Residual learning rates in lead-acid batteries: Effects on emerging technologies

Schuyler Matteson, Eric Williams

Golisano Institute for Sustainability, Rochester Institute of Technology, One Lomb Memorial Drive, Rochester, NY 14623, USA

HIGHLIGHTS

- We analyze potential cost reductions in lead-acid batteries.
- Modified experience curve for non-material costs gives good empirical fit.
- Historical learning rate for non-material costs from 1985–2012 is 19–24%.
- Progress in incumbent technology raises barrier to new entrants.

ABSTRACT

The low price of lead-acid, the most popular battery, is often used in setting cost targets for emerging energy storage technologies. Future cost reductions in lead-acid batteries could increase investment and time scales needed for emerging storage technologies to reach cost-parity. In this paper the first documented model of cost reductions for lead-acid batteries is developed. Regression to a standard experience curve using 1989–2012 data yield a poor fit, with \( R^2 \) values of 0.17 for small batteries and 0.05 for larger systems. To address this problem, battery costs are separated into material and residual costs, and experience curves developed for residual costs. Depending on the year, residual costs account for 41–86% of total battery cost. Using running-time averages to address volatility in material costs, a 4-year time average experience curve for residual costs yield much higher \( R^2 \), 0.78 for small and 0.74 for large lead-acid batteries. The learning rate for residual costs in lead-acid batteries is 20%, a discovery with policy implications. Neglecting to consider cost reductions in lead-acid batteries could result in failure of energy storage start-ups and public policy programs. Generalizing this result, learning in incumbent technologies must be understood to assess the potential of emerging ones.

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1. Introduction

As we move into a data-driven future immersed in digital technology, new constraints are imposed on our infrastructure systems. In the case of electricity, reliability has become a premium service, with governments, hospitals, data centers, corporations, and personal mobile technologies requiring a higher quantity, and a better quality of service than ever before. Many organizations, including electric utilities themselves, are now turning to energy storage systems to provide much needed energy security.

The energy storage sector is a burgeoning market, with continuing introductions of new technologies and applications. A recent report predicts that the global market for energy storage for grid use alone could rise from $200 million in 2012 to over $10 billion in 2017 (Warshay, 2013). Even though new systems based on lithium based batteries, flywheels, or compressed air technology have performance qualities distinct from lead-acid, the main contributor to market success is still cost. More mature technologies, namely lead-acid batteries, remain the system of choice for stationary energy storage.

In the world of batteries, the lead-acid chemistry is the most common (Haas and Cairns, 1999; Linden, 2010). Lead-acid batteries were first developed in 1860 by Gaston Plante, and have grown into the most widely used electrical energy storage system due to their high reliability and low cost (Huggins and Robert, 2010). As shown in Table 1, compared to other energy storage technologies, lead-acid batteries remain one of the cheapest options, giving them a distinct advantage in popular applications.

The two primary uses for lead-acid batteries are in automobiles
Table 1

<table>
<thead>
<tr>
<th>Energy storage technology</th>
<th>Cost per kW h</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-acid batteries</td>
<td>$160</td>
</tr>
<tr>
<td>Lithium-ion batteries</td>
<td>$600 *</td>
</tr>
<tr>
<td>Sodium-sulfur batteries</td>
<td>$450</td>
</tr>
<tr>
<td>Flywheels</td>
<td>$500 –</td>
</tr>
</tbody>
</table>

and uninterruptible power supplies (UPS) (Haas and Cairns, 1999). The size of both the automobile and UPS markets have led to massive deployment of lead-acid batteries, causing further reductions in cost due to technological learning and economies of scale. The main result of this growth has been a strong hold of lead-acid on the battery market for decades. However, due to the recent growth of electric vehicles, which are expected to primarily utilize lithium-ion battery chemistries, and the development of new back-up energy storage technologies, it remains to be seen whether lead-acid batteries can maintain their hold on the electrical energy storage market. Future costs of energy storage technologies are particularly critical given the increasing drive to integrate intermittent renewable energy production into the electrical grid.

The relative cost of lead-acid versus emerging storage technologies is an important factor in determining what storage technology will be successful. It is typically (often implicitly) assumed that learning in lead-acid battery production is “finished”. The literature analyzing the price-point goal for emerging energy storage technologies refers to a static value of current lead-acid battery prices (Bayunov et al., 2010; DOE 2013; Gyuk et al., 2013; Haas and Cairns, 1999; Howell, 2012). If, however, lead-acid battery prices can be expected to fall in the future, the competitive price point for emerging technologies is a moving target, not a stationary one. A moving target could have radical effects on energy storage markets. If a venture firm developing a storage alternative must beat a future reduced cost for lead-acid, this could imply much higher capital and time required to reach cost parity. The firm could face bankruptcy if not prepared for such dynamic market conditions.

Given this context, we analyze historical price and production data to develop a retrospective forecasting model for future reductions in the cost of lead-acid batteries. We start by using the standard experience curve that describes total costs decline as a power law function of cumulative production (Neij et al., 2003). As will be seen, the standard experience curve does not reliably reproduce historical costs, leading to the need for an alternative model. We propose a modified experience curve that separates total cost into material and residual portions, and fits a power law to the residual costs. This model is motivated by the observation that the materials content of lead-acid batteries has been nearly constant for decades and that volatility in materials prices has significantly affected prices of lead-acid batteries. We also calculate the minimum theoretical cost of the batteries, called the asymptotic cost, based on the maximum potential energy density of the primary lead-acid battery chemistry. This value allows us to determine how far current technology is from reaching its theoretical potential, and also begins a discussion on the practical capabilities of a technology to achieve its maximum potential.

Having constructed a model that reasonably describes historical costs for lead-acid batteries, we extrapolate to the future and explore implications of future cost reductions for markets for alternative storage technologies. Drawing on recent work on experience curves for lithium ion batteries (Matteson and Williams, 2015), we estimate how future cost reductions in lead-acid batteries affect the investment and progress needs for lithium batteries to be price competitive to lead-acid for bulk storage. We then analyze what implications these results have for policy that aims to develop new technologies in energy storage.

We argue this work makes the following contributions to the literature. By proposing a modified form of the experience curve, we provide the first documented experience curve for lead-acid batteries. This method will find applications for other technologies as well. Combining the forecast of cost reductions for lead-acid with prior work on lithium batteries provides a concrete example of how learning in an incumbent technology could influence the development of an emerging one. The results have specific implications for energy storage and also illustrate a general phenomenon for technology emergence in energy systems.

To comment on the scope of the analysis, only price (in $/kW h) of a storage technology is considered. While price is a critical indicator of success in the energy storage market, other characteristics of a technology are also important. Performance characteristics such as energy density, power, and cycle life affect what batteries can be used for what application. Also, the environmental impact of energy storage technologies has been an area of concern in recent years as countries attempt to move toward a more sustainable energy system. As a result, some studies have analyzed the environmental impact of various energy storage technologies, such as (McKenna et al., 2013; Notter et al., 2010; Rydh, 1999), while others have assessed the impact of environmental policies on energy storage technology development (Ainley, 1995; McManus, 2012). While these considerations are important, to reasonably bound the analysis here we focus on the price factor.

This paper proceeds by presenting our methods and providing necessary data in Section 2, while Section 3 builds the residual experience curve for non-material costs, Section 4 explores the implications of the curve for lead and emerging battery technologies. Section 5 concludes with the policy implications of the research.

2. Methods

2.1. Experience curve

Since they were first developed to explain the cost reductions in airplane manufacturing (Wright, 1936), experience curves have become a useful tool for the retrospective forecasting of energy technologies (Neij et al., 2003). The basic concept comes from the observation that many industrial processes experience a power law decay in costs relative to the cumulative experience accumulated in implementing said processes (Teplitz, 1991; Yelle, 1979). When applying experience curves to the production of energy technologies, it is most common to use the functional form:

\[ C(P) = C_0(P/P_0)^{-\alpha} \]

(1)

where \( C \) represents the cost per unit of energy, usually in $/$Wp or $/kW h, \( C_0 \) is the initial cost of the technology over the time period studied, \( P \) is the cumulative production of the technology, such as the total watt capacity of solar cells produced, \( P_0 \) is the initial production value for the technology, and \( \alpha \) is the learning coefficient, a positive empirical constant used to determine the technology’s learning rate. The learning rate (LR) is defined as the fractional reduction in cost accompanying each doubling of production, and may be calculated using Eq. (2).

\[ LR = 1 - 2^\alpha. \]

(2)

For many technologies, Eq. (1) gives a statistically robust fit using only cost and production data for the given energy...
technology. Some examples of energy technology studies using learning curves include analyzes of photovoltaic technology (Harmon, 2000; Tsuchiya, 1989; Van der Zwaan and Rabl, 2004), wind (Junginger et al., 2005), coal (Yeh and Rubin, 2007), and more recently, lithium-ion batteries (Matteson and Williams, 2015). Other studies review learning over an array of technologies, and consider the affects of experience curves on energy policies (McDonald and Schrattenholzer, 2001; Weiss et al., 2010; Yelle, 1979).

2.2. Residual experience curve

As will be seen in Section 3, the simple experience curve, Eq. (1), will not robustly reproduce historical battery costs. To address this, lead-acid battery material costs are disaggregated from the experience curve to analyze whether the experience curve fit improves when volatile materials cost data is removed. This method of disaggregation is called the residual experience curve. The residual experience curve represents all the technology production costs leftover once materials costs are removed. This also allows us to identify the portions of the technology that are learning. The same methods are used to construct this curve as the previous lead-acid battery experience curve, with a slightly altered formula, shown in Eq. (3).

\[ C_R(P) = C_{R0} - \left( \frac{P}{P_0} \right)^\alpha \]  

where

\[ C_R(P) = \text{Residual Costs} = \text{Total Battery Cost} - \text{Materials Costs} \]  

and

\[ C_{R0} = \text{Initial Residual Cost} = \text{Initial Total Battery Cost} - \text{Initial Materials Costs} \]  

Once we have constructed the residual experience curve and found the residual learning rate, we may use Eq. (6), as recreated from (Herron and Williams, 2013), to create an improved total battery experience curve that accounts for material costs and residual learning separately.

\[ C_I(P) = C_M + C_{R0} - \left( \frac{P}{P_0} \right)^\alpha \]  

where \( C_M \) is the materials costs (the non-learning component) that vary year-by-year according to fluctuations in prices, \( \alpha \) is the residual learning rate (found using Eq. 3), and all other variables are the same as Eq. (1). As will be seen in Section 3, the new form of experience curve yields a superior fit to the data. Decomposition or disaggregation of the simple experience model is also studied in Nemet (2006) to unveil drivers behind cost reductions for solar photovoltaic technology, in McNerny et al. (2011) for analyzing historical trends in the cost of coal-fired electricity generation, and in Koomey and Hultman (2007) to assess future costs of nuclear reactors in the United States. This paper adds to this literature by disaggregating historical lead-acid battery costs in order to determine whether any learning exists within various components in the battery. The results from Eq. (6) will be later on, and are used to project lead-acid battery costs into the future as compared to lithium-ion batteries.

2.3. Learning in an incumbent technology

Using lithium-ion batteries as an example, we determine how learning in lead-acid batteries, the incumbent technology in the energy storage market, may influence the development of an emerging technology. We do this by utilizing a gap-to-parity approach, which is essentially calculating the area between the experience curves for new (lithium-ion) and incumbent (lead-acid) technologies. The larger the area between the curves, the greater investment is needed in the new technology for it to reach parity with the incumbent. Eq. (7) shows the formula for the gap-to-parity calculation.

\[ \text{Gap to Parity} = \int_a^b C_{LI}(P) - C_{LA}(P) \, dP \]  

where \( a \) is the initial level of production, \( b \) is the level of production where the experience curves intersect, and \( C_{LI}(P) \) and \( C_{LA}(P) \) are the disaggregated experience curve formulas (from Eq. 6) for lithium-ion and lead-acid batteries respectively.

The existence of learning in an incumbent is shown to exacerbate the situation for emerging technologies by dampening relative improvements in new technologies and maintaining a positive gap-to-parity over longer time scales. These results are shown to have important implications on the energy storage market as a whole, and particularly on the investment in, or successful subsidizing of, emerging technologies.

2.4. Assessing future development potential

No technology will ever reach zero cost, an asymptotic (or irreducible) cost refers to an attempt to assess the future minimum cost of a technology. To characterize the asymptotic cost of lead-acid batteries, we use the maximum theoretical energy density for the most common lead-acid battery chemistry to assess the minimum material input requirements for the batteries. Higher theoretical energy density, in watt–hours per kilogram, implies lower material inputs required to meet a given energy output. Using current cost trends and the previously mentioned bill of materials, we calculated the minimum theoretical production cost (materials only) of lead-acid batteries. For example, if the theoretical energy density of the battery chemistry is twice the current energy density, only half the quantity of material inputs will be required to produce the same energy output.

The distance the current technology is away from this theoretical limit is one way to determine the potential for further cost reductions in lead-acid batteries. However, this result does not inform how close producers can come in practice to the theoretical limit. We will illustrate practical barriers to technological progress by comparing the theoretical limit of energy density of lead-acid batteries with historical trends.

2.5. Cost and cumulative production data

We perform our analysis on lead-acid batteries using data for small batteries up to the size of an automotive battery – BCI (Battery Council International) dimensional group 8D and smaller – and large batteries, which include heavy-duty batteries, UPS batteries, etc. – batteries larger than BCI dimensional group 8D. These two size groups cover the two most popular applications for lead-acid batteries and allow us to view trends in learning for batteries with different applications separately.

In order to produce an experience curve model and determine the learning rate of an energy technology, two types of data are necessary. First, historical data on the cost of the technology must be found for a significant amount of time, usually on the order of decades. Second, data must be collected on the production of the energy technology. Regardless if the production data collected is on a per year or cumulative basis, the data must be converted into cumulative production values in order to be used within the model given by Eq. (1).

Data from the United States Geological Survey (Wilburn and Buckingham 2006) shows that U.S. production accounts for over
80% of the lead-acid batteries consumed in the U.S. by weight. We therefore set the geographical bounds of our analysis as costs and production in the United States. Price data for the experience curve model was found using historical data from the Producer Price Index (PPI) [PPI, 2013; PPI, 2014]. This data was collected for lead-acid batteries both larger than automotive batteries, and of equal or smaller size than automotive batteries. The PPI data follows cost trends in a technology relative to a base year, in this case 1984. The data initially presents cost in each year as a percentage of the base year cost. For example, the base year PPI cost will always be 100, and should the nominal price of the technology increase, the PPI cost will show a value of over 100 and vise versa.

Once the price data is collected from the PPI, it was transferred from 1984 terms into a real 2012 dollars cost index using annual inflation data (Inflation Calculator, 2013). With the $/kW h price in 2012 as the reference year, we calculated the real dollar cost in each year from the literature (Moseley, 1998; Schoenung and Hassenzah, 2003). The resulting cost calculations are shown by Fig. 1a and b, for use in Eq. (1).

Production data was found in reports published by the United States Geological Survey. Data was taken from (Wilburn and Buckingham, 2006) and (“Lead End-Use Statistics”, 2005) for the amount of lead contained in batteries and then translated into total kilowatt–hours of batteries produced using the multiplier found in (Linden, 2010) and the typical energy density of lead-acid batteries. The original data shows the quantity of lead, in kilograms, contained within batteries. Linden (2010) calculates that lead makes up about 60% of the battery by weight, allowing us to divide the original data by 0.6 to find the total kilograms of lead-acid batteries produced in a given year. The data is then multiplied by 0.035 kW h/kg, the typical energy density of lead-acid batteries over this period, to find the total quantity, in kilowatt–hours, of lead-acid batteries produced. Fig. 2 shows the results of this calculation over the period from 1975–2012.

When these tasks have been completed the price and production data are in the necessary form to make use of Eq. (1).

### 2.6. Materials cost

The next step in our analysis is to disaggregate the cost data input into the experience curve model so that we may assess how materials prices may affect overall technological learning. The first step is to identify the material components of a lead-acid battery. This information was found in reference (Rydh, 1999), and shows the list of material inputs for lead-acid battery production. Table 2 shows the material requirements for lead-acid battery production, expressed as mass per kilowatt–hour. The year-by-year materials cost was obtained by multiplying the materials requirement by materials price in that year:

\[
C_{kh} = \text{Materials Cost in year } k\text{[$]} \\
= \sum_{j=1}^{7} \text{Material content}_j \frac{\text{kg}}{\text{kWh}} \times \text{Price}_j \frac{\text{[$]}}{\text{kg}}
\]

where the index \( j \) runs through the seven materials accounted for, lead, sulfuric acid, polypropylene, Sb/Sn/As (an alloy used in battery grid construction), polyethylene, polyester and Cu (Rydh, 1999). The material requirement was assumed be constant through time because of the consistency of the energy density of lead-acid batteries over the time period assessed in this paper (Linden, 2010). The materials prices are global spot prices obtained

![Fig. 1. a) and b) Prices of lead-acid batteries) in the U.S., 1989–2012 for a) smaller size (e.g. automotive) and b) larger size (e.g. uninterruptible power supply).](image)

![Fig. 2. Cumulative production, in Gigawatt-hours, of lead-acid batteries in the United States, from 1975–2012, reconstructed from (Wilburn and Buckingham, 2006; “Lead End-Use Statistics” 2005).](image)

<table>
<thead>
<tr>
<th>Material input</th>
<th>Quantity (in kg/kWh)</th>
<th>Price per sample year (2014) (in $/kg)</th>
<th>Cost per kW h ($/kWh)</th>
<th>Cost reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead</td>
<td>17.5</td>
<td>2.40</td>
<td>41.97</td>
<td>(“Lead Prices”, 2014)</td>
</tr>
<tr>
<td>Water</td>
<td>3.8</td>
<td>0.00</td>
<td>0.00</td>
<td>Assumed to be 0</td>
</tr>
<tr>
<td>Sulfuric acid</td>
<td>2.7</td>
<td>0.09</td>
<td>0.25</td>
<td>(Sell, 2012; Weatherlake, 2014)</td>
</tr>
<tr>
<td>Polypropylene</td>
<td>2.3</td>
<td>1.50</td>
<td>3.51</td>
<td>(Polypropylene”, 2014)</td>
</tr>
<tr>
<td>Sb, Sn, As</td>
<td>0.6</td>
<td>10.00</td>
<td>6.00</td>
<td>(“Tin Prices”, 2014), (“Pricing”, 2013; “Arsenic Prices” (2014))</td>
</tr>
<tr>
<td>Polyethylene</td>
<td>0.6</td>
<td>1.50</td>
<td>0.86</td>
<td>(“Polyethylene”, 2014)</td>
</tr>
<tr>
<td>Polyester</td>
<td>0.1</td>
<td>1.50</td>
<td>0.13</td>
<td>(“Polyester”, 2014)</td>
</tr>
<tr>
<td>Copper</td>
<td>0.1</td>
<td>6.60</td>
<td>0.57</td>
<td>(“Copper Prices” 2014)</td>
</tr>
<tr>
<td>Total</td>
<td>27.7 kg/\text{h}</td>
<td>$53.28/\text{kWh}</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

![Table 2](image)
from a variety of sources, detailed in Table 2. In addition to the materials shown in Table 2, additional inputs of undisclosed materials, representing 3% of the battery weight per kilowatt–hour were omitted from the analysis due to lack of sufficient data.

Historical cost trends are found in the literature for each input and used to construct a materials cost trends for lead acid batteries. This trend curve may then be compared to the experience curve as a preliminary assessment of how materials costs may influence technological learning. Particularly in the material intensive battery industry, materials cost volatility may be expected to have a significant influence on technology prices. This observation may be even more important due to the recent cost volatility in many material inputs for battery manufacturing.

3. Results

3.1. Fitting data to the traditional experience curve (equation 1)

Following the methods described above we test empirically if the traditional experience model, Eq. (1), is suitable to describe historical trends. The data and empirical fit for lead–acid batteries is shown as a log–log plot in Fig. 3a and b below. The value for the learning coefficient, $\alpha$, is given by the slope of the trendline.

For small batteries, shown in Fig. 3a, $\alpha$ is 0.159. Using Eq. (2), the average learning rate for lead–acid batteries from 1989–2012 is 10%. However, due to the initial volatility of the experience curve, the resulting $R$-squared value of the trendline is 0.17. This provides very little confidence or certainty in the learning rate calculated through this experience curve.

To show the degree to which the 2007 spike alters the $R$-squared value of the trendline fit, we have calculated the experience curve for the years before 2007. When the volatile data from 2007 onward is removed from the model, the $R$-squared value improves from 0.17 to 0.91. Also, $\alpha$ increases from 0.159 to 0.307, representing a change in learning rate from 10% to 19%, respectively.

Next, analyzing larger lead–acid batteries, BCI dimensional group 8D, Fig. 3b shows the results for fitting the traditional experience curve to annual historical data. Similar to the results for smaller batteries, significant price oscillations cause a very poor fit to the learning curve model. The value for $\alpha$ in Fig. 3b, 0.065, results in an average learning rate of 4%, although this time the $R$-squared value is calculated to be 0.05 even lower than Fig. 3a. However, removing the years after 2007 once again results in a much better fit to the curve, showing more consistent learning from 1989–2006. This new experience curve results in a value of 0.19 for $\alpha$, representing a learning rate of 13%. The $R$-squared value has also improved to 0.68 from 0.05 in Fig. 3b. Unfortunately, in the case of both small and large lead–acid batteries, when constructing an experience curve, one cannot simply remove segments of data in order to clean up the results. However, this exercise has shown that a majority of the data collected for this study provides clear technological learning in lead–acid batteries. We work to explain the disruption of the learning curve in the following sections.

3.2. Materials costs

In Fig. 3a and b the primary culprit responsible for the poor fit is a spike in the cost parameters at the end of the curve. In Fig. 3a and b, the spike is visible over the value of $\log (P) = 9.4$ on the $x$-axis. When considering this spike, we observe that it occurs around 2007 and prices still have not recovered to the original levels shown on the curve.

One explanation for the volatility in the experience curve is fluctuations in materials price that cause unpredicted increases in production cost. In order to address this issue and improve the fit of the experience curve to the data we now analyze the affects of material costs by calculating material cost trends for all of the primary material components of lead–acid batteries, as described in Table 2. If this hypothesis is successful, we should observe a large spike in materials costs around 2007. This spike would cause volatility in the experience curve, and the poor fit to our model shown above.

Using a variety of data sources, shown in Table 2, we calculate cost trends for the material components of lead–acid batteries. Due to data constraints, we were only able to determine materials costs back to 1989. Fig. 4 shows the trends in materials costs for lead–acid batteries, separated into Lead Cost, and Other Materials Costs, on a per kW h of lead–acid battery produced basis.

There are two primary conclusions to be drawn from Fig. 4. First, the chart shows mostly consistent decreases in all materials costs up until the cost spike. This observation is consistent with the previously determined experience curve. The second conclusion is that there were drastic increases in materials cost, potentially explaining the volatility in the experience curve. However, we cannot be sure to what degree material costs influenced technological progress unless we incorporate the material costs into the learning model. As discussed in Section 2.2, we address this by subtracting materials costs (Fig. 4) from overall battery costs (Fig. 3a and b) and fit this residual cost to the learning curve model (Eq. 1).

3.3. Residual experience curve (equation 3)

The stage is now set to use the residual experience model defined in Section 2.2, Eq. (3). In addition to pulling out residual from

![Fig. 3. a) and b). Price and cumulative production data fit to traditional experience curve (Eq. 1), 1989–2012, (a) smaller size (e.g. automotive) and b) larger size (e.g. uninterruptible power supply).](image-url)
material costs, we also do a 4-year moving time-average of annual data. Fig. 5a and b show the results of constructing the residual experience curve, Eq. (3), for small lead-acid batteries from 1989–2012.

We compare the residual experience curves, Fig. 5a and b, with the original experience curve model, Fig. 3a and b. The residual experience curve shows a better fit to the trendline, with an R-squared value of 0.78 in Fig. 5a compared to a value of 0.17 in Fig. 3a. Also, removing the volatile material costs yields a much higher learning rate for residual costs as compared to learning for a total-battery cost shown in Fig. 5a. The value for α in Fig. 5a, 0.39, yields a learning rate of 24% for the residual costs in lead-acid battery production.

The remaining volatility in the residual learning curve can be explained by material price shock. From 2004 to 2007, lead-acid battery materials costs increased by 400%. The affects on total battery costs were subdued to an increase of only 20%, due to the reactive 30% decrease in residual costs (the downward spike above 9.4 in Fig. 5a and b). Essentially, residual prices were forcibly held down in order to keep lead-acid battery costs to a minimum during the material price shocks. Since that point, Fig. 5a and b show some continued oscillation around the experience curve as material costs (from Fig. 4), and thus the residual costs, begin to retreat to pre-2007 values.

Fig. 5b shows the residual experience curve for large lead-acid batteries, from 1989 to 2012. In comparison to Fig. 3b, this curve shows both a better fit to the data as well as a larger learning rate. The R-squared value improves from 0.05 in Fig. 3b, to 0.74 in Fig. 5b, an even larger improvement than was shown in the case of small lead-acid batteries. Also, the learning rate for residual costs is calculated to be 19%, up from 4% for total cost.

Removing material costs from the experience curve has a great affect on the observed learning trends in large lead-acid batteries. These results show that removing volatile material costs from the lead-acid battery experience curve improves the model’s fit to the available cost and production data. While overall volatility in the experience curve is less than ideal, an improved fit may offer more opportunities for future analysis.

To separate out the contributions of residual costs and time-averaging, Table 3 shows the results of traditional and residual cost learning curves for small and large lead-acid batteries with 1, 2 and 4-year moving averages. Taking moving averages is another way to mitigate variability in the year-to-year data set. For instance, a time step of 2 means the results being presented are for a 2-year moving average assessment of the given technology.

For both small and large batteries, accounting for residual versus total costs caused the largest improvements in R-squared and yield higher learning rates than total battery costs. Using moving averages also increased both the R-squared value and the learning rate. On the whole, small lead-acid batteries showed more rapid learning than large batteries from 1989–2012.

The traditional experience curve also yields very different learning rates for large versus small lead-acid batteries. Switching to residual learning largely closes this gap, with at most around a 20% difference. As the technologies for large and small lead-acid batteries are very similar, obtaining similar learning rates is another advantage of the residual model. Overall, as the market is made up of some combination (e.g. 50–50 or 60–40) of small and large lead-acid batteries, learning rates for the entire lead-acid battery market will lie somewhere between these two cases.

### 3.4. Asymptotic cost assessment

The maximum theoretical energy density of a typical lead-acid battery is 175 W h/kg (Hughes and Roberts, 2010). This value is five times the current energy density, meaning that if lead-acid batteries were to reach this potential, battery production would

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**Table 3**

<table>
<thead>
<tr>
<th>Battery size</th>
<th>Time step (Years)</th>
<th>Aggregation level</th>
<th>$R^2$</th>
<th>Learning rate(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>1</td>
<td>Total battery</td>
<td>0.37</td>
<td>7.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.51</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Total battery</td>
<td>0.26</td>
<td>9.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.63</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Total battery</td>
<td>0.44</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.78</td>
<td>24</td>
</tr>
<tr>
<td>Large</td>
<td>1</td>
<td>Total battery</td>
<td>0.05</td>
<td>4.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.41</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Total battery</td>
<td>0.09</td>
<td>5.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.57</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Total battery</td>
<td>0.18</td>
<td>6.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>residual</td>
<td>0.74</td>
<td>19</td>
</tr>
</tbody>
</table>
require 80% less material inputs than are used in current battery production. Using current materials cost data from Table 2, we are able to calculate the minimum potential cost, called the asymptotic cost, of lead-acid battery production.

At current price points, the asymptotic cost of a lead-acid battery is found to be $11/kWh. The current materials cost, as shown in Fig. 4, is around $53/kWh. This means that, learning effects aside, energy density improvements have the potential to reduce materials costs by 79%. While this seems encouraging, as with many mature technologies, lead-acid batteries have demonstrated little improvement in energy density over the years, consistently remaining around 30–40 W h/kg for the last four decades (Huggins and Robert, 2010; Linden 2010). Given that the energy density of lead-acid battery has so long been stagnant, the practical potential for improvement may be significantly less than is shown by the asymptotic cost assessment.

4. Discussion

In this section, the results from Section 3 are applied to a broader assessment of the energy storage market, including a comparison with lithium-ion batteries. Comparing lead-acid and lithium batteries allows us to better grasp the market implications of technological progress in lead-acid, and more generally how emerging technologies may be affected by progress in the incumbent.

4.1. Lead-acid battery learning compared to other energy technologies

Section 3 showed how lead-acid batteries have experienced technological learning over the past few decades. To place these new results for lead-acid battery learning in perspective, Table 4 shows the residual learning rates in lead-acid batteries with learning rates obtained as well for other energy technologies in prior studies.

When volatile material costs are removed, the residual learning rate calculated for lead-acid batteries resembles those for other fast-learning technologies like lithium-ion batteries and photovoltaics. However, when material costs and learning are considered as a whole, lead-acid batteries rank near the bottom in terms of learning rates.

As new energy storage technologies are developed, lead-acid batteries will have a growing number of competitors in the marketplace. Learning studies such as this one are important to inform policy and suggest potential winners and losers in the competition for economically viable energy storage technologies. If material cost volatility continues to hinder lead-acid batteries and other technologies, such as lithium-ion batteries, continue to progress down their learning curves, lead-acid batteries may lose their hold on the market. However, if materials costs stabilize and residual learning continues, lead-acid batteries could continue to dominate the energy storage market for years to come.

4.2. Forecasting cost reductions for lead-acid and lithium batteries

In this section, we develop cost forecasts for small and large lead-acid battery and lithium batteries. We assume future costs follow an equation in form of Eq. (6); the task is to find empirically-based values for parameters.

Lead-acid cost forecast: We assume residual learning follows historical trends: small lead-acid batteries have a residual learning rate of 23%, and large batteries have a residual learning rate of 19%. The materials cost factor is assumed to be a constant $50/kWh, representing the materials costs shown in 2014 in Fig. 4. This choice of asymptotic cost assumes that there will be no significant improvement to the energy density of lead-acid batteries. Note that in Section 3.4 we discussed an asymptotic cost showing theoretical potential for an 80% improvement in energy density and materials costs. However, a constant energy density is representative of historical trends. Even if lead-acid batteries close in on the maximum theoretical energy density, uncertainties in learning and material costs may still hinder lead-acid batteries in the marketplace. Eqs. (9) and (10) show cost forecasts in $/kWh for large lead-acid (C_{SLA}) and small lead-acid batteries (C_{SLA}):

\[
C_{SLA} = 50 + (155 - 50) \times \left( \frac{P}{3.1 \times 10^3} \right)^{-0.2822}
\]

\[
C_{SLA} = 50 + (155 - 50) \times \left( \frac{P}{3.1 \times 10^3} \right)^{-0.3713}
\]

Lithium-ion cost forecast: The experience curve for lithium-ion batteries was constructed based on results from (Matteson and Williams, 2015), using $600/kWh as the current price, a 22% learning rate, and 7.8 x 10^9 kW h of cumulative production. Due to their high energy density, lithium-ion batteries have an asymptotic cost of around $1 (Matteson and Williams, 2015). This $1 is an asymptotic, not current materials cost. This choice to use asymptotic cost is based on rapid historical improvements in energy density in lithium batteries. If these trends continue lithium-ion batteries could conceivably near their maximum theoretical energy density of 456 W h/kg (Haas and Cairns, 1999) (for lithium-manganese spinel). Note that since current material cost were used for lead, our choices reflect a best-case comparison for lithium-ion and lead-acid batteries. Eq. (11) shows the cost forecast in $/kWh for lithium batteries (C_{Li-ion}):

\[
C_{Li-ion} = 11 + (600 - 11) \times \left( \frac{P}{7.8 \times 10^7} \right)^{-0.3536}
\]

To compare cost forecasts of lead versus lithium batteries, Equations (9–11) are plotted in Fig. 6. Lithium-ion batteries are currently around $600/kWh (Global EV Outlook, 2013; Matteson and Williams, 2015), compared to around $150–200/kWh for lead-acid batteries. However, high materials prices in lead-acid batteries put a cap on the potential for future improvement. As a result, lithium-ion batteries have the ability to catch lead-acid batteries in price as long as production and technological learning continue at historical trends. Discussed further in Section 4.3, the critical issue is that while lead-acid batteries costs are falling more slowly than lithium-ion, reaching cost parity has been pushed out much further than if lead acid battery prices were considered constant. This pattern is important not only to lead-acid battery producers, but also to the producers of other energy storage technologies and the government. Costs and learning in these important energy technologies must be monitored in order to develop new applications for these technologies, and also to

<table>
<thead>
<tr>
<th>Energy technology</th>
<th>Learning rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-Acid batteries, small (residual)</td>
<td>23</td>
</tr>
<tr>
<td>Lead-Acid batteries, large (residual)</td>
<td>19</td>
</tr>
<tr>
<td>Lithium-Ion batteries</td>
<td>22*</td>
</tr>
<tr>
<td>Natural gas</td>
<td>12</td>
</tr>
<tr>
<td>Nuclear</td>
<td>9.0b</td>
</tr>
<tr>
<td>Photovoltaics</td>
<td>22b</td>
</tr>
<tr>
<td>Wind</td>
<td>12b</td>
</tr>
</tbody>
</table>

Table 4 Learning rates for Lead-Acid batteries (residual component only) and various energy technologies; a – (Matteson and Williams, 2015) b – (Weiss et al, 2010).
inform future policy on the usage and incentivizing of energy storage technologies.

4.3. Implications for alternative battery technologies given an evolving incumbent

The goal of achieving “price parity” with an incumbent technology is embedded in the discourse on R&D and subsidy policy for new energy technologies. Focusing on batteries, lead-acid has been the cheap and reliable standard, thus established as the entrenched technology for emerging ones to beat. Future cost reductions in lead-acid batteries, even only in residual components and processes, implies advanced energy storage technologies must match a lower price parity. Considering lithium-ion batteries as an example, if the trends in technological learning continue, lithium-ion batteries will catch up with current lead-acid battery prices at $155/kWh after 4.2 × 10^9 kWh of cumulative production. At current growth rates in cumulative lithium-ion battery production, around 20% annually, lithium-ion batteries could surpass this value in only 7 years. This would be distressing for lead-acid battery producers and a huge success for proponents of lithium-ion batteries. However, this study has shown that there is potential for additional learning in the residual components and processes in lead-acid battery production.

Analyzing Fig. 6 through this lens, lithium-ion batteries are projected to catch large lead-acid batteries at $134/kWh after $5.5 × 10^9 kWh (6500 GW h) of production, and small lead-acid batteries at $120/kWh after 9.3 × 10^9 kWh (9300 GW h) of production. At current growth rates, lithium-ion battery will not fall below that of lead-acid batteries for 24–26 years. Additionally, if improvements are made in lead-acid battery energy density or materials costs, or if lithium-ion batteries fail to perform as expected, the cost-parity point may be pushed off even further into the future.

This scenario suggests that lead-acid batteries are likely to continue to be cheaper than lithium-ion batteries for up to two additional decades compared to the constant lead-acid battery price assumption. Using Eq. (7), we find that this increase in production to parity could result in an additional $2.2 Billion of investment needed for lithium-ion batteries to become competitive with using large lead-acid batteries, and an additional $24 Billion of investment for lithium-ion batteries to become competitive with using small lead-acid batteries, assuming lithium-ion batteries are supplanting small and large lead-acid battery in their current applications. The fact that lead-acid batteries may be a moving parity target impacts other technologies in addition to lithium-ion batteries. The results are also relevant to storage technologies that compete with lead-acid, such as flow batteries or flywheels.

5. Conclusions and policy implications

The methods and results of this work have implications for policymakers and investors concerned with emerging energy technologies. The idea of benchmarking an emerging technology with respect to its distance from an unchanging incumbent is pervasive. For example, goal setting for alternatives to the internal combustion engine are typically framed as if no further progress will occur (Plotkin and Singh, 2009; Van Vliet et al., 2010). There may be cases where assuming a constant incumbent is safe, but our analysis indicates the importance of disaggregating cost components in a learning assessment so that learning trends may be revealed.

When the incumbent technology is evolving, as with lead batteries studied here, expectations for market readiness of emerging technologies need to be readjusted accordingly. Unexpected changes in the distance to parity could result in a failed subsidy program, or require additional funds before institutional goals are met. Investors choose to support growing technologies in the hope of widespread adoption and accompanying profits. Extended timelines to reach parity could result in investors discontinuing support of a technology. For example, research and development (R&D) programs of the U.S. Department of Energy typically set a technology trajectory to reach performance targets that make the developing technology competitive (Howell, 2012). If the incumbent technology is evolving, R&D performance targets need to be more ambitious. We argue that analyzes as done here are needed to mitigate risk for a variety of R&D and subsidy policies for energy technologies.

To comment specifically on batteries, there are significant R&D efforts ongoing for a variety of alternative materials and designs. Lithium was discussed earlier, but there are also other battery systems under development, such as Aquion Energy’s aqueous hybrid ion battery (Whitacre et al., 2014). There are both public (e.g. DOE, NYSERDA) and private (e.g. Aquion) investments underway. The success of many of these alternatives depends on beating the price and/or performance point of lead batteries. While the effective learning for lead batteries is slower than these emerging technologies, the combination of some learning and
entrenchment-driven growth result in cost reductions in lead batteries that could significantly delay alternatives reaching price parity. It is crucial that battery technology investors be aware of and account for this risk.

Acknowledgments

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References


PPI: Lead Acid Batteries, BCI Dimensional Group 8D or Smaller 2013. Economagic.

“This work was supported by the Environmental Sustainability Program of the National Science Foundation (Grant # CBET 0933837).”


