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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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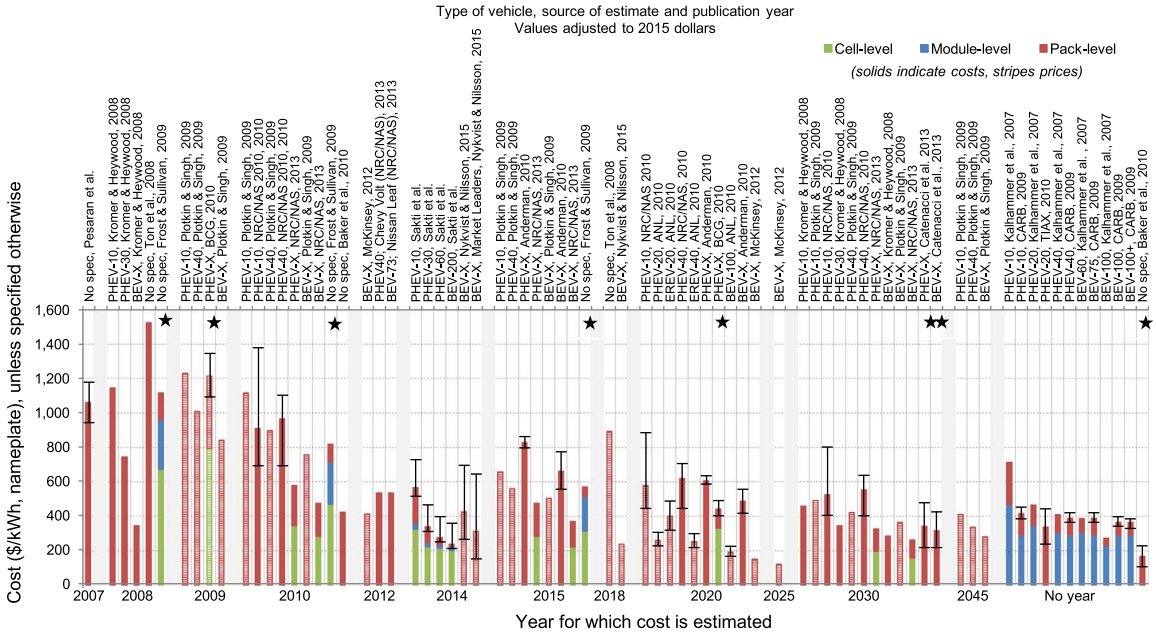

Fig. 1. Summary of available cost estimates of lithium-ion batteries for different vehicular applications (Sakti et al., 2015; Nykvist and Nillson, 2015; Hensley et al., 2009; National Research Council, 2013, 2010; Boston Consulting Group, 2010; Barnett et al., 2009; Santini et al., 2010; Baker et al., 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

Table 1
Summary of key assumptions/considerations in Li-ion battery cost studies. Information adapted from Sakti et al. (2015).

Study	Quantity reported	Key Assumptions/Considerations
Sakti et al., 2015	Cost per rated kW h in 2013 dollars.	Optimal battery pack designs for a PHEV10, 30, 60 and a BEV200 reported by varying design decision variables like electrode coating thickness, cathode width etc. Assumed an annual production volume of 20,000 battery packs using NMC-G prismatic pouch cells.
Nykvist and Nillson, 2015	Cost per rated kW h. 2014 dollars.	Cost at the pack-level for BEV manufacturers based on 85 different estimates. Paper shows industry-wide cost estimates declined by 8–14% annually between 2007 and 2014. Cost reduction due to learning from the cumulative doubling of production was shown to be between 6–9%.
NRC/NAS, 2013	Actual cost per rated kW h in 2012.	Assumes costs for Chevy Volt and Nissan Leaf are $500/kW h, future costs are projected based on historical cost pattern for 18650 cells. 18650 cells declined by more than 95% in 20 years. Midrange BEV pack cost assumed to decline by 45%. PHEV pack costs assumed to be $60–70/kW h higher than BEV packs.
Hensley et al., 2009	Prices in 2011 dollars per effective kW h.	Uses a 70% depth-of-discharge. Three major contributors to decrease in prices by 2025: manufacturing at scale, lower component prices, and battery capacity-boosting technologies. Plot shows McKinsey's price estimate scaled to dollars per nameplate kW h.
Boston Consulting Group, 2010	Price for OEM in 2009 dollars.	15 kWh NCA pack. The 2009 cost structure include a complete pack-level bill of materials, direct and indirect plant labor, equipment depreciation, R & D, scrap rates, and overhead markup. Costs estimated at a production volume of 50,000 cells or 500 battery packs in 2009 and 73 million cells or 1.1 million packs in 2020. Based on BCG analysis, information from Argonne National Laboratory, and interviews with component manufacturers, cell producers, tier one suppliers, OEMs, and academic experts.
NRC/NAS, 2010	Cost per effective kW h. 2010 dollars assumed.	Report includes three cost ranges for probable, conservative and an optimistic case for $PHEV_{10}$ and $PHEV_{40}$ batteries. Report considers a 4 kW h battery pack for a $PHEV_{10}$ and a 16 kW h battery pack for a $PHEV_{40}$.
Barnett et al., 2009	Cost per effective kW h. 2010 dollars assumed.	Estimates for a $PHEV_{20}$. 5.5 kW h of useable energy. Packs designed for capacities of 6.9–9.8 kW h to account for 30% capacity fade. Report studies 5 chemistries: NCA, NCM, LFP, LMO, LL-NMC. Prismatic (wound) cells.
Santini et al., 2010	Price to OEM per rated kW h. 2010 dollars assumed.	Four chemistries reported: LMO-G, NMC-G, LFP-G, NCA-G. PHEV20: 62 kW (10 s), 10.3kWh packs. $EREV_{20}$: 148 kW (10 s), 9.6 kW h packs. $EREV_{40}$: 158 kW (10 s), 18.7 kW h packs. BEV_{100}: 154 kW (10 s), 33.3 kW h packs.
Baker et al., 2010	Capital costs per rated kW h. 2010 dollars assumed.	Expert elicitation. 10 year funding trajectories considered. With $150 M/year funding for 10 years, there is a 66% chance of the cost being less than $200/yr and a 20% chance of it being less than $90/kW h. We chose an expected value of $150/kW h and show $200/kW h and $90/kW h with error bars. The values, adjusted to 2015 dollars, were plotted under the "No Year" category although it seems that they could be applicable for the year 2020. Baker et al. use $384/kW h as the base value in 2010.
Anderman, 2010	Cost per nameplate kW h. 2010 dollars assumed.	Feedback to CARB cost estimate. Gives ranges for EV battery costs at 500MWh in 2015 and at 2,500 MW h in the 2018–2020) timeframe. Cost of PHEV batteries per nominal kW h greater than EV batteries by 20–30%.
Plotkin and Singh, 2009	Factory gate prices (for OEM) in 2008 dollars per rated kW h	Factory gate prices for $PHEV_{10}$, $PHEV_{40}$, and BEV_{100} batteries in 2008$. Costs based on literature and include optimistic and 'still more optimistic' outlook based on DOE goals.
California Air Resources Board, 2009	Cost per rated kW h. 2009 dollars assumed.	Cost ranges at module and pack level provided for batteries for a $PHEV_{10}$, $PHEV_{40}/BEV_{75}$, BEV_{100}, and a BEV_{100+}. Upper bound is for an APV of 500MWh and the lower bound for 2,500 MW h. Battery pack sizes-$PHEV_{10}$:~7 kW h, $PHEV_{40}/BEV_{75}$:~16 kW h, BEV: 24+kW h. Numbers updated since Kalhammer (2007) using $PHEV_{20}$ pack size from TIAX (2009) and the same scaling factors as Kalhammer (2007).
Frost and Sullivan, 2009	Cost per rated kW h. 2009 dollars assumed.	Based on interviews with 12 companies: battery manufacturers and OEMs. Reports cost. However, states that prices will drop by 20–70% when cell production rises from 1 million per annum to reach more than 50 million per annum.
Kromer and Heywood, 2008	Cost per rated kW h. 2008 dollars assumed.	Uses the formula: Battery Cost=(Cost_High Energy)xf(Power-to-Energy Ratio). Current costs based on cost multipliers from Ford Motor Company, a base cost of $300/kW h base cost, and assumes improvements in energy density etc. Assumes decrease in material costs for high-energy battery at a rate of 2.5% per year for 20 years. Future high-energy battery cost estimated to be $250/kW h and $200/kW h in the optimistic case. Present-day high-power lithium-ion batteries incur a factor of 4.5–5 cost penalty compared to high-energy batteries. Future high-power battery uses a factor of 3 for the cost penalty.
Ton et al., 2008	Capital cost per rated kW h. 2008 dollars assumed.	Capital cost, no further description provided. Results of a literature review and discussions with technology leaders at national laboratories and in industry
Kalhammer et al., 2007	Cost per rated kW h. 2007 dollars assumed.	Based on estimates from three different manufacturers at production rates of 500 MW h and 2,500 MW h using 45 A h cells, and numbers from ANL (Nelson). Uses scaling factors to convert data into module-level specific costs. The following pack capacities were used: Full BEV: 40 kW h (120 A h cells), Small BEV: 25 kW h (45 A h cells), $PHEV_{40}$: 14 kW h (45 A h cells), $PHEV_{20}$: 7 kW h (25 A h cells), $PHEV_{10}$: 4 kW h (12 A h cells)
Pesaran et al., 2007	Cost per rated kW h. 2007 dollars assumed.	High-energy Li-ion batteries, no further specification.
Catenacci et al., 2013	Cost per rated kW h. 2013 dollars assumed.	14 experts interviewed. Cost estimates for BEV and PHEV batteries in 2030 assume the RD & D funding levels being maintained till 2030. Cost estimate shown represents values agreed upon by more than 50% of the experts.

$300/kW h have been reported for the battery packs used in the Tesla Model S in 2013, and the Nissan Leaf in 2014 (Nykvist and Nillson, 2015). A recent study of BEV cost estimates from 2007 to 2014, suggests that costs have been declining at an annual industry-wide rate of 14% – and at 8% for market-leaders (Nykvist and Nillson, 2015). Sakti et al. (2015) summarize the literature on EV Li-ion battery cost estimates in 2013 dollars separated into cell, module, and pack level costs where available. They calculate the optimal designs and associated costs for a PHEV10 (16 km all electric range, or AER), PHEV30 (48 km AER), PHEV60 (96 km AER), and a BEV100 (160 km AER), and find pack production costs fall between $230/kW h and $545/kW h, depending on vehicle application. Fig. 1 and Table 1, adapted

from (Sakti et al., 2015) and complemented with other recent studies (Nykvist and Nillson, 2015), provide a summary of past studies on the production costs of EV batteries (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). The estimates suggest consensus that production costs are expected to decrease over time; however, much variation across studies, even for a given year. Except Sakti et al. (2015), these studies do not distinguish between different design and process assumptions.

The range of methods applied is also wide. The McKinsey study (Hensley et al., 2009) builds upon Argonne National Laboratory's BatPaC tool (which assumes Li-ion prismatic pouch cells) (Nelson et al., 2011). Baker et al. (2010) elicit from seven experts advances in battery technologies for electrified vehicles focusing on Li-ion and Li-metal batteries in the U.S context. Catenacci et al. (2013) perform an elicitation with 14 experts to estimate the capacity of both PHEVs and BEVs to reach commercial success in the next twenty years under three different European Union (EU) public R & D funding scenarios and for a variety of batteries (Catenacci et al., 2013). In both Baker et al. (2010) and Catenacci et al. (2013), generic battery-pack designs (e.g. estimates are made without specific information in terms of battery chemistry, cell and pack capacities, cell form factors such as cylindrical or prismatic etc.—all of which are known to greatly influence production and cost) and electrified vehicles types (e.g. estimates did not differentiate between the different all-electric ranges of the vehicles) were used. To date, no work has used a combination of direct energy technology performance and cost estimates at the aggregate- as well as component-levels, and an assessment of key process-level parameters in production of the technology, and compared the resulting systems-level estimates from these three sources. Our work provides a contribution in that space.

Some existing studies on other technologies have combined expert elicitation with cost modeling by using data provided by the experts as inputs into their cost models to predict the future of a technology. For instance, Nemet et al. (2013) use expert elicitations of energy penalties to estimate the overall levelized annual cost and costs of avoided carbon from seven types of carbon capture and sequestration (CCS) technologies applied to a coal power plant. Here, the energy penalty is an aggregated estimate that refers to the decrease in the efficiency of the power plant with CCS (Nemet et al., 2013). However, Nemet et al. (2013) did not investigate for inconsistencies between experts' aggregate, component-level, and process-level estimates. This difference is particularly important given the known challenges humans have with additive and systemic estimates, and the need for disaggregation. In this piece, we conduct expert elicitations of individual process-level inputs, then use those as inputs into a model that simulates each step of the production process and the implications of design changes on each of those steps. The calculated cost of the battery pack from the model using the experts' inputs is then compared with experts cost estimates at the aggregate- and component- levels to check for consistency.

Prior studies on the theory and practice of subjective estimation have shown that decomposition or disaggregation of systems-level quantities into several smaller factors can lead to better overall estimates depending on the level of disaggregation and can be used as an approach for error control (Andradottir and Bier, 1998; Andradottir and Bier, 1997; Azaiez and Bier, 1995; Hora et al., 1993; Mosleh and Bier; Ravinder et al.). Our approach and results build on these findings. This work provides a practical context to these mostly-theoretical studies and our results suggest that decomposition can indeed be used as an approach to improve estimations in forecasting the costs of emerging technologies.

2. Methods and data

We combine the expert elicitation approach developed by Morgan and Henrion (Morgan and Henrion, 1990) with a process-based cost model (PBCM) to estimate 2013 and near-term (2018) designs and costs of Li-ion battery packs for light-duty passenger PEVs. We elicit overall costs, individual component costs, as well as seven process and materials-level parameters, which we then use as inputs into the process based cost model (PBCM) developed by Sakti et al. (2015). These seven parameters (shown in Table 4) were chosen for two reasons: i) some of the parameters, such as the cathode coating thickness, scrap and yield rates were identified by Sakti et al. (2015) as process levers with the greatest potential for future cost reductions, and ii) the experts were expected to have informed opinions about these parameters. Cell and pack-level specific costs ($/kW h) are elicited at the nameplate or rated capacity level. Overall cost estimates from the experts are then compared to the aggregate of the expert's individual component cost estimates as well as to the cost values calculated using the PBCM.

Over three months, we interviewed twelve experts from different industry sectors (7 battery manufacturers, and 1 car original equipment manufacturer, OEM) and consulting firms (4 consultants) via video conference. We used a standardized protocol with two parts. We refer the reader to the Supplemental information, sections A and B, for a full version of the protocol. Section A (Parts I–VIII) was provided to each expert prior to the interview, while Section B (Part IX–XIII) was introduced during the interview. To maintain anonymity, we de-identify the experts and assign them a letter for their identification.

In Part I we provide an introduction of the goals of the assessment and in Part II, an explanation of the elicitation process. In Part II we also ask for demographic information and self-reported level of expertise while in Part IV we provide definitions and background information concerning Li-ion batteries. A particular concern when performing elicitations regarding the costs of energy technologies is the difference between costs and prices. We therefore explicitly note we are eliciting manufacturing costs. Part V of the elicitation showed an example of an elicitation response. In part VI, we elicit 2013 and near-future (2018) costs for Li-ion cells ($/kW h) and packs ($/kW h), and for the combined contribution of the battery management system (BMS) and thermal management system (TMS) to the pack-level cost ($/pack), separately for $PHEV_{10}$, $PHEV_{40}$ and BEV_{100} applications. We inform each expert that he or she was free to assume any design that would result in the cheapest battery pack for these electrified vehicles.

Table 2
Characteristics assumed for battery Designs 1 and 2 and presented to the experts during Part VII of Section A of the elicitation. Rows with a shaded background correspond to characteristics that were also elicited from experts during the interviews. Data are based on assumptions and the best available information from various sources including personal communications.

	Design 1	Design 2
Design reference	Ford C-Max Energi	Nissan Leaf
Design reference vehicle type	PHEV-21	BEV-73
Pack energy (kW h, total)	**8**	**24**
Pack power (10 s, kW)	68	> 90
State of charge swing window (%)	~85	~80
Cell form factor	Prismatic	Pouch
Chemistry	NMC-G	LMO-G
Cell capacity (A h)	25	33.1
Pack cooling	Air	Air
Cathode		
Specific capacity (mA h/g)	150	100
Single side electrode coating thickness, (μm)	60	80
Anode		
Specific capacity (mA h/g)	330	330

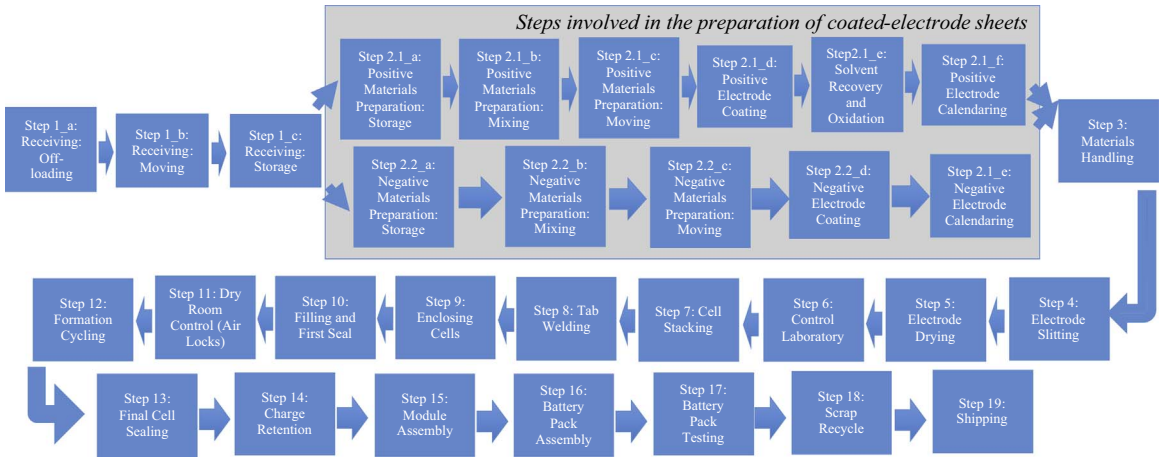

Fig. 2. Process steps involved in Li-ion battery manufacturing (adapted from ANL's BatPaC (Nelson et al., 2011)). For more information on the individual process steps, see the SI, Section C.

Additionally, we elicit key drivers of cost reductions by 2018.

Using specific designs (Part VII), based on publically available information on battery packs currently commercially available in EVs (see Table 2), we perform an elicitation for costs. Design 1 is based on the Ford C-Max Energi's battery pack, and Design 2 is based on the Nissan Leaf's. Experts were asked whether these designs were representative of the designs by 2018 and expected changes in the design of these packs, specifically, cell capacities, cathode coating thickness, specific capacities of the cathode and the anode, and the state-of-charge swing (percent usable capacity). We then asked the experts about the cost of these designs in 2013 and in 2018.

In Section B, we show a schematic of manufacturing steps for a Li-ion battery pack (see Fig. 2) to the experts and provide them with definitions of active material scrap rates and cumulative cell-level manufacturing yield. The total scrap rate for the active material m (S_m), is defined as the percent of active material m, entering the mixing step (Step 2.1b or Step 2.2b) that does not end up in the final stacked cells at the end of Step 7 (Cell Stacking) as shown in Eq. (1):

$$S_m = 1 - \prod_{i=2.1b \text{ or } 2.3b}^{7} Y_{i,m}^{\text{Material}} \tag{1}$$

$Y_{i,m}^{\text{Material}}$ is the yield of active material m in the process step i. The yield rate is the percent of active material entering the process step i that is present in the output of the process step that enters the next process step $i+1$.

The cumulative cell yield ($Y^{\text{Cumulative}}$) is the yield of Step 12 (Formation Cycling) of the process (Y^{Step12}). This yield is computed as the percent of cells entering Step 12 that are confirmed at the end of Step 12 as "good cells" ($N^{\text{Cells-Good}}$), which is shown in Eq. (2), where $N^{\text{Cells-Total}}$ is the total number of cells entering Step 12 (see Fig. 2).

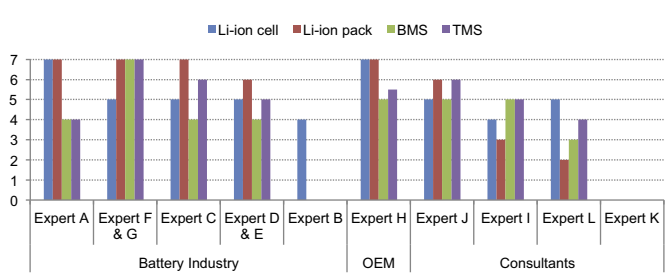

Fig. 3. Experts' self-assessed expertise in four areas: i) Li-ion cell manufacturing process, ii) Li-ion pack manufacturing process, iii) Battery Management Systems (BMS), and iv) Thermal Management Systems (TMS). Experts' affiliation has been indicated within the parenthesis: battery industry (BI), original equipment manufacturer (OEM), and consulting (C).

$$Y^{\text{Cumutative}} = Y^{\text{Step12}} = \frac{N^{\text{Cells-Good}}}{N^{\text{Cells-Total}}} * 100 \tag{2}$$

We elicit scrap rates specific to Design 1 and Design 2 as well as cumulative cell level yield, and its variation as a function of the electrode coating thickness and the cell capacity.

After eliciting the experts' estimates of battery design and process parameters in 2013 and 2018, we then placed these estimates in the PBCM to estimate overall cell and pack costs. Specifically, the experts' inputs to cell capacity, cathode coating thickness, cathode and anode active material specific capacities, scrap and yield rates (see Table 4) were used as inputs to the process based cost model previously developed (Sakti et al., 2015). More details regarding the PBCM are provided in Sakti et al. (2015).

3. Results and discussion

3.1. Characterization of the experts

We asked the twelve experts we interviewed to characterize their expertise on a scale of 0–7 for the following four areas: Li-ion cell manufacturing, Li-ion pack manufacturing, battery management systems (BMS), and thermal management systems (TMS). The experts' self-assessed expertise level along with the experts' affiliation with the battery industry (BI), original equipment manufacturer (OEM), and consulting (C) are shown in Fig. 3. Expert B was only familiar with the Li-ion cell manufacturing process, while Expert K did not provide any inputs on this section. From Fig. 3, we can see that most of the experts considered themselves more knowledgeable in Li-ion cell and pack level manufacturing than BMS and TMS. Experts that were interviewed together are listed together.

3.2. How do experts' cost estimates for 2013 compare with 2013 observed Li-ion battery costs?

At the very outset, it is important to highlight that we only have observed 2013 prices for BEVs,[1] and not observed costs. As noted earlier in the paper, prices will not equal costs. Prices represent the willingness to pay by a segment of the market, while costs represent the quantity of inputs required times the prices of each of those inputs, given technical and organizational capabilities to turn those inputs into the desired output. In high-margin products and for niche markets with low cost elasticity of demand, firms may be able to charge much

[1] We compare the experts' estimates with the costs reported by Nykvist and Nillson (2015) for leading BEV manufacturers in 2013. We interpret their reported costs as the price the BEV manufacturers will need to pay for the battery packs

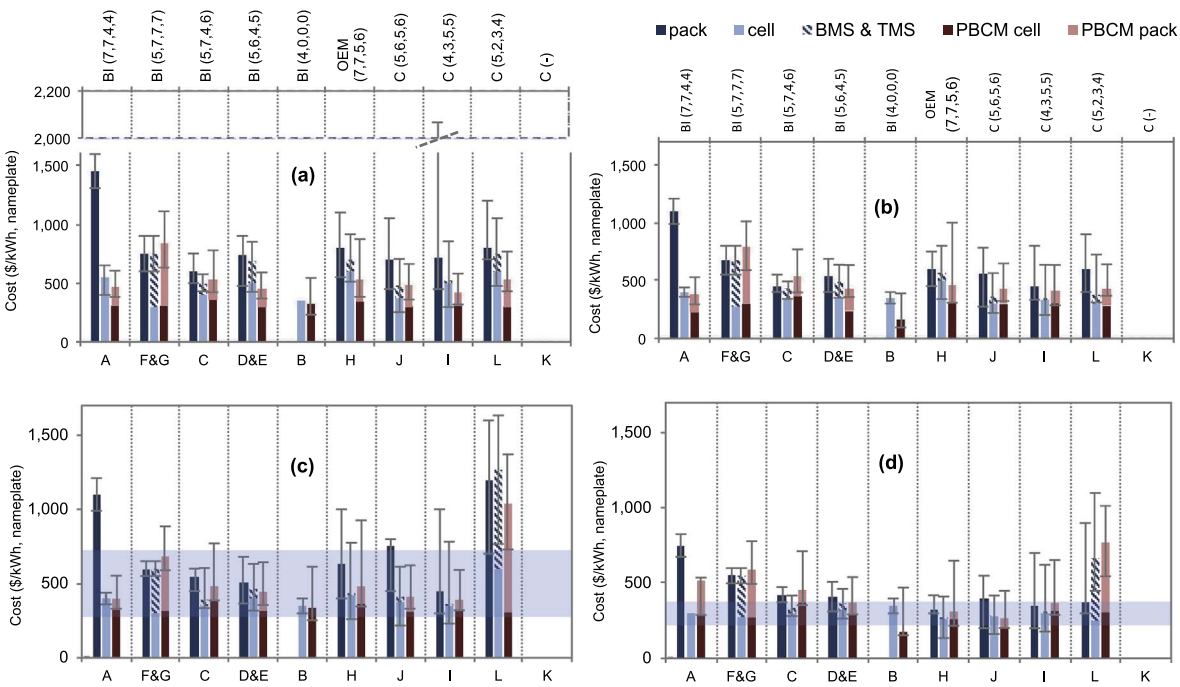

Fig. 4. Experts assessment of nameplate costs (in $/kW h) for quantities related to the following cases (a) Design 1, which is based on a PHEV21, in 2013; (b) Design 1 in 2018, (c) Design 2, which is based on a BEV73, in 2013; and (d) Design 2 in 2018. Each expert (A–K) is labeled with a letter. The affiliation (BI, OEM or C) and expert's self-assessed level of expertise regarding cell, pack, BMS and TMS technologies is shown in parenthesis at the top of the plot (1=minimum level of expertise; 7=maximum expertise). Each expert was asked first the overall pack costs for each design (dark blue bar). Then they were asked to assess the cell (light blue), and BMS+TMS cost (dashed blue bar). We stack the cell and BMS+TMS bars as these can be compared to the direct pack level estimates. In some cases, experts did not provide BMS+TMS estimates, and that explains why in some cases we only have light blue bars. The red and pink bars provide the cost estimates that results from asking experts about processes yields and other parameters, which are then fed into our process based cost model, resulting in estimates of cell and pack costs. Blue horizontal shaded regions indicate the cost estimate ranges for BEV battery packs from the literature (see Table 3). Uncertainty bars correspond to the lower and upper bounds of the experts' estimates for a 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

more than production cost to earn greater profits. In early-stage products, firms may price under cost, to gain market share. The comparisons between price and cost that follow are made for the readers' information, however, we are careful to avoid drawing significant conclusions there from.

Second, electric vehicle batteries aren't commodities—production costs vary widely depending on the battery's design and the details of the intended application. True to our study, we limit our observed price and estimated cost comparisons to within design, keeping BEVs and PEVs separate. It is important to note, however, that even within PHEV10s or BEVs, it's very hard to compare apples to apples in this domain. For example, the Sakti et al. (2015) PHEV10 assumed the vehicle ran with an all-electric control strategy, which means high power requirements for the battery. If some of the other studies that made cost estimates for PHEV10s assumed a blended control strategy, they may have much lower power requirements and therefore much lower costs. For BEVs, the cell requirements may be more standardized (as thick as you can manage to make the electrodes, etc.), but even then the specific cost ($/kW h) of packaging is going to be less for a large vehicle than a small vehicle, and costs like cooling system are going to be quite different for cylindrical vs. prismatic cells.

Battery-pack prices for BEV manufacturers were reported to be roughly around $275–715/kW h in 2013 (Nykvist and Nillson, 2015). When our experts were free to assume any design for a BEV100 battery pack, their estimates were higher, ranging from $450–1200/kW h with a median value of $600/kW h. However, once we specified a BEV design (Design 2, BEV73), all of our experts' pack-level cost estimates except for Expert A, were within the range reported in the literature, as shown in the shaded region in Fig. 4c.

For PHEV battery packs, there is limited information in the literature to allow for a similar comparison. A National Academies' study estimates the cost of a Nissan Leaf (PHEV with a 40-miles AER, PHEV40) battery-pack to be $500/kW h in 2012, at lower production volumes (National Research Council, 2013). While it is unclear in the report, we assume here they intend to report production cost and not price. In the case of our experts, when they were free to assume any design for a PHEV40, their pack-level cost estimates are higher, ranging from $550–1350/kW h with a median value of $675/kW h. The design that was specified to the experts (Design 1) is representative of a PHEV21. A PHEV21 battery pack can be expected to have a higher specific cost ($/kW h) compared to a PHEV40 and our experts' estimates are seen to be in line with that difference ranging from $600–1450/kW h with a median value of $745/kW h. These results have been listed in Table 3. Elicitation results after we specified the two designs (Design 1 and Design 2 in Part VII of the elicitation protocol onwards) have been shown in Fig. 4 and it summarizes the main findings of our study.

Fig. 4 shows the nameplate manufacturing cost in $/kW h for four cases: Design 1, which is based on a PHEV21 in 2013 (panel a) and 2018 (panel b) and Design 2, which is based on a BEV73 in 2013 (panel a) and 2018 (panel b). To highlight how the expert's affiliation and self-rated expertise relates to their responses, we also explicitly include the experts' information, codified at the top of the plot. Each expert (A–K) is labeled with a letter to remove any identifiable information. Affiliation is categorized as being with the battery industry (BI), original equipment manufacturer (OEM) or consulting firms (C). The expert's self-assessed ratings on their level of expertise on cell, pack, BMS and TMS technologies are also shown (with 7 representing the highest level of expertise, and 1 the lowest). Thus, expert A, for example, rated her/himself as having an expertise of 7 in with respect to cell-level manufacturing, 7 for pack-level manufacturing, and 4 for each BMS and TMS.

We first ask each expert about overall pack costs for each design (dark blue bars) followed by their assessment of the cell (light blue

Table 3
Comparison of experts' pack-level cost-estimates with other available and relevant estimates.

$/kW h (nameplate, pack-level)		2013				2018				% decrease in median value 2013–2018)
		Expert			Literature/Market Estimates	Expert			Literature/Market Estimates	
		Low	High	Median		Low	High	Median		
Expert free to assume any battery design	**PHEV10**	600	1500	800	–	450	1350	600	475–900	25
	PHEV40	550	1350	675	500	425	1215	480	475–900	29
	BEV100	450	1200	600	275–715	330	750	415	230–370[a]; 190 (Tesla-current)	31
Battery design provided to the expert	**Design 1 (PHEV21)**	600	1450	745	–	450	1305	580	–	22
	Design 2 (BEV73)	450	1100	615	275–715	300	600	410	230–370[a]; 190 (Tesla-current)	33

[a] Includes Nykvist and Nilsson's estimate for costs in 2017–2018 (Nykvist and Nillson, 2015).

bar), and BMS+TMS (dashed blue bar) costs. In Fig. 4, we stack the cell and the BMS+TMS estimates so that these can be directly compared with the pack level estimates. In some cases, experts did not provide BMS+TMS estimates, in which case we only show the cell-level cost estimates. The red and pink bars show the cost estimates that results from asking experts about process-level parameters as described in Table 5, which are then fed into our process based cost model, resulting in estimates of costs for cell and pack. Again, we stack these estimates so that the overall pack level estimates can be compared with the direct pack and cell level elicited values.

3.3. What do we learn from the 2018 cost estimates from our experts?

In the first phase of the elicitation (Part VI) we ask the experts to assume any design of their choosing, which according to them will result in the cheapest battery pack for a PHEV10, a PHEV40, and a BEV100 in 2018. For a PHEV10, the experts' estimates range from $450–1350/kW h with a median of $600/kW h, for a PHEV40 a range of $425–1215/kW h and a median of $480/kW h, and finally for a BEV100 a range of $330–750/kW h with a median of $415/kW h.

Upon specifying the designs, experts' pack-level cost estimates for Design 1 are in the range of $450–1305/kW h with a median of $580/kW h, while for Design 2 they are in the range of $300–600/kW h with a median of $410/kW h. Existing projections (Fig. 1) for 2015–2018 predict the cost of PHEV battery packs to be in the range of $475–900/kW h, and between $240–370/kW h for BEV packs. Thus the experts' estimate ranges (listed in Table 3) are in line, but somewhat wider than the cost-ranges reported in the literature.

Furthermore, while all experts predict reductions in manufacturing costs over time, the rate at which the experts anticipate that to happen between 2013 and 2018 varies widely, with some expecting reductions as-low-as 8% while others are more optimistic at 68%, with the median cost reduction across all experts at 25%. Median values of the ranges provided by the experts indicate a sharper decline of BEV battery costs compared to PHEVs (Table 3) For our top three experts with the highest self-assessed expertise level, F & G and H, the range of cost decline was somewhat narrower between 8% and 48%. According to experts F & G, PHEV and BEV battery costs will witness similar rates of cost-decline by 2018. Expert H, on the other hand, and who also happens to be from the automotive manufacturing industry, expects BEV100 battery costs to decline by 48% compared to a 25–40% decline for a PHEV10 and PHEV40 battery pack.

Interestingly, the experts' BEV 2018 production cost estimates are higher than prices currently reported by market-leading BEV manufacturers (Green Car Reports, 2016). Tesla reports paying a price of less than $190/kW h for the battery packs it uses in its BEVs while in GM reports paying $145/kW h for its batteries at the cell-level (Green Car Reports, 2016).[2] While both of these prices are BEVs, the design and application differ across them as well as with our own application. Most importantly, as discussed in Section 3.2, without knowing how manufacturers are setting prices it is hard to arrive at an apples-to-apples comparison with the manufacturing costs that we report in this study. For example, history shows that in order to gain early market share, firms may often only charge marginal (variable) costs, despite incurring the cost of capital, the percentage of which is used toward that particular product which should amortized over the life of the capital to represent true costs to the firm. Likewise, firms have for the same reasons of gaining market share been known to price under cost.

3.4. Are experts' component cost estimates compatible with their total pack estimates?

Experts' individual estimates of component- versus total- pack costs offer insight into internal consistency (Tversky and Koehler, 1994). The sum of the elicited costs of the pack components (i.e., the cell, BMS, and TMS) should be the same or no more than 5–15% less than the elicited total pack costs (same if the experts assume that any module-level state-of-charge regulators, wiring or packaging – such as enclosures – necessary for the cell, BMS, and TMS are included in the individual component costs, less if the experts assume that regulators, wiring and packaging are in addition to the components themselves). For our PBCM, we do consider these costs separately.[3] Four of the nine experts (D–G) that provided component-level costs provide internally consistent estimates (Fig. 4). Four experts (C, H, I, and J) have at least one design where the aggregate of their component costs are more than 15% less than their total pack costs. These results may indicate one of two things: (i) experts are inconsistent; (ii) in their mental accounting, they are including other costs. One expert (L) estimated (impossibly) in two of four cases component costs whose sum was significantly higher than total pack costs (Fig. 4c–d). These inconsistencies are evident from Fig. 5 where we plot the difference between the sum of the component-level costs and their pack-level estimates (blue columns). We highlight the net-zero difference in the case of experts F & G's

[2] Nykvist and Nillson (2015), based on their meta-analysis, estimate the cost of BEV battery packs will be ~$230/kWh in the 2017–2018 timeframe. Again, the Nykvist and Nilsson paper (Nykvist and Nillson, 2015) does not distinguish between price and cost (some of the sources contributing to their meta-analysis measure price, and others production cost.)

[3] The cost of the pack can be represented by the following simplified equation, $C^{PACK}=C^{CELL}+C^{Mod\_Ass}+C^{Pack\_Ass}+C^{BMS\,\&\,TMS}$, where C^{PACK} is the cost of the pack, C^{CELL} is the cost of the cells, C^{Mod_Ass} is the cost of assembling the cells into modules, $C^{Pack.Ass}$ is the cost of assembling the modules into packs and $C^{BMS\,\&\,TMS}$ is the cost associated with the BMS and TMS. $C^{Mod\_Ass}+C^{Pack\_Ass}$ should be no more than 5–15% of the total pack cost. See Sakti et al. (2015) for more information.

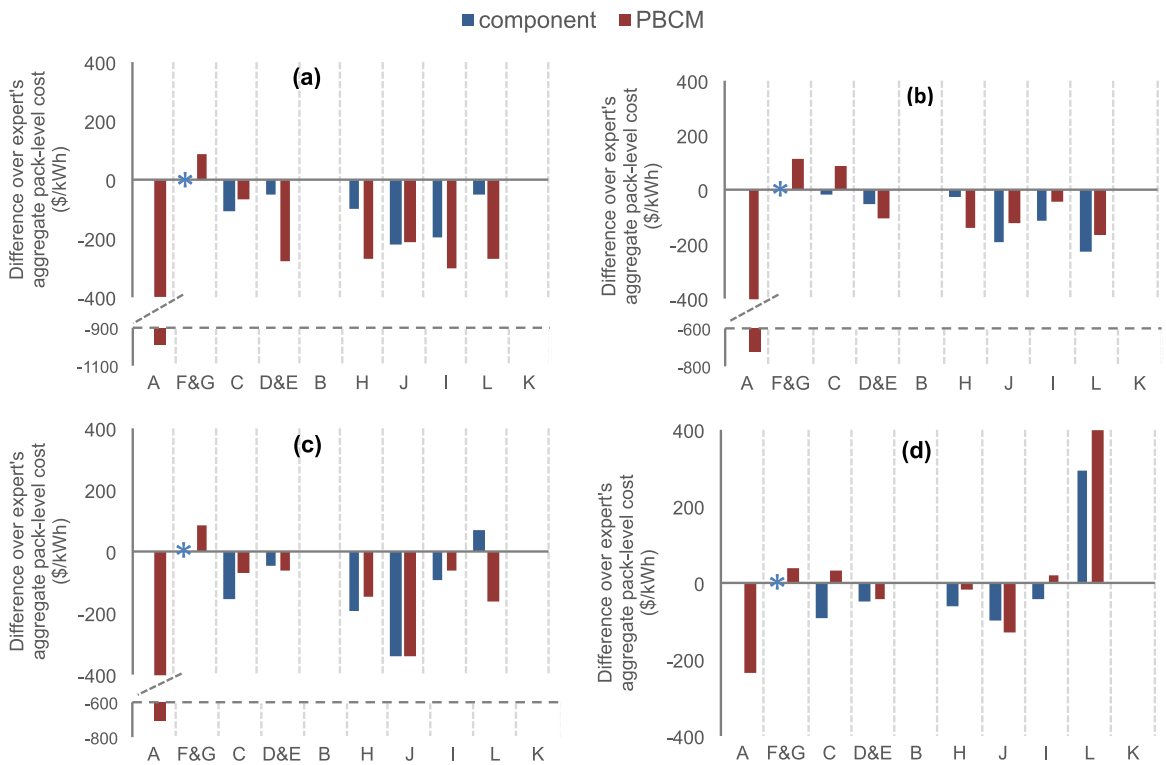

Fig. 5. Difference between the experts' aggregate pack-level cost estimates from their component-level estimates and the results from the PBCM using their process-level inputs. The experts' aggregate pack-level cost estimate was subtracted from the other quantity in each case. We highlight the net-zero difference in the case of Experts F & G's responses for the pack- and component-level costs asterisks. Unlike other experts, F & G made sure during the interview that their component- and pack-level estimates matched. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

responses for the pack- and component-level costs with an asterisk. Unlike other experts, F & G made sure during the interview that their component- and pack-level estimates matched.

The inconsistencies in experts' reporting of the component versus the total pack costs align, in part, with their type of expertise. Experts D–G are all from the battery industry. Experts I and J – (who have the largest cost delta) and Expert L (whose estimates aggregate component costs greater than total pack costs) are consultants not directly involved in the production of batteries in the industry. These differences may suggest that greater internal consistency (if not also accuracy) across estimates is possible by going directly to those with experience in production. They may also highlight differences in sources of information informing respective estimates – whereas the battery industry experts' information may come from production experience with individual components, the consultants' estimates may be based on external sources of data (such as industry pricing, historical trends, and previously published papers).

3.5. What do experts believe battery design parameters will be in the future?

Cell Capacity (Ampere-hour,[4] *Ah)*, a measure of charge manufactured cells are able to store under normal charge/discharge conditions, determines the minimum unit of production and so drives crucial parameters such as yield per kWh produced and cell-level safety. Generally, the experts expect cell sizes to be larger for BEV applications and that BEV cells will increase in size more than PHEV cells by 2018.

Electrode coating thickness determines the power to energy ratio and total energy of a cell. (Thicker electrode cells have higher energy and lower power/energy.) Among experts who responded there was consensus - there is little possibility of changing electrode dimensionality in the near term. This finding is technically sound, given that electrode thickness is largely dictated by electrolyte conductivity and there is low probability of introducing a substantially different electrolyte solution in the near term.

Cathode and anode specific capacities are active material attributes that influence cell-level energy content. Experts expected marginal improvements by 2018, except for Expert B, who commented that the cathode specific capacity could improve by a factor of two for both Design 1 (NMC-G) and Design 2 (LMO-G), and anode specific capacity could be 500 mA h/g.

State of charge window indicates the useful range of capacity and potentials during frequent cycling. Generally, experts expected that PHEV cells would be able to be more deeply cycled, but only by 10%. *Changes in Design:* Experts were asked whether they would change cell form-factor, cell chemistry, or pack cooling to lower Design 1 and 2's costs. All but one expert suggested air cooling and a pouch cell form factor. Most experts suggested variations of NMC-G (NMCx-G) would be most economical by 2018.

A figure summarizing elicitation results on the design parameters has been included in the Supplemental information (Figure S.1).

3.6. What do experts assess production process variables are now? What do they assess they will be for their future designs?

Research suggests that material is the major driver of production costs, and that active material scrap rates and overall cell-level manufacturing yield are major areas of process improvement for reducing costs (Sakti et al., 2015; Nelson et al., 2011). Generally, experts estimated equivalent or higher material scrap rates and equivalent or lower cell-level manufacturing yields. Thus, experts' estimates are more pessimistic than the data in existing production models. Full design and process information elicited from experts for

[4] Ampere hour (Ah) is a unit of electric charge with 1Ah equivalent to 3,600C. 1Ah is equal to the charge transferred by a steady current of one Ampere flowing for one hour.

Table 4
Summary of expert assessment on changes in the design that may result in cheaper manufacturing costs for Design 1 and Design 2 by 2018. For more information on the Designs, please see Supplementary information. The base value specified for the designs have been listed. Cell color indicates whether the expert changed the base value from the reference 2013 level (red) or not (green). The responses to the open-ended questions at the end have also been summarized along with other notes and comments.

	Design 1 (similar to Ford C-Max Energi)			Design 2 (similar to Nissan Leaf)			
Expert	**Cell form factor** (Base: Prismatic)	**Chemistry** (Base: NMC-G)	**Pack Cooling** (Base: Air)	**Cell form factor** (Base: Pouch)	**Chemistry** (Base: LMO-G)	**Pack Cooling** (Base: Air)	**Notes/Comments and Responses to open ended questions**
A (BI)	Pouch	Li-titanate anode	Air	Pouch	LMO-G	Air	Designs representative of 2018 designs. High capacity cathodes and anodes may come into play by 2018.
B (BI)	Pouch	-	Air	Pouch	-	Air	Designs representative of 2018 designs Super-capacitors may come into play by 2018
C (BI)	Prismatic	NMCx-G	Air	Prismatic	NMCx-G	Air	Designs representative of 2018 designs. Shift more towards higher range PHEVs ($PHEV_{40}$ over $PHEV_{10}$) No technological breakthroughs before 2020. Small improvements in cell chemistry by 2018.
D & E (BI)	Pouch or /Prismatic	NMCx-G (energy), LFP-G (power)	-	Pouch or Prismatic	NMCx-G (energy), LFP-G (power)	Liquid	Air cooling is not mainstream Cells may be pouch or prismatic. Active liquid cooling by 2018 No breakthroughs by 2018
F & G (BI)	Pouch	LMO-G	Air	Pouch	LMO-G	Air	Designs representative of 2018 designs with incremental improvements Technological breakthroughs by 2018 include improved electrolytes, improved higher capacity anodes and other safety improvements.
H (OEM)	Prismatic	NMCx-G	Air	Pouch	NMCx-G	Air	Shift towards higher range PHEVs by 2018 Increase in cell size/capacity by 2018. Market will be dominated by 12-16kWh packs. No breakthroughs. Substantial evolutionary changes in electrode materials and significant manufacturing improvements in terms of densification of the electrodes and increase in the electrode coating thicknesses by up to 100 microns.
I (C)	Prismatic	-	Air	Pouch	-	Air	Designs representative of 2018 designs No technological breakthroughs by 2018
J (C)	Pouch	-	Air	Pouch	-	Air	Cell capacities will go up by 2018 No technological breakthrough by 2018, beyond that high voltage Li-ion cells can be a breakthrough.
K (C)	-	-	-	-	-	-	Si anodes may accelerate cost curves Work by Envia may be disruptive by 2018
L (C)	Prismatic	NMCx-G	Air	Pouch	NCA (high Ni)	Air	Prismatic wound cell in a metal can will become dominant in future with high Ni content NCA chemistry No breakthroughs by 2018

2018 are in Tables 4 and 5. A figure summarizing elicitation results on the scrap and yield rates has been included in the Supplemental Information (Figure S.1).

3.7. Are experts' design and process assumptions (if entered as inputs to prior cost modeling work) compatible with their expectations for aggregate future costs?

Comparing costs generated by putting the experts' elicited battery design and process parameters into our PBCM with the experts' elicited costs can offer insights into the internal consistency of the experts' estimates and into differences between what we and the experts may assume for non-elicited parameters in our production model.

In making these comparisons, some of the experts' assumptions were beyond the current capabilities of our model. We assume using a pouch or prismatic cell configuration should not impact production cost. We assume air cooling should produce cheaper pack costs than the liquid cooling assumed in our model. We focus our comparisons on the five Experts (C, D, E, H, and L- Design 1) whose cell chemistry assumptions match the NMCx-G capabilities in our model. We also discuss the three experts who did not specify cell chemistries (B, I, and J).

We find that the expert's elicited BMS and TMS costs are in all cases less than the BMS and TMS costs estimated by the PBCM. These results make sense for the experts (C, H, and L – Design 1) that assumed air- rather than liquid cooling. They do not make sense for Experts D and E, who use liquid cooling: Experts D and E assume the same cost for the BMS and the TMS for both Designs 1 and 2, despite the pack capacity for Design 2 being greater than Design 1 – an assumption that is technically improbable if not impossible. Thus, it is not surprising that the PBCM estimate for BMS and TMS is similar to Expert D & E's elicited BMS and TMS cost for Design 1 but (likely correctly) higher than Expert D & E's elicited BMS and TMS cost for Design 2.

Of the five Experts (C, D, E, H, and L - Design 1) whose cell chemistry assumptions match capabilities in our model, four have elicited cell-level cost estimates which are considerably higher than the

Table 5
Information elicited from the experts, which was used as inputs into the process based cost model (PBCM) from Sakti et al. (2015). For all cases where the expert did not provide an estimate, the default estimate from Sakti et al. (2015) was used. Default base, lower and upper values for scrap and yield rates in the PBCM are 7.8%, 5.9%, 9.8% and 95%, 90%, 99% respectively. Default BMS and TMS cost used in the PBCM is $515+20*(modules per pack). For cell capacity, coating thickness, cathode and anode specific capacities, the PBCM used the values listed in Table 2.

Expert →		A	B	C	D & E	F & G	H	I	J	L
					2013					
Design 1 (PHEV-21, similar to Ford C-Max Energi)										
Scrap rate (%)	Base	12	20	15	–	–	10	–	–	7
	Lower	8	10	10	–	–	6	–	–	5
	Upper	28	30	20	–	–	15	–	–	10
Yield rate (%)	Base	97	94	80	95	–	82	–	97	98
	Lower	95	80	70	90	–	60	–	90	95
	Upper	99	98	85	99	–	92	–	99.5	99
BMS & TMS ($/pack)	Base	–	–	750	1500	3600	800	183	833	1200
	Lower	–	–	650	1000	2600	500	100	433	1000
	Upper	–	–	1000	2000	4600	1300	567	1233	2000
Design 2 (BEV-73, similar to Nissan Leaf)										
Scrap rate (%)	Base	12	20	20	–	–	10	–	–	7
	Lower	8	10	15	–	–	6	–	–	5
	Upper	18	30	25	–	–	15	–	–	10
Yield rate (%)	Base	97	94	80	95	–	82	–	97	98
	Lower	95	80	70	90	–	60	–	90	95
	Upper	99	98	85	99	–	92	–	99.5	99
BMS & TMS ($/pack)	Base	–	–	1000	1500	7200	360	200	850	16,000
	Lower	–	–	850	1000	6600	1200	125	425	10,000
	Upper	–	–	1300	2000	7800	3000	750	1500	20,000
					2018					
Design 1 (PHEV-21, similar to Ford C-Max Energi)										
Cell capacity (A h)	Base	40	50	22	60	23	25	25	–	25
	Lower	30	25	20	60	22	25	18	–	25
	Upper	50	75	25	65	24	25	35	–	25
Cathode coating thickness (μm)	Base	60	–	–	–	70	60	–	60	60
	Lower	60	–	–	–	60	40	–	–	60
	Upper	60	–	–	–	80	75	–	–	60
Cathode specific capacity (mA h/g)	Base	190	300	–	–	–	160	–	158	150
	Lower	170	250	–	–	–	130	–	150	150
	Upper	220	350	–	–	–	180	–	165	150
Anode specific capacity (mA h/g)	Base	330	500	–	–	375	330	–	347	330
	Lower	330	450	–	–	350	330	–	330	330
	Upper	330	550	–	–	400	330	–	363	330
Scrap rate (%)	Base	10.8	15	10	–	–	8	–	–	7
	Lower	7.2	7	5	–	–	6	–	–	5
	Upper	16.2	25	15	–	–	15	–	–	10
Yield rate (%)	Base	97	94	80	95	–	82	–	97	98
	Lower	95	80	70	90	–	60	–	90	95
	Upper	99	98	85	99	–	92	–	99.5	99
BMS & TMS ($/pack)	Base	–	–	650	1100	3200	550	133	500	600
	Lower	–	–	500	800	2400	320	75	317	500
	Upper	–	–	750	1500	4000	800	283	917	1000
Design 2 (BEV-73, similar to Nissan Leaf)										
Cell capacity (A h)	Base	60	50	40	60	69	33	33	45	33
	Lower	40	25	35	60	68	33	20	33	33
	Upper	80	75	45	65	70	40	40	60	33
Cathode coating thickness (μm)	Base	80	–	–	–	90	80	–	–	80
	Lower	80	–	–	–	80	80	–	–	80
	Upper	80	–	–	–	100	90	–	–	80
Cathode specific capacity (mA h/g)	Base	100	200	–	–	–	160	–	156	100
	Lower	100	150	–	–	–	130	–	150	100
	Upper	100	250	–	–	–	180	–	165	100
Anode specific capacity (mA h/g)	Base	330	500	–	–	375	330	–	347	330
	Lower	330	450	–	–	350	330	–	330	330
	Upper	330	550	–	–	400	330	–	363	330
Scrap rate (%)	Base	10.8	15	15	–	–	8	–	–	7
	Lower	7.2	7	10	–	–	6	–	–	5
	Upper	16.2	25	20	–	–	15	–	–	10
Yield rate (%)	Base	97	94	80	95	–	82	–	97	98
	Lower	95	80	70	90	–	60	–	90	95
	Upper	99	98	85	99	–	92	–	99.5	99
BMS & TMS ($/pack)	Base	–	–	850	1100	6600	180	135	450	10,000
	Lower	–	–	750	800	6000	120	75	300	6000
	Upper	–	–	1000	1500	7200	300	500	1000	12,000

cell-level costs predicted by putting an expert's design and process-variable estimates into the PBCM for at least one design (D and E: Design 1 in 2013, H: Design 1 in 2013 and 2018, and L: Design 1 in 2013). While not outside the uncertainty bounds of each estimate, these results suggest reasonably large differences in experts' expected cell-level costs and the costs our process-based model suggests their design and process estimates should equate to.

Of the experts who didn't specify cell chemistry or chose cell chemistries other than NMCx-G, four stand out as also having incompatibilities between their design and process estimates and their elicited costs. Like Experts D and E, Experts J and I did not vary the cost of the BMS and TMS significantly across Design 1 and Design 2. Expert A's elicited total pack costs suggest dramatically higher BMS and TMS costs – at a scale improbable in real-life. The extreme difference (49%) in Expert L's elicited cell-level costs for Design 2 in 2013 and those estimated by the PBCM using Expert L's design and process assumptions also seem improbable. Based on our knowledge of the production process, we would expect NCA - high Ni costs to be similar to the NMCx-G chemistry in our model and at most no more than 10% more. The differences between the experts' aggregate pack-level cost estimates and the results from the PBCM using their process-level inputs have been shown in Fig. 5 (red columns).

3.8. A need for better methods and experts samples

All methods have approach-specific limitations. While we attempted to ensure that the experts based their judgments on similar mental models, we fell short on occasions. First, our set of experts is insufficiently broad to represent the full range of expert views in the industry: with only one expert from vehicle OEMs we do not fully represent this perspective. Second, despite having 7 of our 12 experts in the battery industry, not every expert was familiar with the details required across the full range of questions covered in our survey: Only five of the 12 experts interviewed were comfortable responding to questions on process scrap rates and yields – a significant factor in driving battery costs; and only two of the experts were comfortable speaking to how yields might change with active material thickness. These results may suggest that the number of individuals with the expertise required to estimate future costs of batteries with significant design changes (such as increased thickness) is extremely limited. Finally, the capabilities in the PBCM model did not fully cover expert's projections: Future work should expand the capabilities of the PBCM and explore the implications of experts' assumptions for less-cost-influential variables for the PBCM's assumed ranges of uncertainty. Approaches wherein the experts are provided feedback and made aware of discrepancies or inconsistencies of their inputs, if they occur, and allowed to reassess their answers should be explored to confirm their efficacy at providing better predictions.

4. Conclusions and policy implications

The cost of batteries is a major hurdle facing the widespread adoption of electrified vehicles. These vehicles have the potential to reduce gasoline consumption, air-pollution, and GHG emissions if used with clean electricity sources. While there are accounts of rapidly declining costs of batteries with potentially transformative effects, these accounts often are not based on detailed design and technical information. To gain insights into internal consistency of expert's estimates and sources of bias, we combine and compare two costing methods – process based cost modeling and expert elicitation – with a focus on using detailed design and process information. We provide a practical context to existing theory and practice of subjective estimation and our results suggest that decomposition or disaggregation can be used as an approach to improve estimations in forecasting the costs of emerging technologies. We find that 55% of relevant experts' component-level cost projections are inconsistent with their aggregate 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 PBCM. Experts with direct production experience are seen to be less likely to have inconsistencies between their aggregate component costs and their total pack costs than consultants, who may have been leveraging other sources of information than production in making their estimates. Other inconsistencies are regardless of expert type. The median values of the cost estimates when the expert was free to assume any battery pack design for a PHEV10, a PHEV40, and a BEV100 are within the ranges of those reported in the majority of the literature. These median values indicate that the cost of BEV batteries will experience a more rapid decline compared to PHEV batteries. Interestingly, experts' cost estimates are higher than current values reported by market-leading BEV manufacturers. It's unclear what this difference in reported prices versus cost estimates suggest, since companies may be pricing under cost to gain market share. It could also be an indicator that the experts are conservative in their projections and that technological progress may be occurring at a faster pace than anticipated. Results suggest that understanding whether likely cost ranges may be reasonably ascertained requires paying greater attention to underlying design and technology assumptions as well as human sources of error in existing methods of technology forecasting, and their implications for popular consensus regarding future costs. To that effect, when expert elicitation is used as a tool for technology forecasting, approaches focusing on technological detail first followed by non-aggregated cost components and systemic estimates that informs the experts of discrepancies, may result in more accurate forecasts. Future work will be necessary to build upon these initial results, and to understand better the optimal level of disaggregation.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2017.03.063.

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