Energy & Environmental Science

ROYAL SOCIETY OF CHEMISTRY

ANALYSIS

View Article Online
View Journal | View Issue

Cite this: *Energy Environ. Sci.*, 2021, **14**, 1635

Re-examining rates of lithium-ion battery technology improvement and cost decline†

Micah S. Ziegler [a] and Jessika E. Trancik *[ab]

Lithium-ion technologies are increasingly employed to electrify transportation and provide stationary energy storage for electrical grids, and as such their development has garnered much attention. However, their deployment is still relatively limited, and their broader adoption will depend on their potential for cost reduction and performance improvement. Understanding this potential can inform critical climate change mitigation strategies, including public policies and technology development efforts. However, many existing estimates of past cost decline, which often serve as starting points for forecasting models, rely on limited data series and measures of technological progress. Here we systematically collect, harmonize, and combine various data series of price, market size, research and development, and performance of lithium-ion technologies. We then develop representative series for these measures, while separating cylindrical cells from all types of cells. For both, we find that the real price of lithium-ion cells, scaled by their energy capacity, has declined by about 97% since their commercial introduction in 1991. We estimate that between 1992 and 2016, real price per energy capacity declined 13% per year for both all types of cells and cylindrical cells, and upon a doubling of cumulative market size, decreased 20% for all types of cells and 24% for cylindrical cells. We also consider additional performance characteristics including energy density and specific energy. When energy density is incorporated into the definition of service provided by a lithium-ion battery, estimated technological improvement rates increase considerably. The annual decline in real price per service increases from 13 to 17% for both all types of cells and cylindrical cells while learning rates increase from 20 to 27% for all cell shapes and 24 to 31% for cylindrical cells. These increases suggest that previously reported improvement rates might underestimate the rate of lithium-ion technologies' change. Moreover, our improvement rate estimates suggest the degree to which lithium-ion technologies' price decline might have been limited by performance requirements other than cost per energy capacity. These rates also suggest that battery technologies developed for stationary applications, where restrictions on volume and mass are relaxed, might achieve faster cost declines, though engineering-based mechanistic cost modeling is required to further characterize this potential. The methods employed to collect these data and estimate improvement rates are designed to serve as a blueprint for how to work with sparse data when making consequential measurements of technological change.

Received 19th August 2020,
Accepted 7th December 2020

DOI: 10.1039/d0ee02681f

rsc.li/ees

Broader context

Energy storage technologies have the potential to enable greenhouse gas emissions reductions *via* electrification of transportation systems and integration of intermittent renewable energy resources into the electricity grid. Lithium-ion technologies offer one possible option, but their costs remain high relative to cost-competitiveness targets, which could hinder these technologies' broader adoption. Existing measures of the rate at which lithium-ion technologies' costs have fallen differ considerably, resulting in an ambiguous assessment of their past improvement rates. We collect and harmonize data that describe how lithium-ion technologies have improved and possible drivers of their advancement. We measure how lithium-ion technologies have changed over time as well as with increasing market size and inventive activity. In addition, we present a method to incorporate other dimensions of performance into measures of technological change, allowing us to also consider increases in energy density and specific energy. Our results begin to approximate how previous measures might have underestimated the rate of lithium-ion technologies' improvement and suggest how much faster these technologies might advance when other characteristics are prioritized. Moreover, we delineate methods that can be applied to study how these and other energy and environmentally relevant technologies change over time, to refine efforts to inform public policies, investments, and technology development.

Introduction

Energy storage can help enable renewable energy adoption and greenhouse gas emissions reductions. Toward these goals, electrochemical energy storage technologies are increasingly

[a] *Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Cambridge, MA, USA. E-mail: trancik@mit.edu*
[b] *Santa Fe Institute, Santa Fe, NM, USA*

† Electronic supplementary information (ESI) available. See DOI: 10.1039/d0ee02681f

employed to both electrify transportation systems and aid electricity production and grid reliability.[1–3] While these storage technologies have the potential for substantially wider adoption, their costs remain relatively high, especially in comparison to cost-competitiveness targets absent a robust price on greenhouse gas emissions.[4–9] As such, considerable interest exists in elucidating how storage technologies' costs change over time and which research directions, business strategies, and policy incentives could help lower these costs.[4,6,8,10–14] Increasingly, many researchers, technology developers, and electricity providers have focused on lithium-ion technologies, whose historic cost decline has been cited as a significant achievement and promising trend.[2,15–18] However, uncertainty remains as to the rate at which lithium-ion technologies' costs and prices have fallen, adding to uncertainty about the potential for their continued decline.[10,11,14,19–21] In addition, there is growing recognition that characteristics beyond energy capacity cost, including cycle-life and capacity-loss characteristics, could influence the adoption of energy storage technologies.[4,20,22]

The need for better characterization of technological improvement rates applies to many technologies. Technologies are constantly changing, and especially for those expected to help enable climate change mitigation, such as energy storage, it is important for society to be able to accurately measure and interpret estimates of their rates of technological change. In this paper, we return to this challenge. We carefully examine the case of lithium-ion battery technologies, with the goal of better characterizing improvement rates for these technologies and developing a more general blueprint that can be applied to other technologies.

To analyze the rates of energy storage systems' cost declines, some researchers and industry analysts have turned to phenomenological models of cost change.[23–30] These models are often exponential or power relationships between the cost or price of a technology and possible determinants, such as: time, production quantity, proxies for research and development activity, or a combination of these variables.[27] The rates estimated from these analyses are then sometimes used to project future cost changes, especially how a technology's cost could decline as its production is increased, though such projections should always be accompanied by an error model.[27] Over the past few decades, this approach has been employed to study and forecast cost reduction for a variety of climate-relevant energy technologies,[31–38] such as photovoltaic panels and wind turbines. More recently, similar analyses have been performed for energy storage technologies, with a focus on lithium-ion batteries for both mobile and stationary applications.[12,14,21,39–49] These analyses have primarily examined the relationship between the historical price of lithium-ion cells (typically in terms of price per energy capacity, such as USD per kW h) and cumulative production (in total energy capacity, in units of MW h) and derived rates of price decline, often denoted ''learning rates''.‡ These learning rates represent the price decline observed upon a doubling of cumulative production and are often employed to project further price declines from increased production. Additional work has detailed the uncertainty associated with these rates[50] and has outlined the need for error models to accompany forecasts based on past trends.[27]

Analyses of price *versus* production for small lithium-ion cells have estimated a wide range of learning rates, spanning 14 to 30%.[46,51] Simple projections based on this range of rates arrive at widely varying conclusions as to when lithium-ion technologies might cross cost or price targets and the associated investment required. Such sensitivity of target dates and investment requirements to small changes in technology improvement rates is described by the nonlinear power law and exponential relationships. Variations in the datasets for other energy technologies have led to similar discrepancies between retrospective analyses, highlighting the importance of reducing data uncertainty.[26,38,50,52–54] Moreover, nearly all of these analyses focus on one performance metric of lithium-ion technologies: the cost or price per energy capacity. However, since their commercial introduction lithium-ion technologies have improved along many dimensions of performance, notably packing more energy and power into cells, expanding their utility in a variety of applications.[17,55–58] Despite being prominent objectives of research and development and drivers of technological adoption, these physical performance improvements are often considered separately from cost and price declines, possibly distorting estimates of technological improvement rates.

A clear understanding of past trajectories can help to determine reliable measures, rates, and directions of technological improvement, as well as estimates of uncertainty in data, for lithium-ion and other technologies. In addition, reliable estimates of historical trends are a key component of mechanistic models of cost change, which seek to elucidate the impact individual factors have on a technology's overall cost and explain how a technology's cost has changed in an effort to inform future reductions.[59,60] In this work, to develop improved estimates of the rates of lithium-ion technologies' change, we collect, harmonize, and combine multiple historical data sources describing the price, production, and development of lithium-ion technologies. We then systematically develop representative data series that estimate how lithium-ion technologies and their proposed drivers have changed over time, in the process transparently outlining the definition of ''representative'' so that it might be adapted or improved as required to answer other research questions. When possible, data are split into subgroups based on cell type, with a focus on separating cylindrical cells from all cell shapes. We then explore the relationships between the price decline of lithium-ion technologies and a range of factors, including time, market size, and research and development activity. Throughout, we delineate our analyses to enable fair comparison between various models of technological improvement and with previously published results.

We also consider other characteristics of lithium-ion cells that have changed over time, notably energy density (or volumetric energy density) and specific energy (or gravimetric energy density), both of which have improved substantially. We propose a method to expand the definition of service provided by a

‡ We refer to these relationships and others that relate a performance measure to a prevalence measure generally as ''performance curves''.[52,120]

lithium-ion cell to include multiple characteristics. We then develop performance curves that represent how these physical characteristics have changed over time and use these curves along with the representative price series to explore how lithium-ion technologies have improved more broadly. We find that incorporating these additional characteristics considerably increases estimated rates of technological change, suggesting that these technologies have improved faster than estimated based on cost metrics that do not account for the service improvement that higher energy density and specific energy have provided for some applications, such as in mobile devices and electric vehicles. Overall these results provide a more complete picture of the actual rate of past improvement of lithium-ion technologies and begin to suggest that faster cost improvement may be possible in the future for applications with relaxed volume and mass restrictions, as in the case of stationary energy storage.

Methods

Data series collection

We collected data from articles, reports, and presentations from the academic, government, and business literature with a focus on tracing data as far as possible to the original source. Original data were sought in order to improve data and metadata quality and reduce the chance of double-counting data points. For example, a variety of recent performance metric series were excluded as their underlying data could be obtained and used directly.[14,15,32,42,46,51,61–67] However, data series that combined previously reported data with otherwise unreported data were included. Similarly, we included data series reported with unclear references or assumptions, even if the data series closely resembled a series reported earlier. When a researcher or organization presented the same series or updated versions of a given series over the course of multiple presentations or reports, the most recent available data were incorporated. Modeled estimates of cost were excluded from this analysis. Data series of patent filing counts were acquired from multiple patent databases.[68,69]

When developing representative series employed in this analysis, data series that were clearly derived from other sources included in our analysis were excluded to prevent over-reliance on those data. Additional details and a flowchart (Fig. S1, ESI†) describing the collection and harmonization of the data series employed in this analysis can be found in the ESI.†

Lithium-ion technology database

Data on individual battery specifications and prices were collected from a variety of academic, government, industrial, and commercial sources and compiled into a human- and machine-readable database. The database contains 1716 unique records of cells employing lithium-ion and lithium-ion polymer technologies for the years 1990 through 2019. Additional details describing the development and structure of the database, as well as how energy density and specific energy values were calculated from other reported metrics, are available in the ESI.†

General computational methods

Currency conversion, inflation adjustment, database parsing, and plotting were performed using *R* (v3.6.2).[70] String manipulation and comparison were implemented using stringi.[71] Data series and the database of battery performance metrics were stored in Microsoft Excel files (xlsx format) and read and modified in *R* with the help of the readxl[72] and openxlsx[73] packages. Conversion of calendar dates to decimal dates for use in modeling was performed using lubridate.[74]

Modeling

Relationships between the prices of lithium-ion cells and various determinants were examined by first taking the base-10 logarithm of the price series and determinant values, if appropriate, and then performing a linear regression. Linear regressions were performed using the ordinary least squares method *via* *R*'s *lm* function, and the resulting R^2 values reported herein are adjusted. Unless otherwise stated, shaded regions plotted alongside trend lines are prediction intervals calculated at the 0.95 level using the *predict* function in *R*.

Currency conversions

Historical foreign exchange rates for the conversion of Japanese Yen and Australian Dollars (AUS) to US Dollars (USD) were obtained from the Board of Governors of the Federal Reserve System.[75] The Yen to USD dataset includes yearly, monthly, and daily rates, all released on 2020-06-01. The AUS to USD dataset comprises yearly rates, released on 2020-06-15.

Inflation adjustment

Unless otherwise noted, nominal currency values in US Dollars were adjusted for inflation using the Implicit Price Deflator for Gross Domestic Product (table 1.1.9) published by the US Department of Commerce's Bureau of Economic Analysis,[76] as has been employed previously.[77] The dataset was revised on 2020-05-28 and contains series with both yearly and quarterly resolution. Quarterly resolution GDP deflator values were employed to adjust monthly data series.

Limitations

While we strove to collect data from a wide variety of physical and digital sources, searching for and reading of references was primarily conducted in English. When potentially useful resources were encountered in other languages, translation relied on various online tools (*e.g.* Google Translate).

Results

Development of representative price, market size, and patent filing data series

Researchers and analysts have reported a variety of analyses that regress the cost or price of lithium-ion technologies against possible cost change determinants, resulting in a wide range of proposed improvement rates for lithium-ion technologies (Table S2, ESI†). Their analyses examine the decline in cost or price at the cell, pack, and system levels and explore the decline's relationship to determinants including production, inventive activity, time, and material prices. To demonstrate the diversity of data underlying these analyses of lithium-ion technologies' improvement, we collected and harmonized as many distinct data series as possible. In these efforts, we strove to obtain data directly from their original sources and systematically investigated whether data were adjusted for inflation or converted from one currency to another (additional details available in Methods and ESI†). To reconcile the differences between data series, we categorize them, and within each category, we transparently define and construct a "representative" series from the individual data series. These representative series are designed to incorporate the most reliable data available and cover as many years of technology development as possible. We detail the approaches taken to develop these representative series to clarify and mitigate the impact of data uncertainty. We expect these approaches and the resulting series can be improved over time as new data become available and to answer different research questions.

Our data collection yielded 25 series that track lithium-ion cell cost or price change over time. Series were converted to real costs or prices scaled by energy capacity, in units of 2018 USD $kW^{-1}\,h^{-1}$, and are presented along with similarly harmonized single-year records of cell-level prices (Fig. 1 (log scale) and Fig. S2 (ESI†) (linear scale)). Some single-year records are of cell purchases by academic researchers, which are typically much higher than industry-wide price estimates, likely due to price markups associated with ordering small numbers of cells. While cost data are typically preferred for phenomenological studies of cost change,[33,50] empirical price data were much more commonly reported for lithium-ion technologies than cost data were, as has been observed previously.[42,51,78] Taken together, the data reveal a consistent decrease in lithium-ion cell price over time, with a few exceptions around 1995 and 2008. Overall, prices have declined by about 97% since the commercial introduction of lithium-ion cells in 1991.

Fitting these price series with negative exponential growth (decay) curves with time results in a wide range of estimated annual price decrease percentages, from 4.8 to 23% (Fig. 1). A similarly wide range of percentages (8.8–29%) is observed when examining the price series specifically employed in previous analyses of the relationship between the price of lithium-ion cells and cumulative production, installation, or sales, as measured in units of energy capacity (Fig. 2 and Table S2, ESI†). In turn, this wide variation in rates of price decline considerably impacts the estimated learning rates (14–30%) and simple, extrapolation-based projections of when prices could meet certain targets, yielding crossover ranges that span decades (Fig. 2 and Fig. S3–S6, ESI†).

Many factors contribute to the diversity of price data and rates of price decline. Notably, substantial price differences can be observed between different system levels and cell shapes.

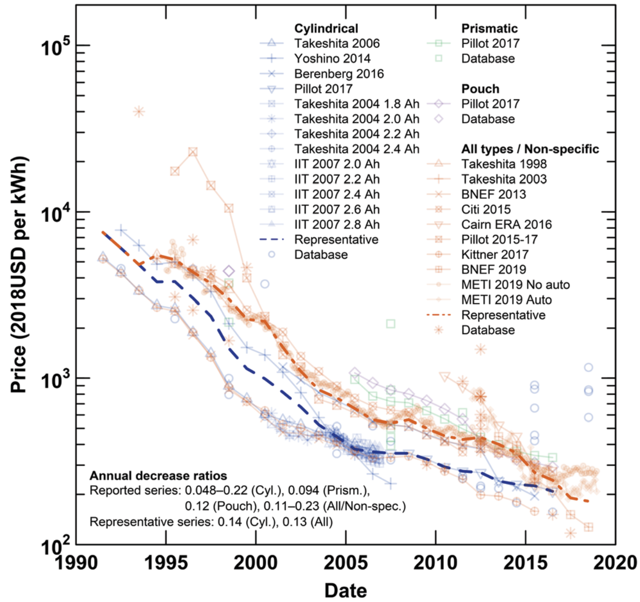

Fig. 1 Lithium-ion cell prices. Time series and single-year records of lithium-ion cell prices for cylindrical (blue), prismatic (green), pouch (purple), and all types (orange) of cells, as well as representative price series for cylindrical (blue, bold, dashed) and all types (orange, bold, dashed) of cells. Records that did not specify cell type are included with series representing all types of cells. Series specifically describing cylindrical cells have annual decrease ratios between 0.048 and 0.22 while those describing all types of cells have ratios that span 0.11 to 0.23. The representative series of cylindrical cell prices has an annual decrease ratio of 0.14 (for 1991 through 2016) while that for all types of cells has a ratio of 0.13 (for 1991 through 2018). A version of this plot with a non-logarithmic dependent axis is included as Fig. S2 (ESI†).

As such, we sought to only combine data series that describe technologies with the same design. For example, one can distinguish between lithium-ion cells, modules, packs, and systems.[14] In this work, we focus on cells and attempt to further differentiate the group of lithium-ion cells based on cell shape. Lithium-ion cells are manufactured in a variety of shapes, the three most prominent being cylindrical, prismatic, and pouch. The earliest cells were cylindrical,[58,79–81] and prismatic and pouch cells were introduced later.[82–84] The price data indicate that cylindrical cells are on average less expensive for a given energy capacity than prismatic or pouch cells are. Examination of the harmonized data (Fig. 1) reveals two major groups of price data series. The first group contains series specific to cylindrical cells and series reported without specifying a cell shape (*i.e.* "non-specific" series) but that appear to be derived from cylindrical-specific series. These derived series were identified by their very close similarity to cylindrical-specific series that had been published previously. The second group contains price series averaging across all cell shapes, including many other non-specific series. Careful parsing of the data allowed us to develop two representative price series, one representing the price for cylindrical lithium-ion cells and another for all cell types (Fig. 1 and 2). Generally, these representative price series were developed by combining series comprising industry-wide cell-level price per energy capacity estimates and averaging

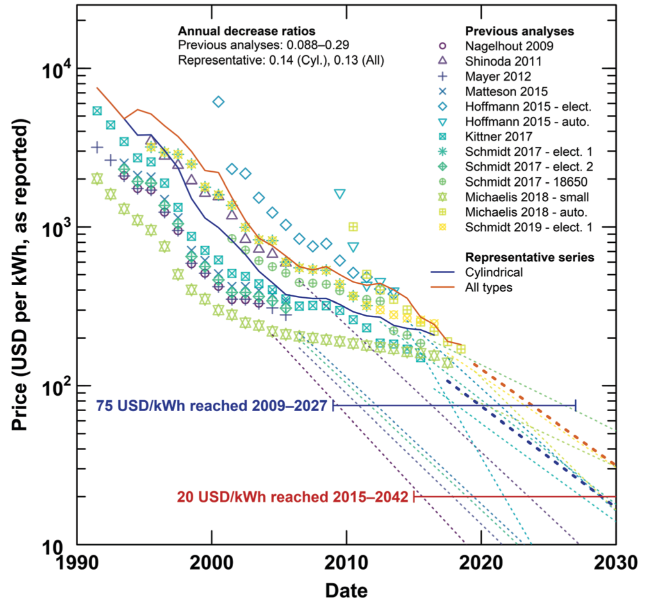

Fig. 2 Reported lithium-ion cell price series and projections based on simple extrapolation to demonstrate the consequences of data uncertainty. The lithium-ion cell price per energy capacity series included here were used in previously reported performance curve analyses of cell-level price *vs.* cumulative market size (*e.g.* production, installation, sales, *etc.*) as measured in energy capacity. The representative series are developed in this work (*vide supra*). Modeling the price *versus* time data series as exponential declines provides estimates of annual decrease ratios which in turn are used to develop the projections. These simple projections, which are intended to examine the differences in the underlying data, suggest a nearly 20 year range for when prices might cross a 75 USD kW^{-1} h^{-1} threshold and a nearly 30 year range for reaching 20 USD kW^{-1} h^{-1}. Additional methodological details are available in the ESI,† along with price projections based on market size projections (Fig. S3–S6, ESI†).

concurrent portions of these series. Single-year price estimates were employed to corroborate these series' data but not incorporated into the averages. Additional details are provided in the ESI.†

In addition to grouping data by the represented technology's design, we also found that price data can be distinguished by a cell's intended application. Notably, lithium-ion technologies can be differentiated based on whether cells were designed and manufactured for use in portable electronics *versus* those destined for automotive applications.[44,85] While most data series did not provide such a distinction, it is observable in the data obtained from Japan's Ministry of Economy, Trade and Industry (METI), which starting in 2012 separated batteries for use in automobiles from those for use in other applications (Fig. 1).[86] Between 2012 and 2015, the decline in price of these automotive cells was considerably greater than the price decline observed in most other series and mirrors the sharp declines in the series reported by Cairn Energy Research Advisors (Cairn ERA) in 2016[87] and Bloomberg New Energy Finance (BNEF) in 2019.[11] Since 2015, the METI data series suggest that the price change in automotive cells has been more gradual. A series including METI data on both types of lithium-ion cells was employed in the development of the aforementioned representative series for all cell types.

We similarly collected and harmonized 27 data series recording the size of the market for lithium-ion cells over time, measured in number of cells per year (Fig. 3). Data series included production, shipment, sales, and demand data, and were relatively consistent with each other. However, the sum of data collected from Japanese, Korean, and Chinese government resources (see Fig. S7, and ESI,† for references) provides a higher estimate of cells produced than other sources suggest, especially between 2015 and 2017. Combining reliable data sources yielded representative series for cylindrical cells, cylindrical and prismatic cells combined, and all cell types (Fig. 3). The representative series for the market size of cylindrical cells was constructed similarly to the price series, with multiple series being combined and averages taken where series overlapped. Considering the divergence observed in the all cell types series and the reliability of different sources, when concurrent data series disagreed on the market size of all cell types, the maximum value was employed. (Additional details are provided in the ESI.†) These representative series indicate that since 1992, the market for cylindrical cells has grown by about 3.4 orders of magnitude, while that for all types of cells has grown 4.1 orders of magnitude.

Market size data in units of energy capacity (MW h) were similarly collected, and a representative series for all cell types was developed (Fig. 4) by combining multiple series and averaging reliable concurrent data. Generally both measures of market size are consistent; they indicate a rapid growth in annual market size between 1991 and 1996, followed by slower

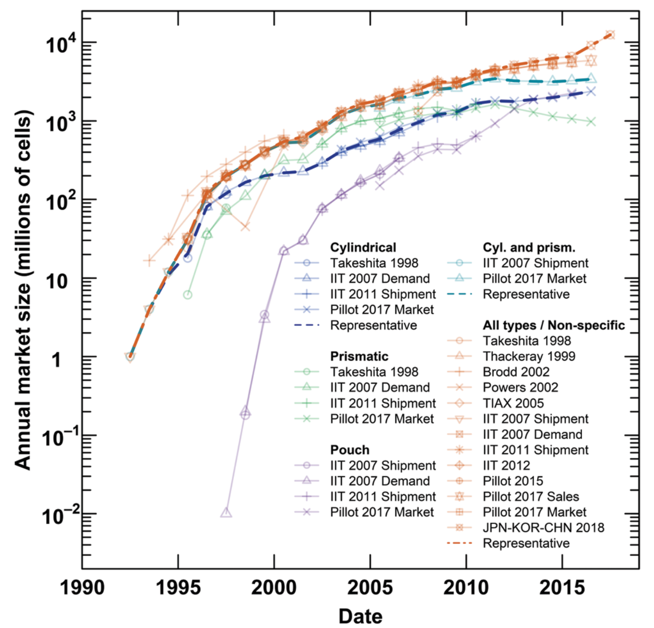

Fig. 3 Lithium-ion market size measured in number of cells. Time series of lithium-ion market size measured in number of cells for cylindrical (blue), prismatic (green), pouch (purple), cylindrical and prismatic (light blue), and all types (orange) of cells, as well as representative series for cylindrical (dark blue, bold, dashed), cylindrical and prismatic (light blue, bold, dashed) and all types (orange, bold, dashed) of cells. Records that did not specify cell type are included with series representing all types of cells.

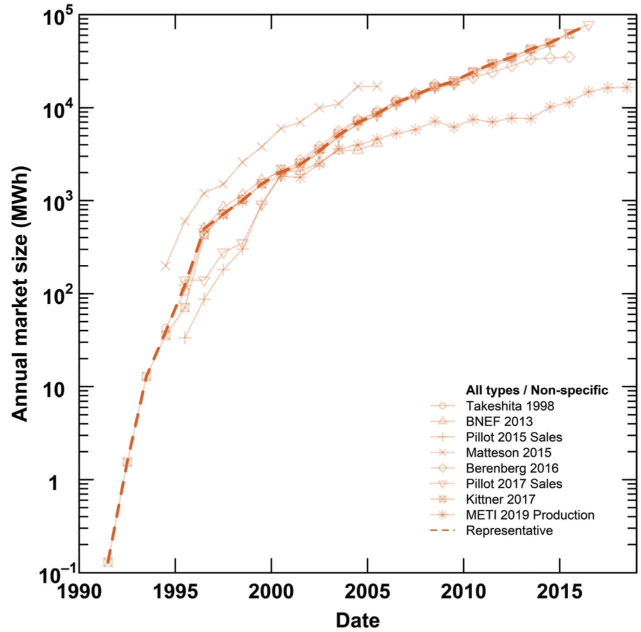

Fig. 4 Lithium-ion market size measured in cell energy capacity. Time series of lithium-ion market size measured in aggregate cell energy capacity for all types of cells, as well as a representative market size series (orange, bold, dashed) for all types of cells. Records that did not specify cell type are included with series representing all types of cells.

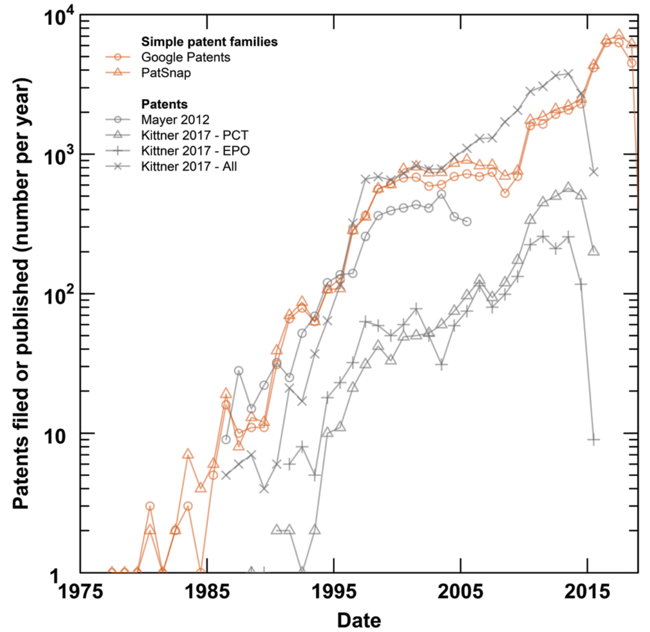

Fig. 5 Annual growth in lithium-ion–related patent filings. Time series of the number of lithium-ion technology patent filings between 1975 and 2018 both developed in this work (orange) and previously reported (gray).

growth from 1997 onward. However, the recent uptick in market growth observed for all cell types as measured in number of cells is not reflected in market size estimates measured in energy capacity. The representative series developed in units of MW h suggests an increase in market size of nearly six orders of magnitude since 1991 and about 4.7 orders of magnitude since 1992.

In addition, data on the annual patent filings associated with lithium-ion technologies were collected from Google Patents[68] and Patsnap's[69] databases using an International Patent Classification symbol specific to lithium-ion batteries. These patent filings were grouped into simple patent families, which comprise different patent documents that describe the same invention.[88,89] (Additional database-specific details are included in the ESI.†) The resulting series (Fig. 5) are generally consistent with those reported by Mayer *et al.*[51] and Kittner *et al.*[12] Nearly all series also display a sharp drop in patent counts in their last year, very likely reflecting mid-year data collection or delays between patent filing and publishing and database updating.[90] As many of the advancements in lithium-ion technologies can be incorporated into cells regardless of their shape, patent filings were not divided into shape-specific subgroups. In this work, the series of data obtained from the PatSnap database is used as the representative series for annual patent filings. This series indicates an increase of simple patent family filings of nearly four orders of magnitude since 1977. The observed increase in patent filings serves as a proxy in this analysis for the growth in research and development activity directed at improving lithium-ion technologies, which is consistent with increased production of cells and the cells' use in an expanding range of energy storage applications.

Analyses of relationships between price and determinants

A variety of performance curve models have been proposed to describe how the cost or price of technologies correlates with possible determinants.[27] These phenomenological models can provide a top-down view of cost reduction trends and potential determinants and complement bottom-up, mechanistic modeling approaches that seek to disentangle cost contributors in an effort to explain cost decline.[59] The models considered here include:

$$\log(y_t) = at + b + e_t, \tag{1}$$

$$\log(y_t) = a\log(x_t) + b + e_t, \tag{2}$$

$$\log(y_t) = a\log(q_t) + b + e_t, \tag{3}$$

$$\log(y_t) = a\log(z_t) + b + e_t, \tag{4}$$

$$\log(y_t) = a\log(v_t) + b + e_t. \tag{5}$$

In all models, y_t is a measure of technological progress or performance, which in the case of energy storage technologies is typically represented by the real price of cells, packs, or systems scaled by their energy capacity (*i.e.* 2018 USD $kW^{-1}\,h^{-1}$). The first model (eqn (1)) describes an exponential trend in technology cost improvement (*e.g.* scaled real cost or price declines) with time and is colloquially known as Moore's law.[91] The second two models (eqn (2) and (3)) describe power law relationships between scaled real cost or price and cumulative production (x_t) and annual production (q_t), commonly referred to as Wright's[29] and Goddard's[92] laws, respectively. In this work, market size is used as a proxy for production, which is consistent with the good agreement between production, sales, demand, and market size data series (*vide supra*). The final two equations (eqn (4) and (5)) describe power law relationships between technological change and cumulative (z_t) and annual (v_t) research and development activity. In this work, annual patent filing counts are employed as a proxy for research and development (*i.e.* "inventive" or "innovation") activity, an approach that has been used in studies of other energy technologies.[90,93,94] An extensive literature has found that patents provide a useful, albeit imperfect, measure of innovative activity.[93,95,96] In this work, we use patent filing counts as a proxy to enable comparison with other studies and across models of technological progress. Constants (a and b) and the residuals (e_t) differ for each model.

These models are used to measure improvement rates that are commonly employed when comparing results of performance curve analyses or projecting future improvements. As a variety of terms are used to describe these improvement rates, here we explicitly define how we calculate these rates to enable clear comparisons with the broader literature. In the case of eqn (1) and employing a base-10 logarithm, the annual decrease ratio (ADR) is given by

$$\mathrm{ADR} = 1-10^{a}. \tag{6}$$

In the case of eqn (2), the learning rate (LR) is defined as:

$$\mathrm{LR} = 1-2^{a}, \tag{7}$$

and is comparable to many of the "experience" and "learning" rates previously reported. The learning rate represents the decrease in cost or price observed upon a doubling of cumulative market size. In the case of eqn (4), an analogous rate, herein referred to as an inventive activity rate (IAR), can be calculated to provide the decrease in cost or price associated with a doubling of research and development activity,

$$\mathrm{IAR} = 1-2^{a}. \tag{8}$$

We refer to these three rates (*i.e.* ADR, LR, and IAR) generally as "improvement rates".

When performing these analyses, we employed price and determinant data that describe the same group or subgroup. For example, the price of all types of cells is regressed against the market size of all types of cells, while the price of cylindrical cells is regressed against the market size of cylindrical cells. Patent data could not be easily separated into inventions that only applied to cylindrical cells as opposed to all types of lithium-ion cells because many inventions could apply to both cell designs. Thus, inventive activity rates were only estimated for all types of lithium-ion cells. In addition, to fairly compare the results, we generally limit these analyses to the time period for which representative series values were available for both all types of cells and cylindrical cells: the years from 1992 through 2016. As additional reliable data become available, this range can be extended.

For the years between 1992 and 2016, the relationship between the all-cell-types representative price and time, cumulative market size, or cumulative patent filings is measured using eqn (1), (2), or (4), respectively (Fig. 6). The goodness of fit of these three models as measured by the coefficient of determination (R^2) ranges from 0.88 to 0.96. Meanwhile, the goodness of fit as measured by R^2 is somewhat lower for eqn (3) and (5), (Fig. S8 and S9, ESI†). Compared to the results for all types of cells, the fits for cylindrical cells are slightly worse for the time-based model (eqn (1)) and better for the cumulative production–based model (eqn (2)), (Fig. 6).

The observed rate of scaled price decline *versus* time is very similar for both representative series, with an annual decrease ratio of 13.1% for all types of cells and 13.3% for cylindrical cells. However, the learning rates differ substantially, with 20.4% for all types of cells and 24.0% for cylindrical cells. Meanwhile, examination of how scaled price varies with cumulative patent filings provides an estimated inventive activity rate of 40.1%.

Many of the improvement rates reported in the literature for lithium-ion technologies were determined by fitting eqn (2) (Wright's law) to data on the price per energy capacity and

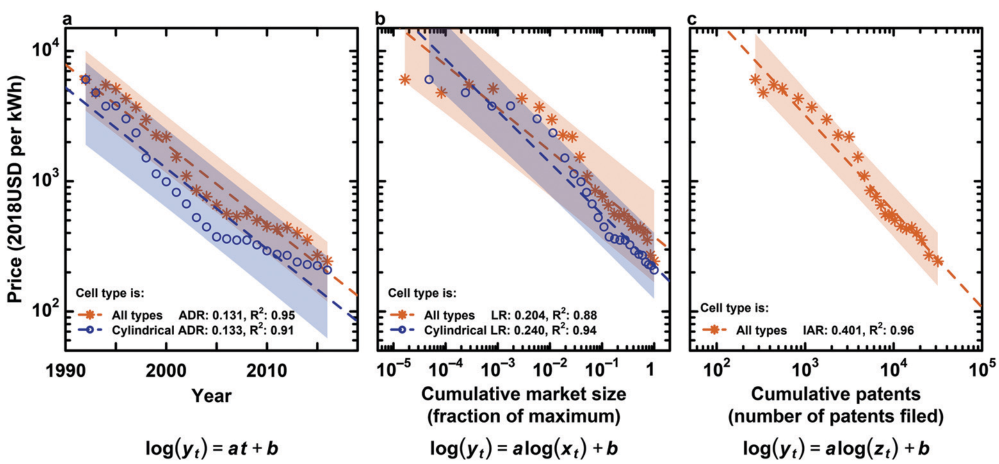

Fig. 6 Lithium-ion price per energy capacity regressed against a variety of possible determinants. Lithium-ion cell price per energy capacity regressed against year (a), cumulative market size (b), and cumulative patent filings (c) for all (orange asterisk marks) and cylindrical (blue circles) cell shapes. Prediction intervals (95% level) are plotted as similarly colored shaded regions. Analyses are restricted to the years 1992 through 2016, for which data are available for both cylindrical and all-cell-types representative price and market size series. Market size for both all types and cylindrical cells is measured in number of cells.

cumulative energy capacity production to measure learning rates (Table S2, ESI†). To investigate the variability observed in previous learning rate estimates, we used the representative price per energy capacity and energy capacity market size series for all types of cells to estimate the learning rate for every possible interval of seven or more years between 1991 and 2016 (Fig. 7). (This analysis includes 1991 to allow for a fair comparison with previously reported analyses because a few also extend back that far.) The results show how even with a single price and market size data series, a wide range of learning rates can be estimated depending on which time period is chosen. As the interval examined lengthens or more recent intervals are employed, the dispersion of learning rates narrows. However, there is no clear trend in the average learning rate as more recent data are employed, unlike the negative trends in learning rate *versus* interval recency that have been observed in some cases.[97] To encompass a broader range of possible analyses, we similarly examined learning rates that could be estimated by fitting eqn (2) to cylindrical cell prices and the same energy capacity market size series (Fig. S10, ESI†), even though this market size series is not specific to cylindrical cells. The range of possible learning rates estimated in this fashion for both all types of cells and cylindrical cells encompasses nearly all previously reported learning rates (Fig. S11, ESI†).

We also explored the impacts that different types of market size estimates have on learning rates. Nearly all published learning rates for lithium-ion technologies rely on cumulative market size estimates measured in energy capacity (*e.g.* MW h) as opposed to number of cells. However, annual energy capacity market size values reflect both the number of cells produced and the energy capacity per cell. Energy capacity for a given cell size has increased as lithium-ion technologies have improved but this trend could itself be considered a consequence of research and development, additional production experience, and other activities. In addition, as lithium-ion technologies have expanded into more varied applications, smaller cells have been produced, such as pin- and button-type batteries, leading to cells with lower energy capacity per cell. To explore the impact of the type of market size measurement on learning rates, the learning rates and their errors[50] were estimated for different measures of cumulative market size (Table 1).

Table 1 Learning rates and error (σ_{IR}) estimated using different combinations of representative price per energy capacity and cumulative market size series, for the period 1992–2016

Price series	Market size estimate: Num. of cylindrical cells	Num. of all cells	Energy capacity (MW h)
Cylindrical	0.240 (0.0108)	0.217 (0.0092)	0.201 (0.0091)
All types	NA	0.204 (0.0140)	0.189 (0.0131)

For a given representative price series, learning rates obtained by regression *versus* cumulative market size measured in number of all types of cells (21.7 and 20.4% for cylindrical and all-cell-types prices, respectively) are slightly higher than those obtained from regression against market size measured in energy capacity (20.1 and 18.9%, for cylindrical and all-cell-types prices). This trend is observed across a range of possible learning rate estimates (Fig. S13 *versus* S14, ESI†). These results suggest that incorporating change in cell energy capacity into the market size estimate leads to an underestimate in the learning rate. These results also indicate that regressing a price series specific for cylindrical cells against a market size series representing all types of cells can result in a learning rate estimate that is up to 4% lower than that calculated when regressing against a series reflecting only cylindrical cells. Both cases lead to underestimates of the rate of technological change upon growth in cumulative market size.

By developing representative series and fitting various performance curve models to these data, we find that a range of proposed determinants correlate reasonably well with the scaled real price decline of lithium-ion cells. Moreover, while the scaled real prices of all types of cells and cylindrical cells declined at very similar rates over time, their rates of price

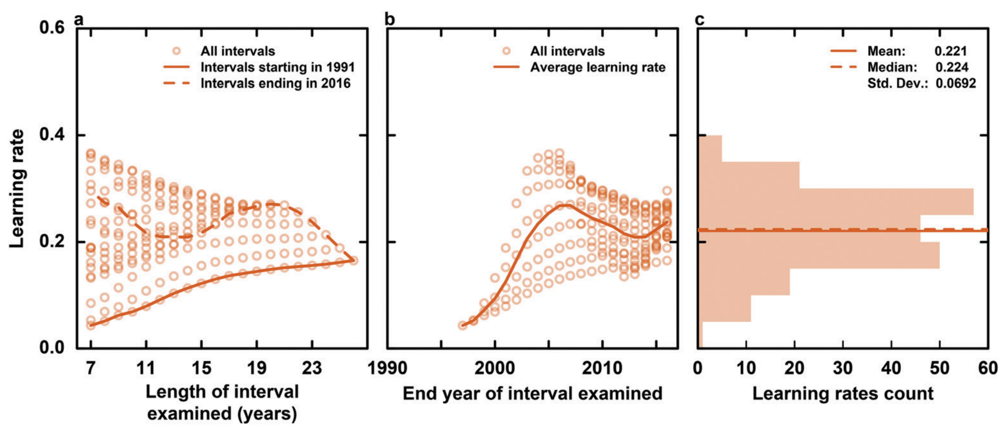

Fig. 7 Learning rates calculable from the representative price and market size series. Learning rates calculated for every interval of seven or more years between 1991 and 2016 by regressing representative price per energy capacity against market size measured in energy capacity, plotted by interval length (a) or interval end year (b), along with a histogram of all improvement rates calculated (c). An alternative plot, where the dependent variable is the slope of the line fit to the logarithmized data, is also available (Fig. S12, ESI†).

decline *versus* cumulative market size differed considerably. We also found that the time period examined can substantially impact learning rate estimates, while using different market size units has a noticeable but smaller impact. The variability in these results can be used to inform appropriate ranges for projections of lithium-ion technology improvement and, along with model-specific error estimates,[27] better capture the uncertainty in energy technology forecasts.

Incorporating other performance characteristics

So far, these analyses have explored improvement in the real price of lithium-ion technologies scaled by energy capacity, in units of 2018 USD per kW h. In this metric, the energy capacity represents the service provided by a lithium-ion cell. However, energy capacity is only one measure of a cell's performance. Other characteristics of lithium-ion cells, such as energy density (W h L^{-1}), specific energy (W h kg^{-1}), power density (W L^{-1}), specific power (W kg^{-1}), cycle-life, self-discharge, temperature sensitivity, and safety, have long been the focus of considerable research and development efforts; and as a result many of these characteristics have improved substantially since the early 1990s.[17,32,81,98–107] Improvements in most of these characteristics were driven by cells' applications. For example, energy density is an important characteristic for small portable electronics while power density is more important for power tools and electric vehicles. Limiting the definition of service to only a cell's energy capacity ignores other changes in performance or quality, as has been observed for other technologies.[27,108–110]

We sought to explore the fit of performance curve models of technological improvement and changes in improvement rates when additional features of lithium-ion technology performance are considered. We are specifically interested in energy density and specific energy. Both characteristics have been and remain important features of lithium-ion technologies that enable their application to portable consumer electronics and transportation systems.[102,104,111] To expand the definition of unit service provided by a lithium-ion cell, we define its service as the product of its cell-level attributes (g_i) weighted by constants (h_i):

$$\text{service per cell} = \prod_i g_i^{h_i}, \tag{9}$$

where these attributes can be energy capacity per cell, energy density, cycle-life, *etc.* Using this formulation, the definition of service provided by a cell can be expanded to include energy density as:

$$\text{service per cell} = \left(\frac{\text{energy capacity}}{\text{cell}}\right)^{h_1} \times (\text{energy density})^{h_2}. \tag{10}$$

The resulting price per service equation is then formulated

$$\text{price per service} = \frac{\text{price/cell}}{(\text{energy capacity/cell})^{h_1}} \times \frac{1}{(\text{energy density})^{h_2}}. \tag{11}$$

This definition of price per service limits price to currency-valued terms. Alternatively, one could define the price of a cell broadly, for example to include both a monetary price per energy capacity and volumetric price per energy capacity, as in:

$$\text{price per service} = \left(\frac{\text{price}}{\text{energy capacity}}\right)^{j_1} \times \left(\frac{\text{volume}}{\text{energy capacity}}\right)^{j_2}. \tag{12}$$

Volumetric price can be interpreted as the space in a mobile device or vehicle that must be available to accommodate the cell. A term combining these two prices could be constructed by their multiplication, yielding a result analogous to that expressed in eqn (11). While in either formulation specific energy could be similarly included as a third factor, energy density and specific energy are strongly correlated (see Fig. S15 and S16, ESI†) at the cell level. Thus, our analysis only considers one of these two performance metrics at a time.

The multiplicative form in eqn (9) is similar to that employed in multiattribute utility theory,[112] among many other phenomenological 'two-factor' models. While this estimation of service does not rely on preferences obtained by interviewing cell manufacturers or purchasers,[113] its multiplicative form is sensible in this context. A cell with no energy capacity provides no service, regardless of its energy density. Similarly, a cell with high energy capacity but very low energy density, such as a large lead-acid cell, is less useful for portable and transportation applications, which have driven the development and deployment of lithium-ion technologies over most of their history. Increasing either energy capacity or energy density for a given cost or price can be considered technological improvement. Without detailed survey data, assignment of values to the weighting constants (h_n, j_n) would be arbitrary, so for this study both are assumed to be equal to one, implying that energy capacity and energy density are considered equally important cell-level attributes and that these preferences have remained consistent over time. Setting the weighting constants to one in either eqn (11) or (12) also provides a physically reasonable relationship between service and energy capacity and allows price per service to be estimated using contemporaneous cell-level price per energy capacity time series and energy density time series. This functional form is proposed as a first-pass model for adjusting cost for other aspects of technology performance.

To determine how energy density and specific energy of lithium-ion technologies improved over time, we collected records of lithium-ion cells between 1990 and 2019. Over this period, commercially available cells' maximum energy density (Fig. 8) and specific energy (Fig. S17, ESI†) increased considerably. Diversification of these characteristics was also observed; many cells had energy densities and specific energies lower than the highest achievable at a given time. A variety of approaches were considered to develop series to represent how these characteristics changed over time (Fig. S18 and S19, ESI†), and series that tracked the 98th percentile annually were chosen (Fig. 8 and Fig. S17, ESI†). Series that tracked annual maxima or prevented decreases were rejected as they gave too much weight to individual data points or years, respectively. Average energy density and specific energy series were also considered because the representative

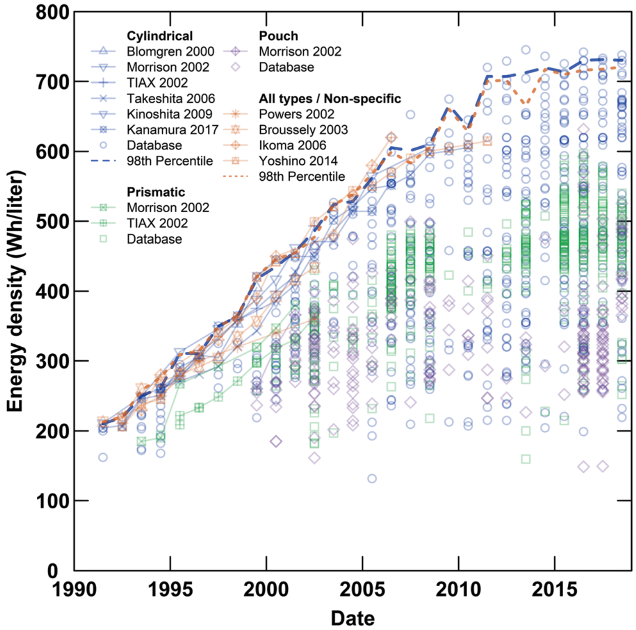

Fig. 8 Lithium-ion cell energy density over time. Time series and single-year records of nameplate energy density values for lithium-ion cells for cylindrical (blue), prismatic (green), pouch (purple), and all types (orange) of cells, as well as representative series for cylindrical (blue, bold, dashed) and all types (orange, bold, dashed) of cells. Series that did not specify cell type are included with series representing all types of cells. An analogous plot for specific energy values is included as Fig. S17 (ESI†).

price series comprise average prices. However, the data necessary to weight performance characteristics by market share were not available.

These data show that from 1991 through 2018, achievable energy density rose from approximately 200 W h L^{-1} to over 700 W h L^{-1} while specific energy rose from approximately 80 W h kg^{-1} to over 250 W h kg^{-1}. For both metrics, the series representing all cell types is similar to that for cylindrical cells as our data indicate that cylindrical cells tend to have the highest annual energy density and specific energy values. These series estimate how technological capabilities changed over time and do not reflect how the market shares of cells with different performance characteristics might have changed.

Given the representative price per energy capacity and energy density series, an annual price per service series can be calculated for both all types of cells and cylindrical cells, where service is defined in eqn (10) and simplified to give a price per service series as defined in eqn (11). Then, the aforementioned performance curve models (eqn (1) through (5)) can be used to relate this price per service series to possible determinants and examine how the empirical relationships change when the definition of service is expanded to include both energy capacity and energy density. As was observed when examining price per energy capacity, application of eqn (1), (2), and (4), reveals reasonably regular relationships between the all-cell-types representative price series and time, cumulative market size, and cumulative patent filings (Fig. 9). However, in all cases the slopes of the trends are considerably steeper when service includes energy density in addition to energy capacity, suggesting that lithium-ion technologies improved more rapidly than estimated from price per energy capacity measures alone. In the case of eqn (1), considering energy density as part of service results in an annual percent decline in price per service of 17.1% for all cell types, markedly higher than that observed for price per energy capacity (13.1%). The learning rate for all cell types similarly increases from 20.4 to nearly 26.6% while the inventive activity rate increases from 40.1% to 49.7%. Including energy density within the scope of service also increases improvement rates calculated when applying eqn (3) (Fig. S20, ESI†) and (5) (Fig. S21, ESI†) to the series representing all types of cells. When service includes energy capacity and specific energy, as opposed to energy density, slightly smaller increases in rates are observed (Fig. S23–S25, ESI†).

Given price per energy capacity and energy density series specific to cylindrical cells, eqn (1)–(3) can also be used to examine how incorporating energy density into the definition of service impacts rates determined for the cylindrical cells subgroup (Fig. S22, ESI†). With all three models, similarly good fits are observed regardless of how service is defined while the slopes of the trend lines are considerably steeper when energy density is incorporated. In the case of eqn (1), the annual decrease in price per service over time increases from 13.3 to 17.4% upon incorporation of energy density, nearly the same as the increase observed for all cell types. Meanwhile, the learning rate increases from 24.0 to 30.9%, which is slightly larger than the increase observed for all cell types. Slightly smaller increases in rates were obtained when service is defined as the product of energy capacity and specific energy (Fig. S26, ESI†).

In addition, the relative fits observed for all types of cells *versus* the cylindrical subgroup are maintained when the definition of service is expanded to include energy density (Fig. 10). Specifically, the fit of eqn (1), relating the price per service to time, is slightly higher for the all-cell-types series, while the fit of eqn (2), relating the price to cumulative market size, is modestly better for the cylindrical cells subgroup.

Discussion

This analysis combines data from and reconciles differences between 90 series that describe how lithium-ion technologies have changed and possible drivers of that change. Representative series that track changes in price, market size, patent filings, and cell-level energy density and specific energy were constructed for all types of lithium-ion cells and in most cases also for cylindrical cells, allowing us to compare trends in this important subgroup to those observed for all cell shapes. By combining and harmonizing data from a variety of sources, we sought to develop more reliable estimates of technological change and improvement rates for lithium-ion technologies. Moreover, by clearly delineating how these representative series were constructed, we aim to provide a methodological framework that can be extended, both as additional data on lithium-ion technologies are collected and to other technologies.

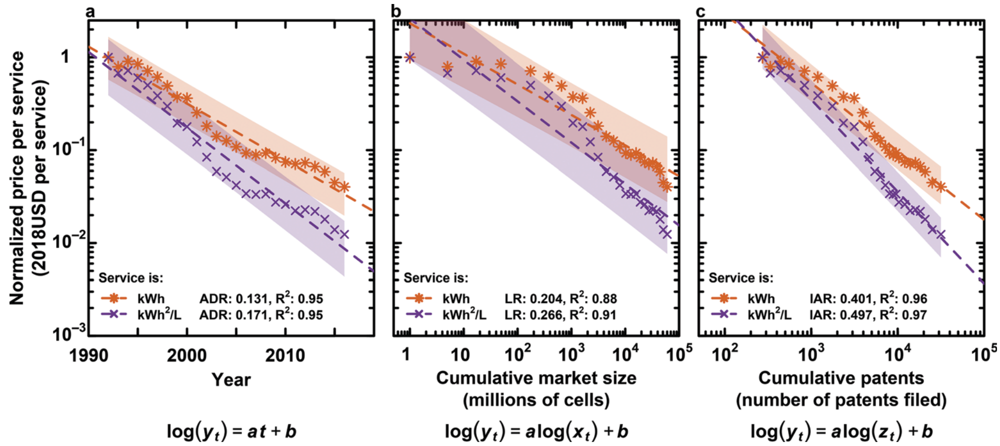

Fig. 9 Lithium-ion price per energy capacity and per service regressed against a variety of possible determinants for all cell types. Lithium-ion cell price per energy capacity (orange asterisk marks) and price per service (purple x marks) regressed against year (a), cumulative market size (b), and cumulative patent filings (c) for all cell shapes. Prediction intervals (95% level) are plotted as similarly colored shaded regions. Analyses are restricted to the years 1992 through 2016, and market size is measured in number of cells.

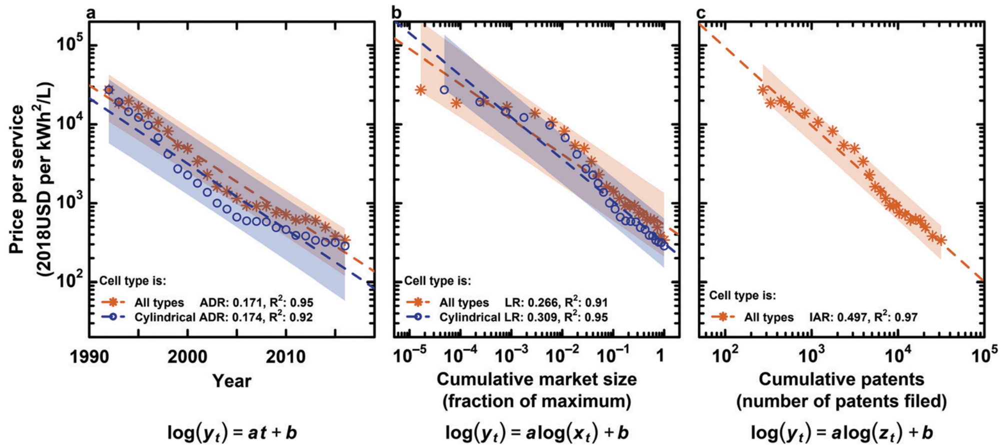

Fig. 10 Lithium-ion price per service regressed against a variety of possible determinants. Lithium-ion cell price per service (in $kW^2\ h^2\ L^{-1}$) regressed against year (a), cumulative market size (b), and cumulative patent filings (c) for all (orange asterisk marks) and cylindrical (blue circles) cells. Prediction intervals (95% level) are plotted as similarly colored shaded regions. Analyses are restricted to the years 1992 through 2016, and market size is measured in number of cells.

We examined how the real price of lithium-ion cells changed with time, cumulative market size, and cumulative inventive activity for the period from 1992 through 2016. In the first case, modeling real prices scaled by energy capacity as decreasing exponentially with time, we observed similar annual price decreases for both all types of cells (13.1%) and cylindrical cells (13.3%) (Fig. 11a). These rates are just below the mean (13.7%) and median (13.6%) of the annual decrease percentages calculated for the price series collected in this work (*cf.* Fig. 1). In addition, these rates suggest prices declined more rapidly than was observed by Anderson for lithium-ion technologies (9.9% for 1998–2005, 5.4% for 2002–2005)[61] and are similar to the rate reported by Deutsche Bank analysts (14% for ''laptop battery costs'').[114,115] The rates are also more rapid than the rate Koh and Magee estimated for a range of energy storage technologies (ADR: 3.1% for USD per W h, as transformed from their ''annual progress'' exponential coefficient for stored energy per unit cost).[32] The low rate observed by Koh and Magee likely results from their cost change analysis relying primarily on lead-acid technologies. In addition, the annual decrease percentages we estimate for lithium-ion technologies are faster than the average annual decrease percentage measured for many other industries (7.6%) (Fig. 11a).[27] Specifically the prices of lithium-ion technologies have undergone a greater annual percent decline than the average observed for a range of chemical technologies (6.1%) and energy technologies (4.8%).

Price per energy capacity also declines with cumulative market size as measured in number of cells, with estimated learning rates of 20.4% for all types of cells and 24.0% for cylindrical cells (Fig. 11b). These rates are faster than those calculated when regressing price per energy capacity against cumulative production in MW h (18.9%) as determined herein,

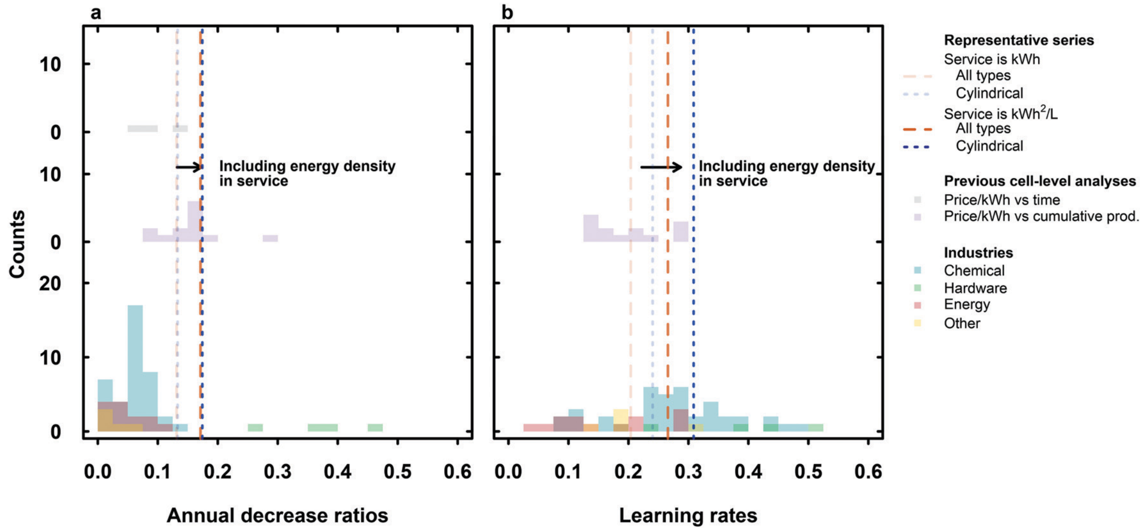

Fig. 11 Annual decrease ratios (ADRs, (a)) and learning rates (LRs, (b)) for lithium-ion cells and other industries. Ratios and rates estimated in this work are denoted with vertical dashed lines for all types of cells (orange) and cylindrical cells (blue), with service defined as real price scaled by kW h (faded) and kW^2 h^2 L^{-1} (bolded). Previous analyses' estimates of lithium-ion cells' price decline *versus* time (a) and cumulative production (b) are plotted in the top two histograms. Analyses *versus* time provide comparable ADRs (gray) while those *versus* cumulative production provide both ADRs and LRs (both purple). (Details on specific analyses are available in Table S2, ESI.†) The lowermost histograms summarize the ADRs and LRs estimated for a range of technologies, grouped by industry type, as reported previously.[27] The ostensible outlier among the previously reported lithium-ion ADRs relies on a short data series representing only cells destined for automotive applications.

as well as those rates Nagelhout *et al.* estimated (17%)[45] and Schmidt *et al.* found specifically for 18650-sized cells (19 ± 3%).[14] The learning rate for all types of cells is also just below the mean (20.7%) and above the median (19.0%) of the previously reported learning rates for lithium-ion cells, while the rate for cylindrical cells is considerably above both. All of the learning rates determined in this analysis are between the rate recently estimated by Kittner and coworkers (15%)[12] and the central cell-level rate employed by Schmidt and coworkers (30%).[14,46] In addition, these learning rates are well within the ranges observed previously for a variety of technologies,[27,97] and specifically are above average compared to those observed for energy technologies (17%) but below the average estimated for a variety of chemical production technologies (28%) (Fig. 11b).

Modeling annual real prices scaled by energy capacity as a function of cumulative patent filings exhibits the highest coefficient of determination (R^2), as was observed by Kittner and coworkers.[12] However, our results reveal a steeper slope, estimating a doubling of cumulative patent filings is associated with a reduction in price of 40.1%, compared to Kittner and coworkers' estimate of 31%.[12]

Better fits, as indicated by their coefficients of determination, are observed between lithium-ion technologies' price per service and cumulative measures of market size and inventive activity than between price and their annual measures. The data are limited but this difference could result from cumulative measures inherently incorporating time-dependent factors, such as research and development and learning-by-doing, along with the economies of scale that are reflected in annual market growth.[27,92]

A variety of factors have contributed to the diversity of previously reported annual decrease ratios and learning rates. Notably, many of the learning rates estimated by regressing price per energy capacity *versus* cumulative production fall within the envelope of rates calculable from consecutive subsets of representative price per energy capacity and market size series, suggesting that some of the variability in reported rates could result from the various time periods considered by different researchers. Additional variability results from data treatment choices, such as whether previous analyses included inflation correction and whether a price series specific to cylindrical cells was regressed against market size estimates for all types of cells. Meanwhile, changing the market size measure from energy capacity to numbers of cells only slightly increases improvement rate estimates.

Grouping data by cell type reveals notable differences between the improvement rates for all types of cells and cylindrical cells. When examining price declines, regardless of how service is defined, we observe that the price of cylindrical cells declines more quickly with increasing cumulative market size than the price of all types of cells does. However, the prices of both cylindrical cells and all types of cells decline similarly with time. The difference in learning rates and similarity in annual decrease ratios were accompanied by higher rates of market size growth for all types of cells compared to cylindrical cells. As more data become available these and other differences can be further investigated.

We also introduce a method to expand the definition of service provided by lithium-ion cells to improve estimates of how their overall performance has improved. While a price per energy capacity metric for energy storage technologies presents a convenient analogue to the cost per installed power capacity metric commonly used to estimate learning rates for electricity generating technologies,[33,35] its use belies the fact that while electricity supplied to a grid is generally fungible, especially when supplied reliably or on-demand, electrochemical cells are not. For example, a less expensive but considerably larger and heavier battery technology would not likely replace lithium-ion cells in most portable electronics. The difficulty of incorporating additional critical metrics has long been a challenge for phenomenological studies of technological progress.[53] Even Wright noted in his seminal study of airplane costs that "time saving" was a difficult-to-value metric required to compare travel in a plane to that in a car.[29] Moreover, researchers have found that when preferences for a given technology's performance characteristics change, deviations from the classic power law relationship between price per unit and cumulative production can be observed, as was the case when Ford shifted focus from producing increasingly inexpensive automobiles to improving characteristics including comfort, performance, and safety.[52,116] In the case of Ford's transition from the Model T to the Model A, measures of price per vehicle and price per pound did not reflect the value of improvements in these other characteristics in their definitions of service (*i.e.* "vehicle" or "pound").

When we include energy density or specific energy in the definition of service to better estimate the overall improvement rates for lithium-ion technologies, we measure much faster rates of technological change than were observed for price per energy capacity alone. For the period from 1992 through 2016, when service includes energy capacity and energy density, annual percent decreases in price per service increase considerably, from 13.1 and 13.3% to 17.1 and 17.4% for all types of cells and cylindrical cells, respectively (Fig. 11a). Similarly, learning rates also increase as the definition of service expands, to 26.6 and 30.9% for all types of cells and cylindrical cells, respectively (Fig. 11b). When regressing against cumulative patent filings, the inventive activity rate increases from 40.1% to 49.7%. Greater rate increases are observed when energy density is incorporated than when specific energy is, reflecting the larger relative gains observed for energy density improvements since the early 1990s.

The increase in improvement rates observed upon incorporating other important metrics suggests the degree to which rates measured from only price per energy capacity series underestimate how rapidly lithium-ion technologies have improved. They similarly provide a rough approximation of how much a focus on non-cost performance characteristics might have limited cost or price decline. As different performance characteristics might be prioritized in the future, incorporating additional relevant characteristics into the definition of price per service could enable more accurate measures, and possibly projections, of technological change, though further research is needed. For example, the requirements of stationary storage applications have already started shifting focus from energy density and specific energy metrics to a variety of other characteristics, such as battery lifetime and degradation.[2,9,20,22,46,111,117] Such cycle-life characteristics were actually incorporated into definitions of service early in the development of lithium-ion technologies.[103] Notably, a few researchers included cycle-life in their comparisons of lithium-ion cells to other battery technologies, summarizing service as "accumulated discharge energy" or the product of energy capacity and cycle-life, sometimes corrected for capacity loss over time.[20,81,101,104,118] Metrics including cycle-life could provide a better estimate of how lithium-ion technologies have improved or could improve with respect to stationary storage applications. While a dearth of reliable, comparable historical records on capacity fade in lithium-ion cells complicates retrospective analysis, prospective use of this type of metric could aid technology comparisons and projections of cost and price decline. However, additional research is needed on cycling and capacity-loss characteristics across applications.

Advancing the study of technological innovation requires careful data collection,[59,119] consideration of data uncertainties, and examination of different technologies.[27] Strengths of this work include systematic, careful collection, harmonization, and combination of data that describe how lithium-ion technologies evolved; and we methodically detail our approach to data collection and analysis and the methods we employ to provide a blueprint for others who seek to perform similar analyses. Notably, we sought to trace data as far as possible to their original sources to explicate various conversions and assumptions, and if available, tried to compare data from different original sources. Moreover, we carefully differentiate between data that reflect either all types of cells or only cylindrical cells when constructing time series and estimating improvement rates. In addition, we expand the definition of service to include other important technology characteristics in order to more comprehensively estimate how rapidly lithium-ion technologies have changed, and to begin to understand how they might change in the future.

A key limitation of this study is its incorporation of data with unknown original sources and collected with sometimes unclear methods. Notably, some of the price and market size series rely in part on data reported by industry consultants, whose data collection could involve a variety of methods or assumptions that are not always presented with the final data. Comparison with government-provided data, especially those provided by Japan's METI, and a variety of other sources helped mitigate this weakness. However, the possibility remains that the consultants themselves used each other's data or the government data to develop their data series, which could create the appearance of more independent data series than actually exist. We worked to address these issues by transparently presenting the methods employed to construct the aforementioned representative series so that these approaches and analyses can be improved as more data become available. The first step toward addressing these issues is to elucidate them. We also expect these methods could aid those dealing with similar sources of data uncertainty inevitably encountered when studying technological change and reduce the cost of this uncertainty through characterizing it such that it can be incorporated into an error model to be used for projections.[27] Another limitation is that our analysis focused on all cell types and cylindrical cells, as insufficient data were available to confidently provide similar results for prismatic and pouch cells. Similarly, data limitations precluded the estimation of improvement rates for specific combinations of cathode and anode materials. However, this limitation does not prevent us from drawing conclusions about lithium-ion technologies generally, as represented and available in the market. Data availability further constrained many of our analyses to the period from 1992 through 2016. Finally, our expansion of the definition of service was limited to incorporating energy density and specific energy performance metrics.

Concluding remarks

Based on a thorough examination of available data, this work provides rigorous estimates of the decline in price, growth in market size and inventive activity, and improvement in technical performance of lithium-ion technologies. We report robust estimates of the rate of advancement of lithium-ion technologies *versus* various possible determinants. We found that while the prices of both cylindrical cells and all types of cells declined similarly with time, a considerably higher learning rate is observed for cylindrical cells. To expand our measures of lithium-ion technologies' change, we propose an approach to incorporate other attributes into the definition of service provided by a lithium-ion cell and find that improvement rate estimates increase substantially when energy density or specific energy are included.

The increase in improvement rates observed when other historically important performance characteristics are incorporated into the definition of service suggests a rough estimate for how much measures based on price per energy capacity alone might underestimate how rapidly lithium-ion technologies improved. The increase similarly gives an approximate indication of how much price decline might have be limited by a focus on these performance characteristics. As the requirements for these performance characteristics are relaxed, as in the case of stationary storage applications, priorities for research, development, and production efforts are expected to transition. As a result, cost or price for a different service may decline more rapidly than would be suggested by rates that only consider price per energy capacity. However, engineering-based mechanistic modeling of lithium-ion technologies' historic and possible future cost change is required to further evaluate this potential.

Measuring technological change often requires working with limited data sets that contain measurement and sampling uncertainty. Our data collection and analysis approaches aim to further delineate a model for performance curve analyses and highlight methods for additional discussion and improvement. We expect that the methodology presented herein and the approach of incorporating important intensive characteristics into broader cost or price per service metrics could be applied to a range of technologies and help improve measures and projections of technological change.

Conflicts of interest

The authors declare no competing financial interests.

Acknowledgements

We thank the Alfred P. Sloan Foundation and MIT Office of Sustainability for funding this research. M. S. Z. was also supported in part by a Research to Policy Engagement Initiative Fellowship from the MIT Technology and Policy Program. We also thank Dr James McNerney, Dr Goksin Kavlak, and Dr Barry I. Graubard for useful conversations and advice as well as David Morrison for copies of conference notes.

References

1 *DOE Global Energy Storage Database*, Sandia National Laboratories and DOE Office of Electricity, US Department of Energy, 2019.
2 P. Ralon, M. Taylor, A. Ilas, H. Diaz-Bone and K.-P. Kairies, *Electricity Storage and Renewables: Costs and Markets to 2030*, International Renewable Energy Agency, Abu Dhabi, 2017.
3 *U.S. Battery Storage Market Trends*, U.S. Energy Information Administration, Washington, DC, 2018.
4 *Batteries: 2018 Annual Progress Report, DOE/EE-1831*, Vehicle Technologies Office, Office of Energy Efficiency and Renewable Energy, 2019.
5 W. A. Braff, J. M. Mueller and J. E. Trancik, Value of Storage Technologies for Wind and Solar Energy, *Nat. Clim. Chang.*, 2016, **6**, 964–969.
6 Duration Addition to electricitY Storage (DAYS) Overview, 2018.
7 M. Miotti, G. J. Supran, E. J. Kim and J. E. Trancik, Personal Vehicles Evaluated against Climate Change Mitigation Targets, *Environ. Sci. Technol.*, 2016, **50**, 10795–10804.
8 K. Mongird, V. Fotedar, V. Viswanathan, V. Koritarov, P. Balducci, B. Hadjerioua and J. Alam, *Energy Storage Technology and Cost Characterization Report, PNNL-28866*, Pacific Northwest National Laboratory, Argonne National Laboratory, Oak Ridge National Laboratory, 2019.
9 M. S. Ziegler, J. M. Mueller, G. D. Pereira, J. Song, M. Ferrara, Y.-M. Chiang and J. E. Trancik, Storage Requirements and Costs of Shaping Renewable Energy Toward Grid Decarbonization, *Joule*, 2019, **3**, 2134–2153.
10 W. Cole and A. W. Frazier, *Cost Projections for Utility-Scale Battery Storage*, Technical Report NREL/TP-6A20-73222, National Renewable Energy Laboratory, Golden, CO, 2019.
11 L. Goldie-Scot, A Behind the Scenes Take on Lithium-Ion Battery Prices, 2019, https://about.newenergyfinance.com/blog/behind-scenes-take-lithium-ion-battery-prices/visited on 03/06/2019.
12 N. Kittner, F. Lill and D. M. Kammen, Energy Storage Deployment and Innovation for the Clean Energy Transition, *Nat. Energy*, 2017, **2**, 17125.
13 Lazard's Levelized Cost of Storage Analysis - Version 2.0, 2016.
14 O. Schmidt, A. Hawkes, A. Gambhir and I. Staffell, The Future Cost of Electrical Energy Storage Based on Experience Rates, *Nat. Energy*, 2017, **2**, 17110.

15 G. Crabtree, E. Kócs and L. Trahey, The Energy-Storage Frontier: Lithium-Ion Batteries and Beyond, *MRS Bull.*, 2015, **40**, 1067–1078.
16 B. R. Sutherland, Charging up Stationary Energy Storage, *Joule*, 2019, **3**, 1–3.
17 A. Yoshino, in *Lithium-Ion Batteries*, ed. G. Pistoia, Elsevier, Amsterdam, 2014, pp. 1–20.
18 H. Takeshita, The current status and future of the battery industry, 2006.
19 *Cost and Price Metrics for Automotive Lithium-Ion Batteries*, DOE/GO-102016-4908, Energy Efficiency & Renewable Energy, Department of Energy, 2017.
20 R. Kempener and E. Borden, *Battery Storage for Renewables: Market Status and Technology Outlook*, International Renewable Energy Agency, Abu Dhabi, 2015.
21 B. Nykvist and M. Nilsson, Rapidly Falling Costs of Battery Packs for Electric Vehicles, *Nat. Clim. Change*, 2015, **5**, 329–332.
22 G. He, Q. Chen, P. Moutis, S. Kar and J. F. Whitacre, An Intertemporal Decision Framework for Electrochemical Energy Storage Management, *Nat. Energy*, 2018, **3**, 404–412.
23 H. Asher, *Cost-Quantity Relationships in the Airframe Industry,* The RAND Corporation, Santa Monica, CA, 1956.
24 J. M. Dutton, A. Thomas and J. E. Butler, The History of Progress Functions as a Managerial Technology, *Business History Review*, 1984, **58**, 204–233.
25 A. R. Fusfeld, The Technological Progress Function: A New Technique for Forecasting, *Technological Forecasting*, 1970, **1**, 301–312.
26 A. McDonald and L. Schrattenholzer, Learning Curves and Technology Assessment, *International Journal of Technology Management*, 2002, **23**, 718–745.
27 B. Nagy, J. D. Farmer, Q. M. Bui and J. E. Trancik, Statistical Basis for Predicting Technological Progress, *PLoS One*, 2013, **8**, e52669.
28 W. D. Nordhaus, The Perils of the Learning Model for Modeling Endogenous Technological Change, *Energy J.*, 2014, **35**, 1–13.
29 T. P. Wright, Factors Affecting the Cost of Airplanes, *J. Aeronaut. Sci.*, 1936, **3**, 122–128.
30 L. E. Yelle, The Learning Curve: Historical Review and Comprehensive Survey, *Decision Sciences*, 1979, **10**, 302–328.
31 T. Jamasb and J. Kohler, *Learning Curves For Energy Technology: A Critical Assessment*, Working Paper, Faculty of Economics, 2007.
32 H. Koh and C. L. Magee, A Functional Approach for Studying Technological Progress: Extension to Energy Technology, *Technol. Forecase. Soc.*, 2008, **75**, 735–758.
33 A. McDonald and L. Schrattenholzer, Learning Rates for Energy Technologies, *Energy Policy*, 2001, **29**, 255–261.
34 L. Neij, Use of Experience Curves to Analyse the Prospects for Diffusion and Adoption of Renewable Energy Technology, *Energy Policy*, 1997, **25**, 1099–1107.
35 E. S. Rubin, I. M. L. Azevedo, P. Jaramillo and S. Yeh, A Review of Learning Rates for Electricity Supply Technologies, *Energy Policy*, 2015, **86**, 198–218.
36 S. Samadi, The Experience Curve Theory and Its Application in the Field of Electricity Generation Technologies - A Literature Review, *Renewable Sustainable Energy Rev.*, 2018, **82**, 2346–2364.
37 B. Steffen, D. Hischier and T. S. Schmidt, Historical and Projected Improvements in Net Energy Performance of Power Generation Technologies, *Energy Environ. Sci.*, 2018, **11**, 3524–3530.
38 C.-O. Wene, *Experience Curves for Energy Technology Policy*, OECD/IEA, Paris, France, 2000.
39 I.-Y. L. Hsieh, M. S. Pan, Y.-M. Chiang and W. H. Green, Learning Only Buys You So Much: Practical Limits on Battery Price Reduction, *Appl. Energy*, 2019, **239**, 218–224.
40 S.-i. Inage, *Prospects for Large-Scale Energy Storage in Decarbonised Power Grids*, Working Paper, OECD, IEA, Paris, France, 2009.
41 M. Liebreich, *Global Trends in Clean Energy Investment*, Clean Energy Ministerial, Delhi, India, 2013.
42 S. Matteson and E. Williams, Learning Dependent Subsidies for Lithium-Ion Electric Vehicle Batteries, *Technol. Forecase. Soc.*, 2015, **92**, 322–331.
43 S. T. Mayer, *Electric Vehicle Dynamic-Stress-Test Cycling Performance of Lithium-Ion Cells*, UCRL-ID-116443, Lawrence Livermore National Laboratory, Livermore, CA, 1994.
44 S. Michaelis, E. Rahimzei, A. Kampker, H. Heimes, C. Lienemann, C. Offermanns, M. Kehrer, A. Thielmann, T. Hettesheimer, C. Neef, A. Kwade, W. Haselrieder, S. Rahlfs, R. Uerlich and N. Bognar, *Roadmap: Battery Production Equipment: 2030*, VDMA Battery Production, Frankfurt, Germany, 2018.
45 D. Nagelhout and J. Ros, *Elektrisch Autorijden: Evaluatie van Transities Op Basis van Systeemopties*, Planbureau voor de Leefomgeving, Bilthoven, The Netherlands, 2009.
46 O. Schmidt, S. Melchior, A. Hawkes and I. Staffell, Projecting the Future Levelized Cost of Electricity Storage Technologies, *Joule*, 2019, **3**, 81–100.
47 Y. Shinoda, H. Tanaka, A. Akisawa and T. Kashiwagi, Evaluation of the Plug-in Hybrid Electric Vehicle Considering Learning Curve on Battery and Power Generation Best Mix, *Electrical Engineering in Japan*, 2011, **176**, 31–40.
48 I. Tsiropoulos, D. Tarvydas and N. Lebedeva, *Li-Ion Batteries for Mobility and Stationary Storage Applications: Scenarios for Costs and Market Growth*, EUR 29440 EN, Joint Research Centre, European Commission, Petten, The Netherlands, 2018.
49 N. Kittner, O. Schmidt, I. Staffell and D. M. Kammen, in *Technological Learning in the Transition to a Low-Carbon Energy System*, ed. M. Junginger and A. Louwen, Academic Press, 2020, pp. 119–143.
50 W. G. J. H. M. van Sark, Introducing Errors in Progress Ratios Determined from Experience Curves, *Technol. Forecase. Soc.*, 2008, **75**, 405–415.
51 T. Mayer, D. Kreyenberg, J. Wind and F. Braun, Feasibility Study of 2020 Target Costs for PEM Fuel Cells and Lithium-Ion Batteries: A Two-Factor Experience Curve Approach, *Int. J. Hydrogen Energy*, 2012, **37**, 14463–14474.

52 J. D. Farmer and J. Trancik, *Dynamics of Technological Development in the Energy Sector*, London Accord Final Publication and Santa Fe Institute Working Paper 07-12-046, Santa Fe Institute, Santa Fe, NM, 2007.
53 G. F. Nemet, Beyond the Learning Curve: Factors Influencing Cost Reductions in Photovoltaics, *Energy Policy*, 2006, **34**, 3218–3232.
54 W. G. J. H. M. van Sark, E. A. Alsema, H. M. Junginger, H. H. C. de Moor and G. J. Schaeffer, Accuracy of Progress Ratios Determined from Experience Curves: The Case of Crystalline Silicon Photovoltaic Module Technology Development, *Prog. Photovoltaics Res. Appl.*, 2008, **16**, 441–453.
55 G. E. Blomgren, The Development and Future of Lithium Ion Batteries, *J. Electrochem. Soc.*, 2017, **164**, A5019–A5025.
56 C. Pillot, *The Rechargeable Battery Market and Main Trends 2016–2025*, 33rd International Battery Seminar & Exhibit, Fort Lauderdale, FL, 2017.
57 H. Takeshita, *Worldwide Battery Market Status & Forecast*, Power2001, 2001.
58 H. Takeshita, Worldwide Market Update on NiMH, Li Ion and Polymer Batteries for Portable Applications and HEVS, 24th International Battery Seminar & Exhibit, Fort Lauderdale, FL, 2007.
59 G. Kavlak, J. McNerney and J. E. Trancik, Evaluating the Causes of Cost Reduction in Photovoltaic Modules, *Energy Policy*, 2018, **123**, 700–710.
60 P. Eash-Gates, M. M. Klemun, G. Kavlak, J. McNerney, J. Buongiorno and J. E. Trancik, *Joule*, 2020, **4**, 2348–2373.
61 D. L. Anderson, Master's thesis, Nicholas School of the Environment, Duke University, Durham, NC, 2009.
62 R. J. Brodd, *Lithium-Ion Batteries*, Springer, New York, NY, 2009, pp. 1–7.
63 J. Janek and W. G. Zeier, A Solid Future for Battery Development, *Nat. Energy*, 2016, **1**, 16141.
64 H. Kamath, Lithium Ion Batteries for Electric Transportation: Costs and Markets, California Air Resources Board (ARB): 2009 ZEV Symposium, Sacramento, CA, 2009.
65 T. Placke, R. Kloepsch, S. Dühnen and M. Winter, Lithium Ion, Lithium Metal, and Alternative Rechargeable Battery Technologies: The Odyssey for High Energy Density, *J. Solid State Electrochem.*, 2017, **21**, 1939–1964.
66 A. Thielmann, A. Sauer and M. Wietschel, *Gesamt-Roadmap Energiespeicher für die Elektromobilität 2030*, Fraunhofer-Institut für System- und Innovationsforschung ISI, Karlsruhe, Germany, 2015.
67 A. Thielmann, Megatrends and Their Impact on the Energy Future from the Perspective of Electrochemical Storage, *AIP Conference Proceedings*, 1765, **2016**, 020001.
68 Google Patents Public Data, 2019, https://console.cloud.google.com/marketplace/details/google_patents_public_datasets/google-patents-public-data visited on 04/25/2019.
69 PatSnap, 2019, https://analytics.patsnap.com/search/input#/classification visited on 04/26/2019.
70 *R Core Team, R: A Language and Environment for Statistical Computing, version 3.6.2*, Vienna, Austria, R Foundation for Statistical Computing, 2019.
71 M. Gagolewski, Stringi: Character String Processing Facilities, in collab. with B. Tartanus, IBM and Unicode, Inc., version 1.2.4, 2018.
72 H. Wickham and J. Bryan, Readxl: Read Excel Files, in collab. with RStudio, M. Kalicinski, K. Valery, C. Leitienne, B. Colbert, D. Hoerl and E. Miller, version 1.2.0, 2018.
73 P. Schauberger, A. Walker and L. Braglia, *Openxlsx: Read, Write and Edit Xlsx Files, version 4.1.4*, 2019.
74 V. Spinu, G. Grolemund, H. Wickham, I. Lyttle, I. Constigan, J. Law, D. Mitarotonda, J. Larmarange, J. Boiser and C. H. Lee, *Lubridate: Make Dealing with Dates a Little Easier, version 1.7.4*, 2018.
75 Foreign Exchange Rates - H.10, 2020, https://www.federalreserve.gov/releases/H10/default.htm visited on 19/06/2020.
76 Interactive Data Tables|National Data|National Income and Product Accounts, 2020, https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=3&isuri=1&categories=survey&nipa_table_list=13 visited on 12/06/2020.
77 P. Conley, Experience Curves as a Planning Tool, *IEEE Spectrum*, 1970, **7**, 63–68.
78 C. Cluzel and C. Douglas, *Cost and Performance of EV Batteries: Final Report for The Committee on Climate Change*, Element Energy Limited, Cambridge, UK, 2012.
79 T. Nagaura, Development of Rechargeable Lithium Batteries: II. Lithium Ion Rechargeable Batteries, *Prog. Batteries Battery Mater.*, 1991, **10**, 218–226.
80 Y. Nishi, in *Lithium Ion Batteries: Fundamentals and Performance*, ed. M. Wakihara and O. Yamamoto, Wiley-VCH Verlag GmbH, 1998, pp. 181–198.
81 T. Nagaura and K. Tozawa, Lithium Ion Rechargeable Battery, *Prog. Batteries Sol. Cells*, 1990, **9**, 209–217.
82 M. Broussely, P. Biensan and B. Simon, Lithium Insertion into Host Materials: The Key to Success for Li Ion Batteries, *Electrochim. Acta*, 1999, **45**, 3–22.
83 D. G. Morrison, Li-Ion Batteries Reach for Higher Performance, *Elect. Des.*, 2002, **50**, 59–68.
84 D. Morrison, Thinner Li-Ion Batteries Power next-Generation Portable Devices, *Elect. Des.*, 2000, **48**, 95–106.
85 W. Hoffmann, *Importance of and Evidence for Cost Efficient Electricity Storage: Price Experience Curve for Li-Ion Batteries*, Intersolar 2015, Munich, Germany, 2015.
86 Yearbook of Machinery Statistics, Research and Statistics Department, Minister's Secretariat, Ministry of Economy, Trade and Industry (METI), 2012.
87 M. Hocking, J. Kan, P. Young, C. Terry and D. Begleiter, *Lithium 101, GRCM2016PROD035496*, Sydney, Australia, 2016.
88 Patent Families at the EPO, European Patent Office, 2017.
89 Patent Families 101, 2020, https://help.patsnap.com/hc/en-us/articles/115005571829-Patent-Families-101 visited on 10/19/2020.
90 Å. Lindman and P. Söderholm, Wind Energy and Green Economy in Europe: Measuring Policy-Induced Innovation Using Patent Data, *Appl. Energy*, 2016, **179**, 1351–1359.
91 G. E. Moore, Cramming More Components Onto Integrated Circuits, *Electronics*, 1965, **38**, 114.

92 C. Goddard, Debunking the Learning Curve, *IEEE Trans. Compon., Hybrids, Manuf. Technol.*, 1982, **5**, 328–335.
93 L. M. A. Bettencourt, J. E. Trancik and J. Kaur, Determinants of the Pace of Global Innovation in Energy Technologies, *PLoS One*, 2013, **8**, e67864.
94 R. M. Margolis and D. M. Kammen, Evidence of Under-Investment in Energy R&D in the United States and the Impact of Federal Policy, *Energy Policy*, 1999, **27**, 575–584.
95 Z. Griliches, Patent Statistics as Economic Indicators: A Survey, *J. Economic Literature*, 1990, **28**, 1661–1707.
96 D. Strumsky, J. Lobo and J. A. Tainter, Complexity and the Productivity of Innovation, *Systems Research and Behavioral Science*, 2010, **27**, 496–509.
97 G. F. Nemet, Interim Monitoring of Cost Dynamics for Publicly Supported Energy Technologies, *Energy Policy*, 2009, **37**, 825–835.
98 D. Friel, Understanding Lithium Battery Tradeoffs In Mobile Devices, *Elect. Des.*, 2013.
99 T. Hazama, M. Miyabayashi, H. Andoh, R. Ishikawa, S. Furuta, H. Ishihara and J. Shonaka, Lithium Secondary Batteries in Japan, *J. Power Sources*, 1995, **54**, 306–309.
100 S. C. Levy, Safety and Reliability Considerations for Lithium Batteries, *J. Power Sources*, 1997, **68**, 75–77.
101 S. Megahed and B. Scrosati, Lithium-Ion Rechargeable Batteries, *J. Power Sources*, 1994, **51**, 79–104.
102 Y. Nishi, in *Lithium-Ion Batteries*, ed. G. Pistoia, Elsevier, Amsterdam, 2014, pp. 21–39.
103 B. B. Owens and T. Osaka, Panel Discussion Future Prospects of Lithium Batteries, *J. Power Sources*, 1997, **68**, 173–186.
104 L. Xie, D. Fouchard and S. Megahed, *MRS Proceedings, Symposium W - Materials for Electrochemical Energy Storage and Conversion*, Cambridge University Press, 1995, vol. 393, pp. 285–304.
105 B. Andersson, B. Hallgren, A. Johansson and P. Selånger, *Lithium Batteries for Electric Road Vehicle Applications*, Swedish National Board for Industrial and Technical Development, Stockholm, Sweden, 1995.
106 M. W. Juzkow and S. T. Mayer, *The Twelfth Annual Battery Conference on Applications and Advances, The Twelfth Annual Battery Conference on Applications and Advances*, Long Beach, CA, USA, 1997, pp. 181–188.
107 M. Li, J. Lu, Z. Chen and K. Amine, 30 Years of Lithium-Ion Batteries, *Adv. Mater.*, 2018, **30**, 1800561.
108 L. Coulomb and K. Neuhoff, *Learning Curves and Changing Product Attributes: The Case of Wind Turbines*, Working Paper CWPE 0618/EPRG 0601, Faculty of Economics, University of Cambridge, 2006.
109 S. Payson, Quality Improvement versus Cost Reduction: A Broader Perspective on Evolutionary Economic Change, *Technology Analysis & Strategic Management*, 1998, **10**, 69–88.
110 P. Thompson, How Much Did the Liberty Shipbuilders Learn? New Evidence for an Old Case Study, *Journal of Political Economy*, 2001, **109**, 103–137.
111 R. Schmuch, R. Wagner, G. Hörpel, T. Placke and M. Winter, Performance and Cost of Materials for Lithium-Based Rechargeable Automotive Batteries, *Nat. Energy*, 2018, **3**, 267–278.
112 R. L. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*, John Wiley & Sons, Inc., New York, NY, 1976.
113 F. R. Field, J. P. Clark and M. F. Ashby, Market Drivers for Materials and Process Development in the 21st Century, *MRS Bull.*, 2001, **26**, 716–725.
114 R. Lache, D. Galves and P. Nolan, *Electric Cars: Plugged In 2*, Deutsche Bank, New York, NY, 2009.
115 P. Sankey, D. T. Clark and S. Micheloto, *The End of the Oil Age: 2011 and beyond: A Reality Check*, Deutsche Bank, New York, NY, 2010.
116 W. J. Abernathy and K. Wayne, Limits of the Learning Curve, *Harvard Bus. Rev.*, 1974, **52**, 109–119.
117 L. Trahey, F. R. Brushett, N. P. Balsara, G. Ceder, L. Cheng, Y.-M. Chiang, N. T. Hahn, B. J. Ingram, S. D. Minteer, J. S. Moore, K. T. Mueller, L. F. Nazar, K. A. Persson, D. J. Siegel, K. Xu, K. R. Zavadil, V. Srinivasan and G. W. Crabtree, Energy Storage Emerging: A Perspective from the Joint Center for Energy Storage Research, *Proc. Natl. Acad. Sci. U. S. A.*, 2020, **117**, 12550–12557.
118 F. R. Kalhammer, A. Kozawa, C. B. Moyer and B. B. Owens, *Performance and Availability of Batteries for Electric Vehicles: A Report of the Battery Technical Advisory Panel, CARB CPRA 049-022318 000002*, California Air Resources Board, El Monte, CA, 1995.
119 J. McNerney, J. Doyne Farmer and J. E. Trancik, Historical Costs of Coal-Fired Electricity and Implications for the Future, *Energy Policy*, 2011, **39**, 3042–3054.
120 J. McNerney, J. D. Farmer, S. Redner and J. E. Trancik, Role of Design Complexity in Technology Improvement, *Proc. Natl. Acad. Sci. U. S. A.*, 2011, **108**, 9008–9013.