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Consistency and robustness of forecasting for emerging technologies: The case of Li-ion batteries for electric vehicles

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ABSTRACT

There are a large number of accounts about rapidly declining costs of batteries with potentially transformative effects, but these accounts often are not based on detailed design and technical information. Using a method ideally suited for that purpose, we find that when experts are free to assume any battery pack design, a majority of the cost estimates are consistent with the ranges reported in the literature, although the range is notably large. However, we also find that 55% of relevant experts' component-level cost projections are inconsistent with their total pack-level projections, and 55% of relevant experts' elicited cost projections are inconsistent with the cost projections generated by putting their design- and process-level assumptions into our process-based cost model (PBCM). These results suggest a need for better understanding of the technical assumptions driving popular consensus regarding future costs. Approaches focusing on technological details first, followed by non-aggregated and systemic cost estimates while keeping the experts aware of any discrepancies, should they arise, may result in more accurate forecasts.

1. Introduction

Predicting current and future costs of emerging technologies is central to identifying viable solutions to energy problems, and yet existing forecasting methods are fraught with problems. Past approaches include: (a) expert elicitations; (b) technical cost modeling; and (c) extrapolation using learning or experience curves. Each of these approaches, even when pursued in a format consistent with the state-of-the art, has limitations. For example, in expert elicitation, respondents often rely on cognitive heuristics (Hastie and Dawes, 2010; Tversky and Kahneman, 1974; Kahneman et al., 1982; Kahneman, 2011), and while a proper protocol can limit the introduction of bias (Morgan, 2014; Morgan and Henrion, 1990), challenges still remain (Kahneman, 2011; Morgan, 2014; Henrion and Fischhoff, 1986; Baker et al., 2015; Anadon et al., 2014; Verdolini et al., 2015). Perhaps most importantly for the case of estimating future costs, research suggests that individuals are poor at estimates that are additive in nature, or where small perturbations have ramifications throughout a system (Tversky and Koehler, 1994; Ford and Sterman, 1998).

A range of methods, collectively referred to as technical cost modeling (TCM), have been developed to explore the economic implications of new technologies (e.g. Daschbach and Apgar 1988; Weustink et al. 2000) and to estimate production costs for new products prior to large-scale investment (e.g. LaTrobe-Bateman and Wild, 2003). While some TCM approaches rely only on past data, TCM approaches such as process-based cost modeling (PBCM) (Busch and Field, 1998) involve detailed simulation of the implications of a new technology for each step of the production process and the interactions across these steps in the full production system (for instance, the PBCM used in this study, developed previously by Sakti et al. (2015) leverages empirical data to simulate the process consequences of design decisions across 19 different process steps with more two hundred input parameters). The model combines industry data on existing products and processes with scientific principles to map changes in design architecture, material and process to their potential consequences for industrial-scale production processes, given uncertainty. The benefit of PBCM is that by gathering individual design and per-step process data, the problem of individuals being poor at making

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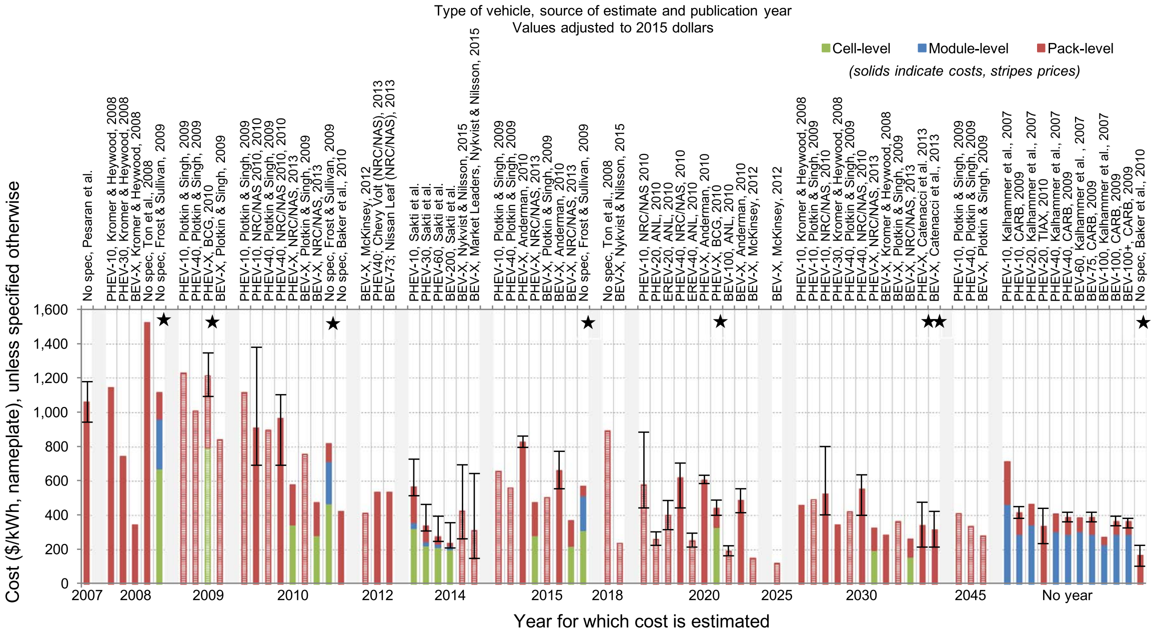

Fig. 1. Summary of available cost estimates of lithium-ion batteries for different vehicular applications (Sakti et al., 2015; Nykvist and Nillson, 2015; Hensley et al., 2009; National Research Council, 2013, 2010; Boston Consulting Group, 2010; Barnett et al., 2009; Santini et al., 2010; Baker et al., 2010; Anderman, 2010; Plotkin and Singh, 2009; California Air Resources Board, 2009; Frost and Sullivan, 2009; Kromer and Heywood, 2008; Ton et al., 2008; Kalhammer et al., 2007; Pesaran et al., 2007; Catenacci et al., 2013). The costs were assumed to be at the pack-level for the nameplate capacity unless otherwise specified in the reports. Wherever ranges were specified, error bars have been used to show the upper and the lower bounds. For reports with ranges, unless the most probable cost estimate was specified, the average of the lower and the upper cost estimates has been shown as the base estimate. In the case of McKinsey, the estimates were for the price, which included estimated margins that the automakers would pay. Price estimates have been shown using striped columns and costs with solid ones. Estimated battery cost estimates for the Chevy Volt ($PHEV_{40}$) and a Nissan Leaf (BEV_{73}) in 2012 is also shown. Studies that use expert elicitation have been highlighted with a star. All cost estimates were adjusted to 2015 dollars using GDP deflators for the US (White House, 2015). Figure adapted from Sakti et al. (2015).

estimates that are systematic or additive in nature is avoided. The downside is that the process of data collection has not been as extensively vetted and formalized as that of expert elicitation [e.g. Morgan, 2014; Morgan and Henrion, 1990], and future estimates can only be as information inputted.

While PBCMs can account for some types of organizational learning embedded in routines and other tasks (Argote and Epple, 1990) or via projections of future equipment capabilities, some studies instead adopt learning-curves to model reductions in cost (or labor hours per unit) as a consequence of organizational experience (cumulative production volume), all else being held equal (constant technology, capital, etc.) (Argote and Epple, 1990; Levitt and March, 1998; Yelle, 1979). Past research has suggested a wide range of organizational learning curve rates across industries (Dutton and Thomas, 1984; Rubin et al., 2015), which makes it difficult to know which rates are appropriate, although a broad range of assumptions could be explored.

Industry-wide experience-curve cost reductions capture any reason costs decline over time, including task repetition, organizational learning embedded in routines, capital increases and other forms of investment, economies of scale, technological advancement, and regulatory changes (Henderson, 1974). Notably, while experience curves are used widely in some circles (Nagy et al., 2013; Nykvist and Nillson, 2015), past research has raised significant concerns about whether there is any underlying empirical regularity or predictive potential in industry-wide experience curves (Rubin et al., 2015; Rubin, 2004; Colatat, 2009). Cost reductions from learning and experience may be small compared to the effects of demand, risk management, research and development, and knowledge spillovers (Nemet, 2006). Essential to achieving improved accuracy of forecasts is increased transparency about the underlying assumptions with respect to the mechanisms driving cost declines, including regulatory changes, scientific advances, process improvements, and market changes.

Given the respective weaknesses of expert elicitation and PBCM, and wide variation in organizational learning curve rates, it may be fruitful to explore the cost implications of a range of feasible individual or organizational learning curve rates for individual process-step PBCM process variables. To this end, we elicit expert insights into the most likely near-term and longer-term changes in product design and individual process-step variables – including those where individual task-based learning and changes in organizational routines might be expected and well as changes that might be fueled by scientific or technological advance. We then combine expert elicitation with PBCM to understand the difference in perspective each may offer for future battery costs for plug-in electric vehicles, and assess robustness and consistency of expert predictions. We demonstrate, despite broad consensus at the aggregate level when technical details are not considered, multiple levels of inconsistencies within expert's estimates once technical details are taken into account.

1.1. Past estimates of the current and future cost of batteries

We focus on the case of batteries for plug-in hybrid and battery electric vehicles (PHEVs and BEVs). High battery cost is the single largest economic barrier facing mainstream adoption of plug-in electric vehicle (Plotkin and Singh, 2009; Kammen et al., 2009). Increased adoption can reduce gasoline consumption (Sanna, 2005) and greenhouse gas (GHG) emissions when the electricity is generated from clean sources (Samaras, 2008; Michalek et al., 2011). PHEVs use a mix of gasoline and electricity, and BEVs use only grid electricity. A total of 96,000 EVs were sold in 2013, up 84% since 2012 (Koronowski, 2014), albeit constituting a mere 0.6% of the total vehicle sales for that year (Young, 2014).

Price is influenced by the production cost of the underlying technologies. A producer is unlikely over the long term to sell at prices below production costs. Many studies estimate battery production costs. A 2012 McKinsey study reported automotive Li-ion battery pack production costs in the range of $500–$600/kW h (Hensley et al., 2009). A 2013 National Academies' study estimated production cost of the battery packs in the Nissan Leaf and the Chevy Volt of $500/kW h at low production volumes (National Research Council, 2013). Costs of