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

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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.

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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.

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

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Table 1
Cost, in $/kW h of various energy storage systems Data sources: a – (Matteson and Williams, 2015; "Global EV Outlook" 2013), b – (Díaz-González et al., 2012), c – (Hadjipaschalis et al., 2009).

Energy storage technology	Cost per kW h
Lead-acid batteries	$160
Lithium-ion batteries	$600 [a]
Sodium–sulfur batteries	$450[b]
Flywheels	$600 [c]

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:

$$C\ (P) = C_0\left(P/P_0\right)^{-\alpha} \tag{1}$$

where C represents the cost per unit of energy, usually in $\$/W_p$ 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 α 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).

$$LR = 1 - 2^{\alpha}. \tag{2}$$

For many technologies, Eq. (1) gives a statistically robust fit using only cost and production data for the given energy