price (red). Retail price assumed to stay at 2016 levels after 2016.*

Dashed and dotted lines in both panels represent impact of experience rate uncertainty alone and combined with market growth uncertainty, respectively. Black bars indicate possible timespan for costs to equalise with the conventional technology based on these uncertainties (vertical line: equalisation at central ER; thick bar: equalisation timespan when accounting for ER uncertainty; thin bar: equalisation timespan when accounting for ER and growth rate uncertainty). Numbers in figure specify EES product price. kWh_e - unit of electricity, kWh_{cap} - nominal energy storage capacity. Symbols: circle – system, square – pack. Formulae can be found in Methods. All parameters relevant to the levelised cost calculations can be found in Supplementary Table 7.

A recent study suggested EVs are suitable to replace the majority of vehicles in the US based on daily driving requirements[35]. To assess the economic competitiveness, we use ER analysis to project cost of ownership (in dollars per mile travelled) for the energy inputs and storage components of EVs (Nissan Leaf specifications) and conventional cars (see Methods and Supplementary Table 7). In this simplified example (Fig. 5a), EVs become competitive at Li-ion pack costs of 150 US$/kWh, which has also been found in similar studies[2,36]. In addition, we find that combined uncertainty in ER and growth rates could alter the date at which EVs become competitive by up to 12 years. The required cumulative production lies between 600 and 3,900 GWh of battery packs or 12m and 78m EVs (at 50 kWh per pack; average between Nissan Leaf[37] and Tesla Model S[38]). Note that this is a simplified example, neglecting any differences in vehicle performance or the price of other vehicle components, but this impact of ER uncertainty would carry through into more detailed analyses.

Integrated solar photovoltaic (PV) and storage systems are considered an effective means for reducing the intermittency of the generated electricity and could increase its consumption by residential generators themselves in light of decreasing feed-in tariffs[39]. In the second stylised example (Fig. 5b) we model the levelised cost of storage (LCOS) of such a system in Germany in comparison to the retail power price (see Methods and Supplementary Table 7). We find much greater uncertainty regarding the future competitiveness than in the previous example. Already the spread between central ER projection and high ER combined with high growth rate projection is 11 years, translating into required cumulative capacities of 800 GWh and 155 GWh respectively. Regardless of simplifications, this highlights the emerging state of the residential storage market. The rate at which experience is gained through the early phase will be a significant determinant of whether Li-ion systems will ever become competitive in this application.

Conclusions

In this article, we constructed experience curves of electrical energy storage technologies for portable, transport and stationary applications and identified common cost reduction trajectories. We then quantified the cost reduction potentials and cumulative investment requirements. Our findings imply that in terms of price per energy capacity, the technology that brings most capacity to market is likely to become the most cost-competitive. This could be to the advantage of modular technologies such as Li-ion batteries that can be used in multiple applications and secure high capacity markets like EV packs. An analysis of such spill-over effects that could lead to additional cost reductions across experience curves should be the focus of further studies.

In addition to the parametric and functional uncertainty of our analysis (see previous sections and Supplementary Figure 6 and Supplementary Note 1), the limitation of experience curve analysis to identify cost reduction drivers also makes it structurally uncertain[8,29,40]. Drivers beyond experience in manufacturing (learning-by-doing) could be R&D investments (learning-by-researching), customer feedback (learning-by-using), economies of scale including supply chain improvements, and spill-over effects (learning-by-interacting)[29]. Improvements in product quality (e.g. lifetime) could improve competitiveness, albeit increasing prices. Also, the identification of aggregate compared to component-specific ERs restricts insights into experience dynamics of separate EES components. Variations in all of these factors could lead to diversion from the forecasted cost reductions that are not incorporated in our analysis[20].

To account for these uncertainties, future studies should incorporate further capacity growth and price development to update the analysed experience rates. We therefore openly release our complete dataset of product price and cumulative deployment data and the respective experience curve regression parameters[41]. This enables further refining and improving the EES experience curves by updating with new data, explicitly incorporating the impact of R&D funding to compile two-factor ERs, or identifying more specific ERs for EES components and applications. Future research could also incorporate the released data as a sound statistical basis into analyses of application-specific levelised cost of storage to comprehensively assess the future competitiveness of electrical energy storage.

Methods

Experience curves for electrical energy storage technologies. We draw on peer reviewed literature, research and industry reports, news items, energy storage databases and interviews with manufacturers to identify price and cumulative deployment data or already published experience rates for electrical energy storage technologies[41]. In the literature, learning (based on production cost) and experience rates (based on product price) are sometimes used interchangeably. We therefore double-check the sources in the referenced literature to ensure using actual product price data.

By performing linear regression of the identified product price and cumulative deployment data (see Supplementary Table 1), we derive experience rates according to Wright's law[16]

$$P(x) = A\,X^{-b} \quad (1)$$
$$ER = 1 - 2^{-b} \quad (2),$$

where *P(x)* is the price per energy or power capacity of a storage technology (US$/kWh, US$/kW) at the cumulatively installed energy or power capacity X (kWh, kW) of that technology. The normalisation factor *A* and experience rate *b* are obtained with a regression analysis of the logarithms of the given price and capacity data. Using the experience rate *b* the price reduction for each doubling of installed capacity can be calculated as *ER* (%).

The geographic scope of this analysis is global. Where cumulative deployment data is available on company or country level, the data is scaled to global level. Regarding price data, we assume the global marketplace ensures that these are globally applicable[42] and highlight those technologies where prices are more likely to vary by geography (see Supplementary Table 1).

Technology scope is differentiated into cell, battery, module, pack, ex-works system and system level. While ex-works system refers to the factory-gate price of complete EES systems, system includes the cost for transportation, installation and commissioning if applicable. Additional information on the cost components included at each level can be found in Supplementary Figure 1 and Supplementary Table 2.

Three application categories are distinguished in this analysis with subgroups to indicate technology size and power-to-energy ratio (C-rate): portable (<1kWh, C≈1), transport (hybrid electric vehicle: <5kWh, C>1; electric vehicle: >25kWh, C>1) and stationary (residential: <30kWh, C<1; utility: >100kWh, C<1). Data for lead-acid (module) refer to modules larger than BDI dimensional group 8D which are used in multiple applications, for example uninterruptable power supply or heavy duty transportation[10].

Experience rate uncertainty is calculated for the 95% confidence interval based on standard error using the mean μ and standard error σ of the tabulated experience rate in

$$\mu \pm 1.96\,\sigma \quad (3),$$

Currency conversions are performed in two steps. First, we deflate historic prices in local currency with OECD Consumer Price Indices[43] and then convert prices to USD_{2015} with OECD Purchasing Producer Price Indices[44].

Conversions from energy-based to power-based data (US$/kWh, GWh vs. US$/kW, GW) are performed using the reported C-rates for each technology (see Supplementary Table 1).

We compare technical[18] and economic[19] maturity assessments of EES technologies in the literature to the cumulative installed capacities in our analysis. We find that those technologies termed 'Research & Development' or 'Developing' have less than 1 GWh installed (flow batteries, fuel cells), 'Demonstration & Deployment' or 'Developed' less than 100 GWh (lithium-ion, sodium-sulphur) and 'Commercialisation' or 'Mature' more than 100 GWh (pumped hydro, lead-acid). If applicable, we prioritise the economic maturity assessment. We then rename the categories 'emerging', 'maturing' and 'mature'.

Future costs of electrical energy storage. We use formula (1) to project product prices as a function of increased cumulative installed capacity. Experience rate uncertainty is accounted for by projecting future prices using upper and lower rates of the identified 95% confidence interval while ensuring that the experience rate variations only apply to future projections and not retrospectively.

We compile raw material cost for each storage technology by multiplying reported material inventories[45–49] with commodity prices. Commodity prices are drawn from peer reviewed literature[10], the Bloomberg database[50], a bottom-up engineering model[21] and a range of commercial and academic websites (see Supplementary Table 3). For the majority of commodities we identify price data for the past ten years and determine average, minimum and maximum prices. For others, we only identify a single price figure. Raw material cost uncertainty is based on variations in reported material inventories and commodity prices (see Supplementary Note 2 for additional comments on commodity price uncertainty).

Additional cost factors for cost floors of electrochemical storage technologies beyond material costs include direct labour, variable overhead, general, sales, administration, R&D, depreciation, warranty and profit[21]. These are determined using the bottom-up engineering model BatPac Version 3.0[21], setting annual production to 1 million units, and from the literature[22].

Additional cost factors for cost floors of mechanical storage technologies beyond material costs include electrical connection, infrastructure & logistics, civil works, planning, other installation costs, and are determined from the literature[23]. The potential cost impact of high-volume production for these usually large-scale projects is neglected.

Timeframe of potential cost reductions. To obtain potential EES technology diffusion curves, we derive sigmoid functions (S-curves) for EES application subgroups (consumer electronics, hybrid and battery electric vehicles, residential and utility storage) with the logistic growth function:

$$A_n = \frac{\mathrm{A}_{sat}}{1 + \frac{(A_{sat} - A_{base})}{A_{base}} e^{-r\,n}} \qquad (4)$$

where A_n (GWh) is the annual market capacity in a particular year, A_{base} (GWh) the initial capacity and A_{sat} (GWh) the maximum annual market capacity that will be reached long-term, the saturation capacity. r is the growth rate and n the number of periods after the start period. $\mathrm{A}_{\mathrm{base}}$ and $\mathrm{A}_{\mathrm{sat}}$ are based on the literature or own assumptions. r is then fitted to annual market capacity forecasts from the literature by non-linear regression (Supplementary Figure 8). The non-linear regression also yields the standard error of r to measure goodness-of-fit. Growth rate uncertainty is based on the maximum and minimum r determined in a Monte Carlo analysis of the non-linear regression.

The resulting annual market growth projections enable us to relate future cumulative capacities to time and interpret projected cost reductions. Hereby, we assume that each EES technology obtains 100% market share in its respective application subgroup.

The impact of experience rate uncertainty is modelled with maximum and minimum experience rates of the 95% confidence interval. The impact of additional market growth uncertainty is modelled using maximum and minimum growth rates in combination with maximum and minimum experience rates respectively. We do not discuss the impact of market growth uncertainty in the main article, since the focus of this analysis are experience rates.

Cumulative investment to achieve cost reductions. We calculate the integral of formula (1) to determine the cumulative spend required to go from the current installed capacity X1 to some future amount X2 – thus installing the amount $X_2 - X_1$ while product prices reduce:

$$Cumulative\ Spend\ (X) = \int_{X_1}^{X_2} \left(A\, X^{-b}\right) dx \quad (5)$$

Calculating this integral, while subtracting a target price (P_{target}) from the product, returns the cumulative subsidy required to deploy a defined amount of storage capacity at a subsidised target price.

The compound annual growth rate (CAGR*)* of global clean energy investments is calculated for 2004 to 2015 and then used to project clean energy investments from 2016 to 2030.

Levelised cost analyses. We calculate cost of ownership for the energy inputs and storage components of internal combustion engine (ICEV) and electric vehicles (EV) based on the formula for total cost of ownership (TCO)[51]:

$$TCO = \frac{\left(Capex - \frac{RV}{(1+r)^N}\right) CRF + \frac{1}{N} \Sigma \frac{Opex}{(1+r)^n}}{Mileage} \quad (6)$$

with *RV* as residual value at the end of life, *r* as discount factor, *N* as lifetime in years, mileage as the distance travelled per year and *CRF* as the capital recovery factor; itself a function of the year, *n*:

$$CRF = \frac{r\,(1+r)^n}{(1+r)^n - 1} \quad (7)$$

By considering only fuel tank/battery pack and gasoline/power price, the formula for cost of ownership (CO) is specified as:

$$CO = \frac{\left(capex_{EES} - \frac{RV_{EES}}{(1+r)^{N_{EES}}}\right) CRF}{mileage} + \frac{\left(\frac{P_{fuel}}{\eta_{EES}} DoD_{EES}\right) \frac{1}{CRF}}{\eta_{fuel}\, N_{EES} \sum_{n=1}^{N} (1 - DEG_{EES} n)} \quad (8)$$

with P_{fuel} as gasoline or power price, η_{fuel} the fuel efficiency, η_{EES} the round-trip efficiency of the energy storage device, DoD_{EES} the depth of discharge and DEG_{EES} the annual degradation of the storage device, defined as the fraction of usable storage content lost per year. All parameters can be found in Supplementary Table 7. By comparing average US gasoline prices[52] to crude oil spot prices[53] from 1990 to 2016, we determine our reference price of 2.36 US$/gallon as the average gasoline price observed when crude oil is between 45 and 55 US$/barrel. A reference crude oil price of around 50 US$/barrel is chosen as it is both approximately the current price of oil, and the average price over the last 20, 30 and 40 years (US$54, US$45 and US$47)[53]. We choose the US for this example to complement studies that focus on electrification of personal vehicle transportation in this country[35].

Levelised cost of storage (LCOS) is calculated as[54]:

$$LCOS = \frac{capex_{EES} + \sum_{n=1}^{N} \frac{opex_{EES}}{(1+r)^n} - \frac{RV_{EES}}{(1+r)^{N_{EES}+1}}}{C_{rated\_EES}\, DoD_{EES}\, cycles_{EES} \sum_{n=1}^{N} \frac{(1 - DEG_{EES}\, n)}{(1+r)^n}} + \frac{P_{elec\_in}}{\eta_{EES}} \qquad (9)$$

with C_{rated_EES} as the rated energy capacity, $cycles_{EES}$ the full charging/discharging cycles per year and P_{elec_in} the charging costs. All parameters can be found in Supplementary Table 7. Charging costs are modelled as the levelised cost of electricity (LCOE) for a residential solar PV installation (see Supplementary Figure 11). The 2016 German retail power price is taken as reference power price up to 2040. We choose Germany for this example, because recent growth in residential storage installations suggest that it could be a promising market for this application[55].

In both applications (EV transportation, residential storage), recent deployment data[31,56] shows Li-ion as the most common technology, the reason for calculations performed for this technology.

Data availability statement. A key objective of this publication is to remove a barrier for further analysis of the future competitiveness of electrical energy storage. The complete dataset of historic product price and cumulative deployment data for each technology is deposited in the figshare digital repository (doi: 10.6084/m9.figshare.5048062) (ref. 41) for that purpose. The spreadsheet also contains the regression parameters for each experience curve and the underlying data for Figures 1 to 5 and Supplementary Figures 2 and 3.

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Author contributions

O.S. and I.S. conducted the main part of research design, data gathering and analysis. A.H. and A.G. contributed to research design and analysis. O.S. wrote the paper. I.S., A.H. and A.G. edited the paper.

Additional information

Supplementary information is available for this paper. Reprints and permissions information is available at www.nature.com/reprints. Correspondence and requests for materials should be addressed to O.S.

Competing interests

The authors declare no competing financial interests.

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