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Quantification of performance and cost trajectory of Li-ion battery designs for personal vehicle electrification in the near future.

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering and Public Policy

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Dedicated to my parents

Abstract

Battery cost is among the largest barriers to mainstream adoption of electric vehicles. This dissertation examines near future battery technology and cost by (1) validating existing physics-based battery performance models using laboratory testing and manufacturer specifications, (2) constructing battery design optimization and production cost models to identify the least-cost design and investigating how key design-decision variables affect performance and cost for a variety of vehicle power and energy requirements, and (3) conducting expert elicitation on future battery costs and the key factors that drive cost. The validation, cost, and optimization modeling work use $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2/\text{Li}_x\text{C}_6$ (NMC-G) as the chemistry of choice. Validation results of Battery Design Studio™ (BDS) a Li-ion battery modeling software indicated that BDS predictions of total energy delivered under our constant C-rate battery discharge tests are within 6.5% of laboratory measurements for a full discharge and within 2.8% when a 60% state of charge window is considered. Once validated, BDS is used to develop a power meta-model that predicts the 10–sec power capability of a cell design as a function of its capacity (Ah) and cathode coating thickness (microns). The production cost model is a process-based model and is constructed adopting process step information from existing literature. Subsequently, an optimization model is developed which estimates the cheapest cost battery pack design for a set of five different electrified vehicles (EVs) whereby the role of design-decision variables like cathode coating thickness is investigated among others. The energy and power requirements for the EVs, used as constraints in the optimization model, are calculated using the Powertrain Systems Analysis Toolkit (PSAT). Battery pack costs calculated are in the range of costs reported in the literature. Results indicate that higher capacity cells manufactured using higher electrode coating thicknesses can decrease manufacturing costs by 5-8%. Results suggest that economies of scale can be reached at a plant size of about 200MWh. Expert elicitation indicates that a variation of NMC-G is likely to be the cheaper cell-chemistry by 2018 with no major technological breakthroughs. Some experts also expect manufacturing improvements resulting in higher electrode coating thicknesses and cell capacities expected by 2018.

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1. Introduction

This work is a compilation of three studies that collectively investigate the near-future cost and design developments of Li-ion batteries. The following chapter, Chapter 2, is on the validation of Battery Design Studio[®] (BDS). The chapter is a copy of the published version of the paper¹. For the validation, battery performance simulations from a commercial lithium-ion battery modeling software package against manufacturer performance specifications and laboratory tests were compared to assess model validity. A set of commercially manufactured spiral wound lithium-ion cells were electrochemically tested and then disassembled and physically characterized. The BDS software was then used to create a mathematical model of each battery, and discharge simulations at constant C-rates ranging from C/5 to 2C were compared against laboratory tests and manufacturer performance specifications. Results indicate that BDS predictions of total energy delivered under our constant C-rate battery discharge tests are within 6.5% of laboratory measurements for a full discharge and within 2.8% when a 60% state of charge window is considered. Average discrepancy is substantially lower. Results suggest that BDS can provide sufficient accuracy in discharge performance simulations for many applications.

Chapter 3² is a techno-economic analysis involving three different models that predict: i) the 10-sec power capability of a pack as a function of the cell capacity, the electrode thickness and the number of cells ii) the manufacturing cost of a battery pack as a function of five different design-decision variables: cathode coating thickness, number of bicell-layers, cathode width, number of cells per module, and number of modules per pack, and iii) an optimization model for the cost minimizing battery pack design for different EV applications. The first two models serve as inputs to the third model. Powertrain Systems Analysis Toolkit (PSAT) was used to estimate the energy and power requirements from a set of 5 vehicles (PHEVs 10, 20, 40, 60, and a BEV100). The optimal value of specific cost for the different applications was plotted as a function of the power-to-energy ratio of the battery pack and a meta-model was developed. The model is in agreement with what has been reported in the literature. However, with this study, the design variables and how they affect the optimal cost has also been reported. The specific cost of manufacturing of the cost minimizing battery pack designs for these different applications was seen to be between \$470/kWh for the PHEV10 and \$235/kWh for the BEV100. The cost and power estimates from these have been compared to existing literature as a validation. Results indicate that higher capacity cells manufactured using higher electrode coating thicknesses can positively impact the reduction of Li-ion battery cost.

Chapter 4³ reports the results and analysis from a set of ten elicitation was executed over the course of three months that involved twelve different experts from the battery industry (battery

¹ Sakti, A., Michalek, J.J., Chun, S-E., Whitacre, J.F., 2013, A validation study of lithium-ion cell constant c-rate discharge simulation with Battery Design Studio[®], Int. J. of Energy Research, 37(12), Pp. 1562-68.

² Sakti, A., Michalek, J.J., Fuchs, E.R.H., Whitacre, J.F. 2014, A techno-economic analysis of lithium-ion batteries for personal vehicle electrification, work in progress

³ Sakti, A., Azevedo, I., Fuchs, E.R.H., Michalek, J.J., Gallagher, K., Whitacre, J.F. 2014, An elicitation of expert assessments of current and future lithium-ion battery cell and pack costs, and designs for personal vehicle electrification, work in progress.

manufacturers, suppliers, and car OEMs), and consulting firms. With the manner in which the elicitation protocol was structured, initially the experts were free to assume any battery design that, according to them, will result in the cheapest cost battery pack in 2013 and 2018. Costs were elicited at the cell level (\$/kWh), pack level (\$/kWh), and for the battery management system (BMS) and thermal management system (TMS) contribution to the pack (\$/pack). Subsequently, two different battery pack designs were specified. These designs were based on available information on two existing battery pack designs currently in use in EVs commercially available: Ford C-Max Energi and Nissan Leaf. *Design1* was similar to the battery pack in Ford C-Max Energi while *Design2* that of the Nissan Leaf. Specifying the design did not seem to alter the cost estimates by the experts since they borrowed cost values from when they were able to assume any design. Design specific information was elicited and the experts were unanimous in their response that there will not be any technological breakthroughs by 2018. Improvements will be incremental with respect to the active materials and there may also be a push in the industry towards higher capacity cells and cells using higher electrode coating thicknesses.

The significance of each individual study has been discussed separately in each chapter. Collectively this Ph.D. dissertation contributes by investigating the role of some key battery pack design variables and how they affect the cost and performance of that specific design. The information on the tradeoffs was then used to design the most cost-effective Li-ion battery pack for select EV applications. Testing of actual EV cells in the laboratory prior to using the performance model and elicitation of experts for information specific to the design and cost of Li-ion battery packs helped ground the findings of the study. The validation of Battery Design StudioTM (BDS) using actual battery cells as well as an elicitation involving experts from the battery industry, car manufacturers, and consultants on design and cost specific information was non-existent in the literature.

2. A validation study of Li-ion cell constant C-rate discharge simulation using Battery Design Studio®¹

2.1 Background

Existing battery modeling and simulation literature includes work on the general energy balance of a battery system [1], the heat generation rate using the energy balance model [2], electrochemical-thermal modeling and experimental validation [3], and the simulation and optimization of lithium-ion battery systems [4] amongst others that involve detailed calculations for the internal electrochemical processes using physics-based models [5-9]. Models that avoid such detail and use approximations to represent a battery system with an equivalent circuit have also been developed and have been shown to match well with manufacturer's data [10] or, predict cell performance with accuracy [11]. However, in an equivalent circuit model, where common electrical components like resistors and capacitors are used to represent a battery system, the key elements of battery functionality that are related to ionic diffusion are very difficult to capture since modeling options there involve the use of multiple Warburg diffusion terms. The BDS battery simulation software provides versatility by allowing users to select from a set of battery system simulation models (which include both detailed physics based models as well as equivalent circuit ones) and run simulations through a graphical user interface. For this study, the model used is based on the same system of six coupled and non-linear discretized partial differential equations in the full system model described by Fuller et al. [4]², with time and space as the independent variables. Fuller et al. linearized and solved the equations using the BAND solver with the Crank-Nicholson implicit method to evaluate time derivatives [4]. The BAND solver, developed by Newman, uses tridiagonally banded matrices together with the Newton-Raphson method to solve finite difference representations of ordinary differential equations [12]. However, BDS uses a pentadiagonal BAND solver instead and implements more efficient data structures by saving only solid-phase concentrations at each time step. Cell temperature is determined from the overall energy balance calculations using the equations for insertion battery systems developed by Rao and Newman [2].

We aim to assess whether BDS is able to produce battery performance data that can be directly matched to Li-ion cells acquired on the open market. The main motivation behind this work is that a techno-economic optimization of lithium-ion battery packs for different electrified vehicles is currently in progress in which BDS is being used to predict the performance of the battery packs and this study was intended to ensure that the results from BDS are accurate enough to the extent of our economic modeling. To our knowledge, prior peer-reviewed validation work on BDS exists only for primary lithium ion coin cells in a study by Yeduvaka et al. [13]. Yeduvaka *et al.* discretized discharge curves obtained from manufacturer's data sheets (Sony, Panasonic, Gold Peak, Varta and Maxell) at different loads and temperatures and adjusted several cell parameters using BDS's built-in parameter estimation (optimization) feature to fit the discretized data. Yeduvaka *et al.* used Gering's AEM approach to estimate the electrolyte properties [14]. With the estimated parameters Yeduvaka *et al.* reported that the BDS model simulations match the discharge voltage behavior from the

¹ Published version of the peer-reviewed paper: Sakti, A., Michalek, J.J., Chun, S-E., Whitacre, J.F., 2013, A validation study of lithium-ion cell constant c-rate discharge simulation with Battery Design Studio®, Int. J. of Energy Research, 37(12), Pp. 1562-68.

² The Distributed model was also used to simulate the cells at a later stage and the results were found to be the same.

manufacturer's data sheet "fairly well" with greater discrepancies at higher positive electrode thicknesses (3.457mm, Panasonic CR2354 and 1.8mm, Sony CR2032) and at temperatures less than -10°C. Yeduvaka *et al.* do not provide any metric to quantify the accuracy of their comparisons, but examining their data we find a discrepancy of around 10% between the BDS and the manufacturer's data sheet discharge curves at 23°C for the Sony CR2032 cell by integrating the area under the curves using the trapezoidal rule. Yeduvaka *et al.* suggested that this discrepancy between the actual and modeled data may be due to a difference in the assumed and actual electrolyte formulation. However, in their study, Yeduvaka *et al.* did not test the cells for their discharge performance in the laboratory. We expand on this prior work by testing vehicle-relevant secondary lithium ion cells of LiNiCoMn/graphite chemistry with cylindrical form factor in the laboratory and then comparing the results with the manufacturer's data sheet and the BDS simulations. We quantify the accuracy of the discharge curves, keeping in mind vehicle-relevant state-of-charge swings to determine the suitability of BDS for such modeling work.

2.2 Materials and Methods

To test the veracity of BDS, we compare battery discharge performance data (in the format of cell potential vs. discharged capacity at various current loadings) of a set of spirally wound 18650 cells with a $\text{LiNi}_{0.33}\text{Mn}_{0.33}\text{Co}_{0.33}\text{O}_2$ cathode active material chemistry¹ and a minimum nominal capacity of 2.05Ah that were procured from Sanyo. The intended use of these cells, as listed by Sanyo, included electric vehicles [15] and could be implemented in the approach espoused by Tesla Motors Inc., where a large number of 18650 cells are connected in parallel and series to make a large format automotive pack. Data used to inform the comparisons were obtained from three sources: i) lab tests performed on the cells, ii) the manufacturer's specification sheet, and iii) results from the BDS simulations. The co-ordinates of several points on the manufacturer's discharge curve specifications were read and used to approximate the manufacturer's discharge curve. The flow diagram shown in Figure 2- 1 indicates the entire process.

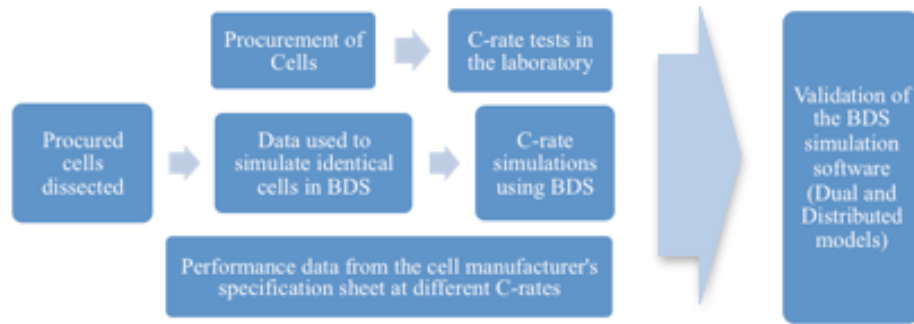


Figure 2- 1: Flow diagram showing the methodology used in the validation study comparing three different data sources to verify Battery Design Studio®. The Dual and Distributed IET (current, potential and temperature) models were used.

¹ Two more chemistries with the following cathode active materials: LiFePO_4 and LiMnNi were also tested and verified in the laboratory, although not as rigorously as the chemistry reported in the published version of the paper ($\text{LiNi}_{0.33}\text{Mn}_{0.33}\text{Co}_{0.33}\text{O}_2$). For more information, please see Appendix B.

The performance of the Sanyo LiNiCoMn cells was then tested in the laboratory under different C-rate discharges using an Arbin BT2000 test stand. For the sake of comparison, C-rates were chosen based on the discharge curves provided by the manufacturer in their specification sheet. Sample cells were then disassembled in the laboratory, and the following parameters were measured and used as BDS input: electrode thickness and length, active material density, collector thickness, separator length and thickness, jellyroll weight, height and diameter, and cell weight. The exact chemistry of the cathode active material was determined using an X-ray diffractometer (X'Pert Pro MPD for powder samples) and the peaks correspond to those seen for $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$ [16] as shown in Figure 2- 2. Electrode structure and morphology in the electrode samples was estimated with the aid of scanning electron microscopy (SEM) (Philips, XL30). Plan-view SEM micrographs, shown in Figure 3, were obtained for the electrode samples and the average particle radius calculated. Table 2- 1 summarizes the measured and calculated parameters for the cell. The density of $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$ was calculated using the lattice dimensions reported by MacNeil et al. [17] and was found to be approximately $4.7\text{g}/\text{cm}^3$. The measured value of the coating density for the cathode, which included the binder and the conductivity aid, was found to be $3.0\text{g}/\text{cm}^3$. In the case of the anode, a coat density of $1.9\text{g}/\text{cm}^3$ was measured and the default graphite density of $2.25\text{g}/\text{cm}^3$ was assumed, which is similar to what has been reported elsewhere in the literature [18]. Other assumptions made while simulating the cells in BDS are shown in Table 2- 2 and elaborated in the next section. The simulated cell was then subjected to the same C-rate discharge tests in BDS.

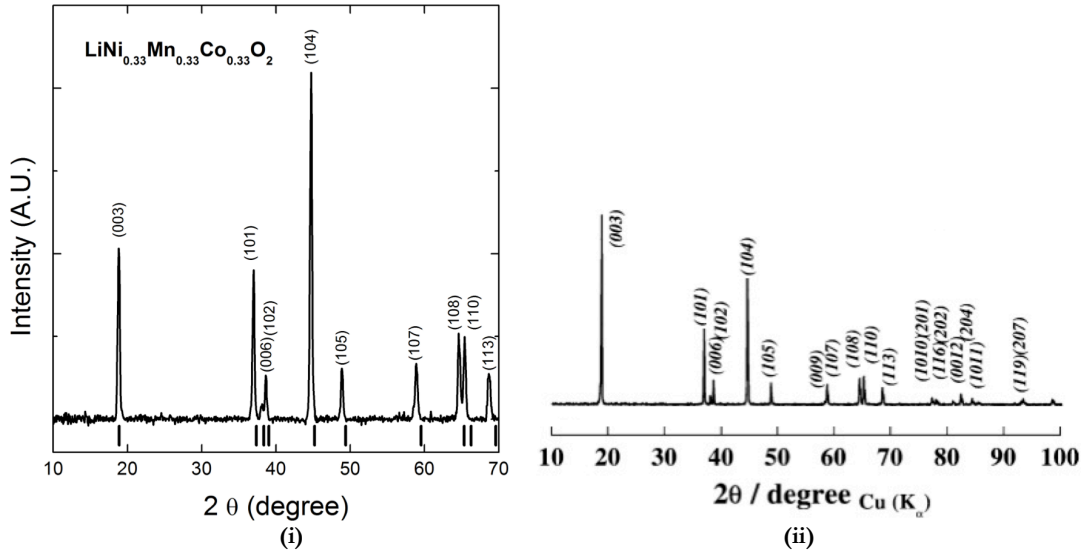


Figure 2- 2: X-ray diffraction data collected from the cathode material has been shown in (i). X-ray diffraction data of $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$ adapted from that reported by Yabuuchi and Obzuku [16] has been shown in (ii). The peaks match up indicating that the cathode active material is $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$.

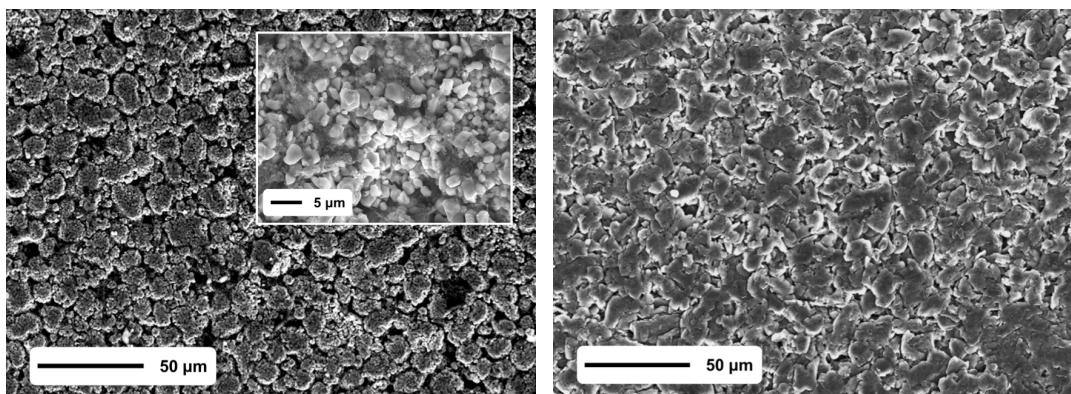


Figure 2- 3: SEM micrographs of the cathode (left) and anode, used to estimate particle size.

2.3 Assumptions

Wherever possible, the parameters measured from the dissected cells were used as direct inputs in BDS. However, where data were not available reasonable assumptions were made. This is justifiable because many of the assumed values are common in the industry. For the density of the electrode active material, the mass fractions of the conductive additive and the binder along with the porosity fraction were varied in BDS within their usual ranges to identify plausible combinations that match the density values calculated from dissecting the physical cells in the laboratory. Both density and porosity estimates are consistent with simple analyses performed on the SEM data presented in Figure 2- 3. The electrolyte was assumed to be LiPF_6 dissolved in equal weight fractions of ethylene carbonate and ethyl methyl carbonate, a common blend used widely [19]. The separator was assumed to be polypropylene with a porosity of 40%, an average value of porosity of separators available commercially [20]. The equilibrium cell potential curve along with all other parameters including the diffusion coefficient, resistivity, reaction rate constant, theoretical specific capacity, tortuosity, conductivity of the active materials (listed in Table 2- 2) were values available in the BDS data base, which is updated frequently. The equilibrium cell potential curves have been shown in Figure 2- 4. The equilibrium cell potential curve of $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$ was seen to be in general agreement with what has been reported in the literature for $\text{Li}[\text{Ni}_x\text{Co}_{1-2x}\text{Mn}_x]\text{O}_2$ ($0 \leq x \leq 1/2$) [17]. The theoretical capacity of $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2$ in the voltage range of 3-4.2V was found to be around 120mAh/g which is within the range of 110-130mAh/g reported by MacNeil *et al.* for $\text{Li}[\text{Ni}_x\text{Co}_{1-2x}\text{Mn}_x]\text{O}_2$ ($0 \leq x \leq 1/2$) [17].

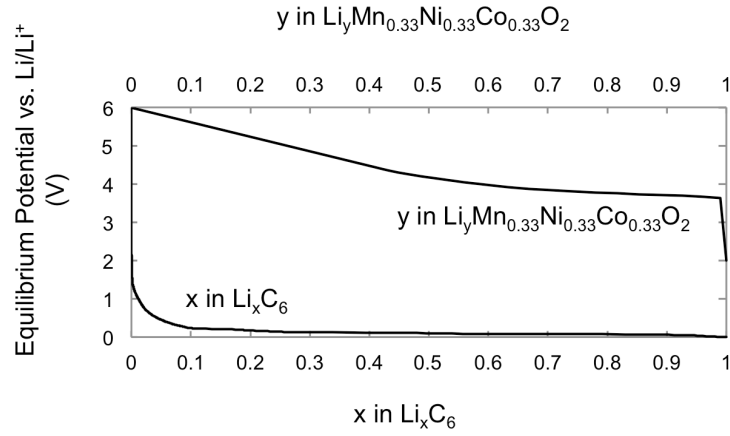


Figure 2- 4: Equilibrium potential curves used in Battery Design Studio® for the $\text{LiNi}_{0.33}\text{Co}_{0.33}\text{Mn}_{0.33}\text{O}_2/\text{Li}_x\text{C}_6$ system.

Table 2- 1: Measured and calculated parameters from the Sanyo LiNiCoMn cell after dissecting them in the laboratory

Cell		
Weight (g)	42 (+/- 1)	
Jellyroll		
Height (cm)	5.6 (+/- 0.1)	
Length (cm)	78.7 (+/- 0.1)	
Separator		
Length (cm)	162 (+/- 1)	
Thickness (mm)	0.015 ((+/- 0.001)	
Electrodes		
	Cathode	Anode
Chemistry (cathode from	LiNi _{0.33} Co _{0.33} Mn _{0.}	graphite
Active material density	4.7	~*
Single side coat thickness	0.15 (+/- 0.01)	0.14 (+/- 0.01)
Collector thickness (Al)	0.014 (+/- 0.001)	0.016 (+/-
Coat density (g/cm ³)	3.0 (+/- 0.1)	1.9 (+/- 0.1)
Particle radius from SEM	0.98 (+/- 0.05)	7.78 (+/- 0.05)

*The default density value of $2.25\text{g}/\text{cm}^3$ was assumed, which was found to be similar to what has been reported elsewhere in the literature [16]

Table 2- 2: Assumptions made for different parameters while simulating the cells using BDS

Electrode Parameters	Cathode	Anode
Mass fraction active material	0.84	0.96
Mass fraction binder (ethylene-propylene copolymer)	0.03	0.015
Mass fraction of conductive aid (graphite)	0.13	0.025
Porosity fraction	0.195	0.17
Active material diffusion coefficient (solid) (cm ² /s at 25°C)	3E-11	6.74E-11
Active material lithium site concentration before formation	275	370
Resistivity (Ωm^2 at 25°C)	6E-3	0.5
Reaction rate constant (mA/cm ²)	1.08E2	2.02E-01
Electrode conductivity (S/cm)	100	100
Tortuosity (Bruggemann Exp)	1.25	1.9
Other Parameters		
Initial salt concentration, LiPF ₆ in EC:EMC (M)	1.0	
Electrolyte density (g/cm ³)	1.25	
Separator material (polypropylene) density (g/cm ³)	0.65	
Aluminum density (g/cm ³)	2.7	
Copper density (g/cm ³)	8.9	

2.4 Results and Discussion

The comparison of the constant current discharge profiles for the cell is shown in Figure 2- 5. The results from the laboratory match closely with the results from the manufacturer's specification sheet, and the results from the BDS simulations predict somewhat higher voltage over most of the range, particularly when mostly discharged. Table 2- 4 summarizes the difference between delivered energy and delivered capacity measured using BDS, laboratory tests, and the manufacturer specification sheet. Delivered energy in the case of the manufacturer's specification sheet was computed by calculating the area under each of the curves using the trapezoidal rule by selecting points at most 0.1Ah apart. In the case of the BDS simulations, reporting parameters of 10s and 0.1V were selected, leading to results with a resolution within 0.01Ah¹. Laboratory results using the Arbin BT2000 test stand reported values using a much higher resolution. The cell simulations predicted capacity and energy within 4.3% of manufacturer specification and within 6.5% of lab tests. Average discrepancies for the cell simulations are substantially lower.

The discharge profiles were also compared under a reduced 60% state of charge (SoC) window. This was done to simulate similar conditions encountered in some battery applications, such as vehicle applications (e.g.: the Chevy Volt battery pack operates within a 65% SoC window [21]). In this case, the magnitude of this SoC swing (in Ah) was calculated based on the measured or modeled total capacity value for each case (Figure 2- 5). The curves were then compared between the 30%-90% SoC window for the energy and capacity delivered. BDS results match more closely within the 60% SoC. The cell simulations predicted energy and capacity values within 1.6% of manufacturer specification and within 2.8% of lab tests. Again, average discrepancies for the cell simulations are substantially lower. The average and maximum difference in the voltage between the discharge curves from the manufacturer's specification sheet and the lab results vs. the BDS simulation results within this SoC window were also calculated (Table 2- 4). The maximum difference is within 0.08V of manufacturer specification and 0.09V of lab results. Average voltage discrepancies are lower.

¹ Simulations with a tighter resolution of 0.5s produced similar energy and capacity results within 0.2%, and tests with a more coarse resolution of 1min produced results within 0.1%.

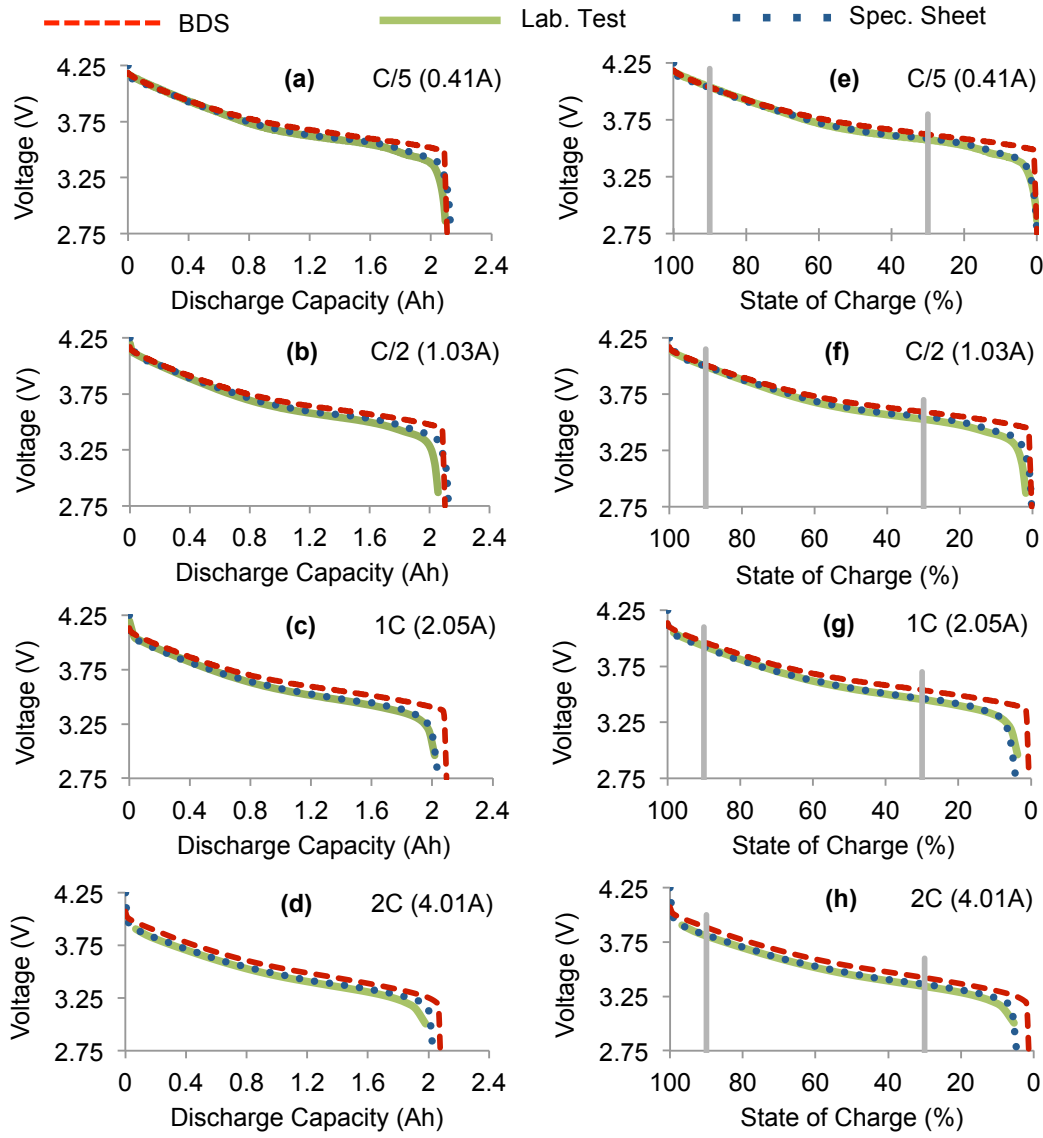


Figure 2- 5: (a-d) shows the comparison of the discharge curves at different C-rate discharges for Sanyo LiNiCoMn cells¹, while (e-h) show the same discharge curves plotted with respect to their state-of-charge (SoC). The 60% SoC window considered in the study has been shown with two vertical lines. The discharge C-rates and the corresponding currents have been specified for each. The discharge rates were selected based on information in the manufacturer's data sheets to facilitate the comparison.

¹ Please see Appendix B for the results of the other two chemistries: LiFePO₄ and LiMnNi

Table 2- 3: The total delivered energy (Wh), calculated by integrating the discharge curve, along with the capacity (Ah) values as shown in Figure 2. The percent difference of the values with respect to the BDS simulation results has been indicated in parenthesis.

Discharge Rate (Current)	BDS Simulation Results		Manufacturer's Specification Sheet		Laboratory Results	
	Capacity (Ah)	Energy (Wh)	Capacity (Ah)	Energy (Wh)	Capacity (Ah)	Energy (Wh)
C/5 (0.41A)	2.11	7.89	2.13 (0.9)	7.89 (0.0)	2.09 (-0.9)	7.75 (-1.8)
C/2 (1.03A)	2.10	7.81	2.13 (1.4)	7.80 (-0.1)	2.05 (-2.4)	7.53 (-3.6)
1C (2.05A)	2.09	7.68	2.04 (-2.4)	7.35 (-4.3)	2.02 (-3.3)	7.26 (-5.5)
2C (4.1A)	2.08	7.41	2.03 (-2.4)	7.13 (-3.8)	1.98 (-4.8)	6.93 (-6.5)

Table 2- 4: The total delivered energy (Wh), calculated by integrating the discharge curve, along with the capacity (Ah) values for a 60% state of charge window as shown in Figure 3. The percent difference of the values with respect to the BDS simulation results is indicated in parenthesis. The average difference in voltage within the state-of-charge (SoC) window has also been listed along with the maximum voltage difference in parenthesis.

Discharge Rate (Current)	BDS Simulation Results		Manufacturer's Specification Sheet			Laboratory Results		
	Capacity (Ah)	Energy (Wh)	Capacity (Ah)	Energy (Wh)	Avg. (Max) V diff. (V)	Capacity (Ah)	Energy (Wh)	Avg. (Max) V diff. (V)
C/5 (0.41A)	1.26	4.79	1.28 (1.6)	4.80 (0.2)	-0.03 (-0.05)	1.26 (0.0)	4.72 (-1.5)	-0.04 (-0.05)
C/2 (1.03A)	1.26	4.75	1.28 (1.6)	4.76 (0.2)	-0.03 (-0.05)	1.26 (0.0)	4.66 (-1.9)	-0.05 (-0.07)
1C (2.05A)	1.26	4.69	1.28 (1.6)	4.66 (-0.6)	-0.06 (-0.08)	1.26 (0.0)	4.58 (-2.3)	-0.06 (-0.09)
2C (4.1A)	1.26	4.57	1.28 (1.6)	4.54 (-0.7)	-0.07 (-0.07)	1.26 (0.0)	4.44 (-2.8)	-0.09 (-0.08)

2.5 Conclusion

The energy and capacity calculated from constant C-rate discharge curves simulated using Battery Design Studio® for the Sanyo LiNiCoMn cells were found to be within 6.5% and 4.8% of laboratory data for a full discharge, respectively, and within 2.8% and an exact match of laboratory data for a 60% state of charge window, respectively. Average discrepancies are substantially lower and are comparable to discrepancies between laboratory tests and manufacturer specifications. Results indicate that relatively accurate performance predictions are possible using BDS if appropriate parameters are used. Furthermore, by showing agreement between actual data and modeled performance through a range of discharge currents, we provide evidence that this model is able to accurately represent key elements of battery functionality that are related to ionic diffusion through the system.

2.6 Limitations

We examine only constant C-rate discharge at room temperature and do not explicitly test charging, variable rate discharge, or elevated temperature. Due to the unavailability of higher C-rate discharge

performance from the manufacturer, the C-rates chosen for the discharges were also lower than what is likely to be encountered in electrified vehicle applications. We also use assumed default values for several unknown cell parameters, such as the diffusion coefficient, resistivity, reaction rate constant, tortuosity, and conductivity of the active materials. Model fit might be expected to improve if precise measurements of these parameters were used.

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3. A techno-economic analysis of Li-ion batteries for personal vehicle electrification¹

3.1 Background

Electrified vehicles (EVs), like plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), offer the potential to greatly reduce the gasoline consumption by the US transportation sector [1] which in 2012 was about 366 million gallons per day accounting for 66% of all energy used in transportation and 47% of all petroleum consumption [2]. When electricity is generated from low carbon sources, especially nuclear or renewable energy, electrified vehicles can also contribute to reducing greenhouse gas (GHG) emissions from the transportation sector [3]. The cost of Li-ion batteries is the single largest barrier to mainstream adoption of plug-in vehicles, including plug-in hybrid electric vehicles (PHEVs) that use a mix of gasoline and electricity and battery electric vehicles (BEVs) that use electricity only [4-6]. Mainstream adoption of alternative powertrain technologies is necessary to achieve substantial displacement of US petroleum consumption and reduction in air emissions like greenhouse gasses. Thus, battery cost is key to addressing oil dependency and global warming in the United States. The overarching goal of this paper is to investigate the role of certain key design decision variables on the cost and performance of Li-ion batteries. This is done by first characterizing the tradeoffs in battery design and subsequently using this knowledge in assessing technical and economic implications of these design trade-offs for EVs. The goal is to inform automakers, policymakers, and the general public about the above-described results.

Often studies on the adoption and emissions reduction potential of plug-in vehicles treat Li-ion batteries as though they are all the same, with a single estimate of cost per kWh of storage [3-4,7]. In practice, Li-ion technology encompasses a wide range of alternative chemistries (e.g.: LiMn_2O_4 , LiFePO_4 , $\text{LiNi}_{0.33}\text{Mn}_{0.33}\text{Co}_{0.33}$, etc.), electrode designs (thin/thick), packaging alternatives (prismatic, jellyroll, etc.), and capacities of the individual cells (Ah) that make up the pack. Each of the potential combinations of these alternatives has different performance, cost, weight, volumetric, thermal, and degradation characteristics that interact with the constraints and needs in the design of a vehicle powertrain system. For example short-range PHEVs require higher-power cells, with implications for cost, weight, and life. Figure 3- 1 summarizes most of the existing cost estimates with breakdowns at the cell, module and pack level, wherever available for different vehicular applications. Some key assumptions and considerations of the studies reported in Figure 3- 1 have been listed in Table 3- 1. The scatter with respect to different types of EVs and sources is apparent as well as their expected decrease over time. Because the cost of Li-ion batteries is so critical, a careful and detailed assessment of battery design and system integration tradeoffs is needed to assess the potential of emerging battery and vehicle systems to successfully displace petroleum and reduce emissions.

In this piece of work, we investigate a set of different design decision variables. Battery Design StudioTM was used to predict the performance of the Li-ion battery packs of different designs. A process based cost model (PBCM) for the Li-ion battery pack manufacturing process was developed

¹ Sakti, A., Michalek, J.J., Fuchs, E.R.H., Whitacre, J.F. 2014, A techno-economic analysis of lithium-ion batteries for personal vehicle electrification, work in progress

Table 3- 1: Some key assumptions/ considerations of the different studies for Li-ion battery cost estimates reported in **Figure 3- 1**.

Study	Key Assumptions/ Considerations
NRC/NAS, 2013	Assuming costs for Chevy Volt and Nissan Leaf at \$500/kWh, 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 was assumed to decline by 45%. PHEV pack costs assumed to be \$60-70/kWh higher than BEV packs.
McKinsey, July 2012	Prices in 2011 dollars per effective kWh. 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 kWh.
Boston Consulting Group, 2010	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 interviews with component manufacturers, cell producers, tier one suppliers, OEMs, and academic experts; Argonne National Laboratory; BCG analysis.
NRC/NAS, 2010	Report includes three cost ranges for probable, conservative and an optimistic case for PHEV10 and PHEV40 batteries. Report considers a 4kWh battery pack for a PHEV10 and a 16kWh battery pack for a PHEV40.
TIAX, 2010	Estimates for a PHEV20: 5.5kWh of useable energy. Packs designed for capacities of 6.9-9.8kWh to account for 30% capacity fade. Report studies 5 chemistries: NCA, NCM, LFP, LMO, LL-NMC. Prismatic (wound) cells.
ANL, 2010	Four chemistries reported: LMO-G, NMC-G, LFP-G, NCA-G. PHEV20: 62kW (10s), 10.3kWh packs. EREV20: 148kW (10s), 9.6kWh packs. EREV40: 158kW (10s), 18.7kWh packs. BEV100: 154kW (10s), 33.3kWh packs.
Baker et al. (Expert Elicitation), 2010	10 year funding trajectories considered. With \$150M/year funding, there is a 66% chance of the cost being less than \$200/yr and a 20% chance of it being less than \$90/kWh. \$384/kWh was the base value mentioned on one instance.
Anderman, ARB Feedback, 2010	Feedback to CARB cost estimate. Gives ranges for EV battery costs at 500MWh in 2015 and at 2,500MWh in the 2018-2020 timeframe. Cost of PHEV batteries per nominal kWh greater than EV batteries by 20-30%.
Plotkin and Singh, 2009	Factory gate prices for PHEV10, PHEV40, and BEV100 batteries in 2008\$. Costs based on literature and include optimistic and 'still more optimistic' outlook. Literature includes: Kromer and Heywood (2007), EPRI (2005), Kalhammer (2007), and Anderman (email comm., 2008)
California ARB, 2009	Cost ranges at module and pack level provided for batteries for a PHEV10, PHEV40/BEV75, BEV100, and a BEV100+. Upper bound is for an APV of 500MWh and the lower bound for 2,500MWh. Battery pack sizes-PHEV10:~7kWh, PHEV40/BEV75:~16kWh, BEV: 24+kWh. Numbers updated since Kalhammer (2007) using PHEV20 pack size from TIAX (2009) and the same scaling factors as Kalhammer (2007).
Frost and Sullivan, 2009	Based on interviews with 12 companies: battery manufacturers and OEMs. Reports cost. However, states that prices will drop by 20-70 percent when cell production rises from 1million per annum to reach more than 50 million per annum.
Kromer and Heywood, 2008	Uses the formula: Battery Cost = (Cost_High Energy) x f(Power-to-Energy Ratio). Current costs based on cost multipliers from Ford Motor Company, a base cost of \$300/kWh 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/kWh and \$200/kWh in the optimistic case. Present-day high-power lithium-ion batteries incur a factor of 4.5 to 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 (Sandia)	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 (California ARB)	Based on estimates from three different manufacturers at production rates of 500MWh and 2,500MWh using 45Ah 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: 40kWh (120Ah cells), Small BEV: 25kWh (45Ah cells), PHEV40: 14kWh (45Ah cells), PHEV20: 7kWh (25Ah cells), PHEV10: 4kWh (12Ah cells)
Pesaran et al., 2007 (NREL)	High-energy Li-ion batteries, no further specification.

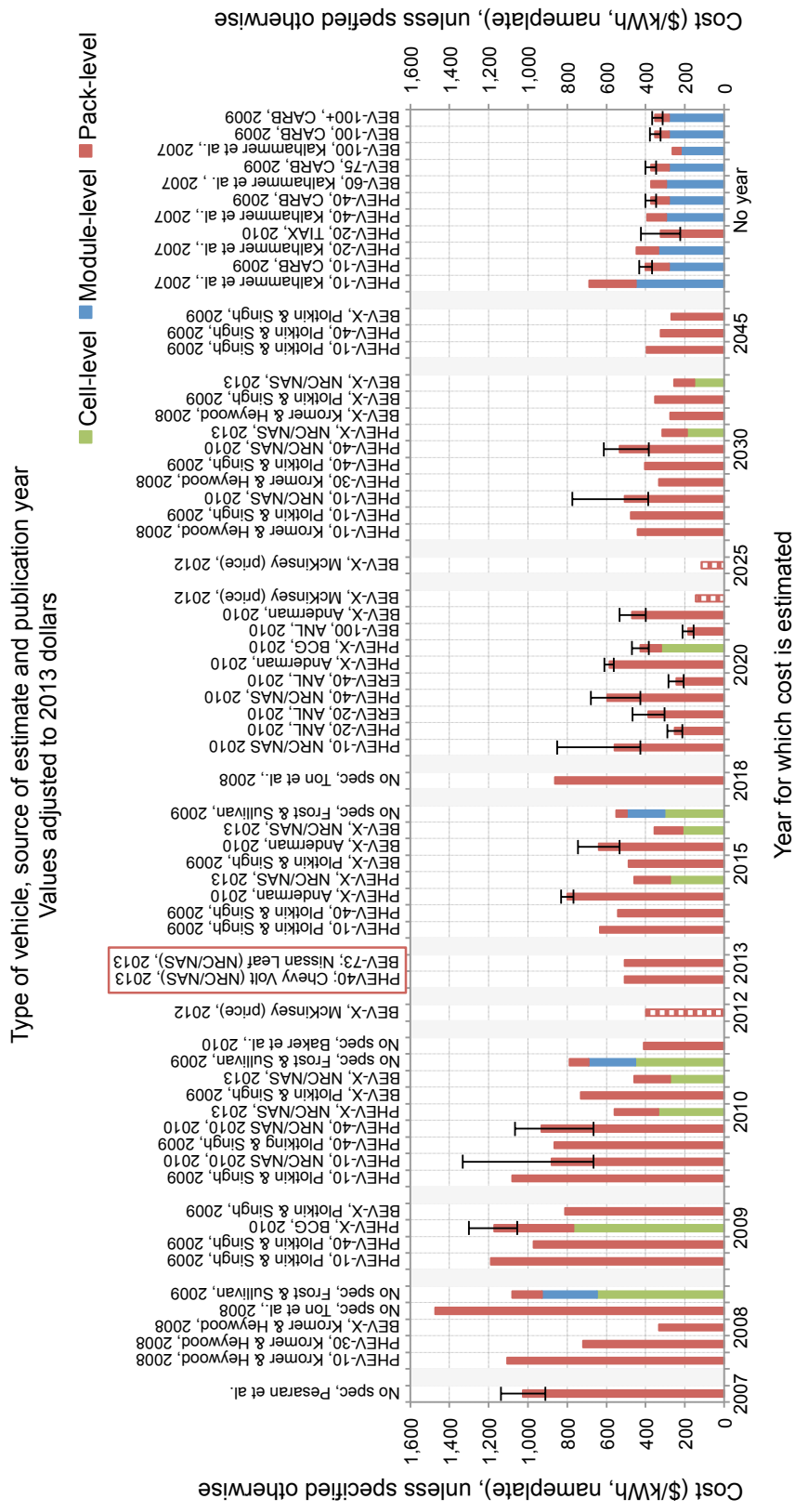


Figure 3-1: Summary of available cost estimates of lithium-ion batteries for different vehicular applications. The costs were assumed to be at the pack-level for the nameplate capacity unless otherwise specified in the reports. Wherever ranges were specified, error bars have been used to show the upper 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 margins that the automakers could pay. Prices have been shown using the red and white striped columns. Estimated battery cost estimates for the Chevy Volt (PHEV 25-50) and a Nissan Leaf (BEV ~75), in 2012, has also been shown [8-21]. All cost estimates have been adjusted to 2013 dollars using GDP deflators for the US [22].

to estimate the cost of the different Li-ion battery pack designs investigated. The design tradeoffs with respect to the performance of the battery pack and its cost was investigated and the least cost battery pack design that is able to meet the performance requirements was estimated for a handful of different EVs.

3.2 Overarching Goal and Scope

The objectives of this research are to characterize tradeoffs in battery design with respect to cost, power density, energy density, and performance and to then use this knowledge in assessing economic implications for electrified vehicle systems and informing public policy.

The aim of this work is to identify the most cost effective battery packs for application in various types of EVs based on their energy and power requirements over the lifetime of the vehicle at the systems level and understand the key factors driving cost and the effect of different vehicle requirements on battery design and the resulting costs. A key parameter that controls the energy and the power capability of the battery pack is the electrode thickness of the individual cells that make up the battery pack. The thickness of the electrode also has a direct impact on the cost of the cell, with thinner electrode cells costing significantly more than ones with thicker electrodes. Thinner electrode cells have a higher power-to-energy ratio capability as compared to those with thicker electrodes. As such, thinner electrode cells are better at handling transient storage of energy because of their higher rate (of charge/discharge) capability (useful for PHEVs with a lower AER) while thicker cell electrodes can store more energy but do not perform as well at higher power levels and are hence more suited to provide for higher levels of energy storage in applications like BEVs or PHEVs with higher AER [23-24]. This is because for applications like a PHEV with a low AER, like a PHEV10, the power requirement is divided over a lower capacity battery pack and so the power-to-energy requirement from each individual cell is higher compared to a vehicle that has a larger battery pack, like a BEV100, where the power-to-energy ratio will be much lower. So the optimum thickness of the cell electrode for any EV application is a design decision variable that can be used to improve the overall cost of the vehicle's battery pack. Table 3- 2 summarizes the attributes discussed above of thin and thick electrode cells.

Table 3- 2: Summary of the key differences between battery packs made of cells with thin electrode and thick electrodes

	Thinner electrode battery pack (higher power-to-energy ratio)	Thicker electrode battery pack (lower power-to-energy ratio)
Cost per kWh	Higher	Lower
Typical application suitability	Transient energy storage/higher power (HEV, PHEV20 etc)	Higher energy storage (PHEV60 or BEV)

Our hypothesis is that application-specific battery pack design and integration for different vehicular applications (taking into account the power and energy requirements for that application) can help in bringing down the corresponding battery cost for the application reported in the literature and in changing the relative economics of different vehicle designs. An application specific design will highlight the design changes that lead to the different and optimal specific battery costs (\$/kWh).

To test this hypothesis, we divide our work into two parts for the techno-economic analysis. In Part I, we describe the two models that we build as first steps towards reliably estimating the cost and performance of different battery packs as a function of their design. Subsequently in Part II, we describe how the two models were applied to a handful of EVs to estimate the optimal least cost battery pack design for each EV.

Part I: Li-ion battery pack cost and performance models

3.3 Methodology

Two separate models: one to estimate the cost to manufacture a Li-ion battery pack of a particular design, and the other to estimate the maximum power (in kW) that the battery pack is able to deliver for at least 10 seconds have been built.

Li-ion battery manufacturing involves multiple process steps. The process steps involved in Li-ion battery manufacturing have been listed in Appendix B. A process based cost model (PBCM) [25-28] simulates production operations in a manufacturing plant, using data at the individual machine level for each of the process steps collected from publications and consultation with experts in industry, academia, and government. Benefits of such a model include providing flexibility to vary the different parameters involved in the manufacturing process steps. Inputs such as main machine and installation cost, equipment processing rate, fractional use of labor, process step yield, batch size, cycle time, unplanned downtime are specific to each process step. We adopt information on equipment cost and their processing rates for most of the process steps from Argonne National Laboratory's Li-ion battery cost and performance model, BatPaC [28]. BatPaC is the only other bottom-up cost model, currently available in the literature. Material requirements to build a Li-ion battery pack of a certain design were also calculated using the equations listed in [29].

The Li-ion battery simulation software BDS, which was validated previously, was used to simulate the hybrid pulse power characterization (HPPC) test on a set of 48 cells that varied in the cathode chemistry, the thickness of the electrode coatings, and the cell capacity. The HPPC test procedure has been defined by the United States Advanced Battery Consortium (USABC), is used to test the dynamic power capability of a battery pack for a given device and consists of both discharge and charging current pulses [30]. The HPPC test result gives the 10-second discharge-pulse and regen-pulse power capability of the battery-pack at 10% depth-of-discharge (DoD) increments [30]. The goal with this test is to determine the pulse power capability of a battery pack at the minimum allowable SoC value.

In the following segments, we first describe ANL's Li-ion battery cost and performance modeling tool, BatPaC and how the cost-model presented in this study builds up on it. Subsequently, we discuss the use of BDS to estimate the 10-second discharge power capability of the different battery pack designs.

3.4 Battery performance and cost estimation using ANL's BatPaC

Amongst the existing Li-ion battery pack cost modeling tools, BatPaC developed by Argonne National Laboratory [28] is the most notable. It is a bottom-up cost model that integrates both battery performance and cost. The model integrates both the design of batteries (for specific power,

energy and type of vehicle) and the cost of designed battery. Each step of the manufacturing process is accounted for in the model. The architecture of the model relies on using known numbers (cost or usage) for equipment, labor and plant floor-space for each step of the manufacturing process for an annual production volume of 100,000 battery-packs and estimates the cost for different annual production volumes from those known values, using the following formula:

$$C = C_0(R / R_0)^p$$

where, C_0 is the cost of the installed equipment or the usage of labor and plant floor-space for the baseline processing rate of R_0 associated with the baseline production volume of 100,000 packs per year. C is the new cost or usage value associated with the new processing rate R . p is the power factor used to scale the cost for that processing step. p values are generally around 0.4-0.5 for labor and relatively higher at 0.6-0.8 for plant floor-space and the cost of capital equipment. For a full description of the ANL BatPaC model please see Appendix E.

Limitations of BatPaC

BatPaC is versatile allowing the user to change all aspects of it. However, the model is limited in the following aspects:

1. With different annual production volumes for the battery-packs, the model does not provide enough detail to show at what production volume additional investment for equipment will be necessary and with that investment what will be the optimum production volume.
2. The model does not account for the time value of money while accounting for the investment necessary for the equipment and building.

The cost model presented in this study uses the data used in BatPaC and uses it to build an actual process based cost model (PBCM). This addresses the first limitation mentioned above. The PBCM also uses a discount rate to account for the time value of money.

BatPaC considers one overall yield for the manufactured cells and does not take into account the yields of individual process steps. The model also does not account for the variation of yield losses that one may encounter when manufacturing cells of a lower capacity which will require the stacking of a lower number of bicell-layers as compared to a higher capacity cell with higher number of bicell-layers. Similarly, the model does not take into account the difference in yield losses associated with manufacturing thinner electrodes as opposed to thicker electrodes. While, in the base case of the PBCM, we consider one overall yield for all cell designs, we investigate an additional scenario to test the difference in manufacturing yield losses associated with lower capacity cells as opposed to higher capacity cells and with thinner vs. thicker electrode coating thicknesses. This has been explained in more detail in the following segment.

3.5 Li-ion cell and pack manufacturing process based cost model (PBCM) architecture

A process based cost model as described in other literature [25-28] uses process data to estimate the resource requirements which include capital, labor, materials, and energy to meet production targets, which include both acceptable and unacceptable units. These requirements are then used to calculate the cost of production of an acceptable unit. The aggregate cost of an acceptable unit as described elsewhere in the literature [27] is given by:

$$C_{\text{TOT}}^{\text{AU}} = \sum_{\alpha} C_{\alpha}^{\text{AU}} \quad (1)$$

$$C_{\alpha}^{\text{AU}} = C_{\alpha}^{\text{ALL}} / X^{\text{P-VOL}} \quad (2)$$

$C_{\text{TOT}}^{\text{AU}}$ is the annual total cost of production per acceptable unit, C_{α}^{AU} is the annual cost of an element α where $\alpha \in \{\text{materials, labor, equipment, tooling, building, and overhead}\}$, and $X^{\text{P-VOL}}$ is the annual production volume of acceptable units.

The requirement for each element is calculated taking into account the yield of each process step, which is incorporated using the following formula for the effective production volume

$$X_n^{\text{E-VOL}} = X^{\text{P-VOL}} / Y_n \quad (3)$$

$$X_i^{\text{E-VOL}} = X_{i+1}^{\text{E-VOL}} / Y_i \quad \forall i \in [1, \dots, n-1] \quad (4)$$

where $X_n^{\text{E-VOL}}$ is the effective production volume required from the nth process step with a step yield of Y_n in order to result in the production volume, $X^{\text{P-VOL}}$, of good and acceptable parts after the nth process step. Thus, the effective production volume from each process step i , $X_i^{\text{E-VOL}}$ is calculated using Equation 4 where $X_{i+1}^{\text{E-VOL}}$ is the effective production volume for the process step $i+1$ and Y_i is the yield of the process step i . For more information on the cost model architecture please refer to Fuchs et al. [27].

A sample workspace for one of the process steps (shipping) has been shown in Table 3- 3 listing the inputs (shaded boxes) and the calculations associated for the process step. In this case, $X^{\text{P-VOL}}$ from Equation (3) above is set at 20,000 battery packs, Y_n is set at 100% and so $X_n^{\text{E-VOL}}$ is equal to $X^{\text{P-VOL}}$. The production volumes for the steps preceding the shipping step are subsequently calculated using Equation 4.

ANL's BatPaC lists the requirements for main machine and installation costs to manufacture 100,000 NCA-G packs. Each pack is 8.7kWh. Process steps for which information on the price of the machines is only available for the given annual production volume without details about the

processing rate per machine is considered as *undedicated*. When a process step is considered *undedicated* the number of machines is a real number (unlike an integer for when there is enough information to consider the machines to be *dedicated*) representing the ratio by which the main machine and installation cost (based on available information for a given annual production volume) needs to be scaled to estimate the cost for the annual production volume of interest. In **Table 3- 3** below, which shows the sample workspace for the process step of shipping; information from ANL's BatPaC is adopted for the main machine and installation cost for 100,000 battery packs at \$5 million. The available line-time is calculated for a year using the unplanned downtime of 5% and the processing rate (seconds per kWh) was calculated accordingly. Subsequently, the line-time required for the annual production volume of interest (85,586kWh) is calculated. The ratio of the required line-time to the available line-time is the required number of machines (0.12). For more information on the PBCM inputs, please see Appendix D. The exogenous inputs that are not process step specific but are applied across the entire production process steps have been listed in **Table 3- 4**. These assumptions were used to calculate some of the different fixed and variable cost components like energy, maintenance, auxiliary equipment etc.

Table 3- 3: Sample inputs and calculation workspace for a single process step (shipping) in the process based cost model. The inputs have been shown in shaded boxes.

Step 19: Shipping					
Variable Cost	\$/year	\$/battery pack	\$/kWh	Percent	
Material Cost	0	0	0	0%	
Labor Cost	84,241	4.21	0.98	25%	
Energy Cost	2,527	0.13	0.03	1%	
Total Variable Cost	86,768	4.34	1.01	26%	
Fixed Cost	\$/year	\$/battery pack	\$/kWh	Percent	Investment
Main Machine and Installation Cost	123,344	6	1.44	37%	740,062
Building Cost	34,073	2	0.40	10%	681,465
Auxiliary Equipment Cost	12,334.37	1	0.14	4%	12,334
Maintenance Cost	12,334.37	1	0.14	4%	12,334
Fixed Overhead	63,729.99	3	0.74	19%	63,730
Total Fixed Cost	245,816	12	2.87	74%	1,509,926
Total Cost	332,583	17	4	100%	
UNDEDICATED					
Related Variables					
Volumes and Times					
Annual Production Volume	20,000	packs/year			
Effective Production Volume	20,000	packs/year			
Effective Production Volume	85,586	kWh			
Unplanned Downtime	5%				
Line Time Available	21,546,000	secs			
Line Time Required	2,546,364	secs			
Machines Required	0.12				
Equipment					
Main Machine and Installation Cost	5,000,000	\$			
Processing Rate	30	secs/kWh			
Labor					
Fractional Use of Labor	6				
Material					
Process Step Yield	100%				

Table 3- 4: Exogenous inputs

Input	Base	Units
Facility wide operating		
Working days/year	300	days/year
No shifts	0	hrs/day
Unpaid breaks	2	hrs/day
Paid breaks	1	hrs/day
Price of building space	3,000	\$/m ²
Direct wage, with benefits	18	\$/hr
Discount rate	10	%
Factor lifetimes		
Capital recovery period	6	yrs
Building recovery period	20	yrs
Facility wide additional costs		
Auxiliary equipment	10	% of main machine cost
Maintenance	10	% of main machine cost
Fixed overhead	35	% of other fixed costs
Energy cost (electricity)	3	% of material and labor costs

Decision Variables and model parameters

The PBCM was built with the following decision variables to define the battery pack: chemistry, the thickness of the cathode coating on one side of the electrode, the number of bicell-layers in a cell, the width of the cathode, the number of cells in a module, and the number of modules in a pack. Please see Appendix B for more on the decision variables at the cell level. Mathematically, we have:

$$C_{TOT}^{PACK} = f(x^{CT}, x^{BCL}, x^{CW}, x^N, x^M)$$

where C_{TOT}^{PACK} is the annual cost of manufacturing a battery pack, x^{CT} is the thickness of the cathode coating on a single side of the collector, x^{BCL} is the number of bicell-layers in a cell, x^{CW} is the width of the cathode, x^N is the number of cells in a module, and x^M is the number of modules in a pack. These variables along with the others that have been used in the subsequent meta-models have been listed in Table 3- 5. Model parameters have been listed in Table 3- 6. The material scrap rates and the overall cell-level yield values for the base case were borrowed from ANL's BatPaC model and have also been listed in Table 3- 6. This yield value was considered in the process step of Cell Stacking (Step # 7 in the manufacturing process). All other process step yield values were considered to be 100%. The affect of cell design on the yield has been investigated as a separate scenario. This has been described in further detail in Section 3.7.1 on sensitivity analysis. The aspect ratio of the cathode was assumed to be 3, following the value considered in BatPaC. Mass-fractions in the cathode and the anode of the active material are common values used in the industry. For the base case, an annual production volume of 20,000 packs was assumed to reflect the upper limit a manufacturer may encounter given present day EV sales. Values used for the sensitivity analysis of the cost model have been reported in Table 3- 7.

Table 3- 5: Decision Variables used to completely define the battery pack.

Symbol	Description	Domain	Units
x^{CT}	Single side cathode coating thickness	[25, 200]	μm
x^{BCL}	Number of bicell-layers each cell	[5, 645*]	-
x^{CW}	Width of the cathode	[50, 250]	mm
x^N	Number of cells in a module	[5, 50]	-
x^M	Number of modules in a pack	[4, 22]	-

*upper limit varied to result in cell capacities between 10Ah and 60Ah

Table 3- 6: Model Parameters

Description	Base	Units
Cell cathode chemistry	NMC333-G	-
Aspect Ratio of each electrode	3	-
Mass fraction of the active material in the cathode	0.89	-
Mass fraction of the active material in the anode	0.95	-
Production volume	20,000	packs/year
Yield rate	95	%
Scrap rates		
Positive electrode material (dry)	7.8	%
Negative electrode material (dry)	7.8	%
Positive current collector (Al)	9.8	%
Negative current collector (Cu)	9.8	%
Separators	2	%

3.6 Meta-model for battery pack performance using Battery Design Studio™ simulations

A set of 48 cell designs was simulated using BDS. These cells had varying single side cathode electrode coating thickness and cell capacities. The single side electrode coating thickness varied from 25 μm to 200 μm with intervals of 25 μm and the cell capacities varied from 10Ah up to 60Ah with 10Ah intervals. The 10-sec maximum power performance was estimated from the BDS simulations. The results were then used to build a meta-model of the following mathematical form (using the data-mining software Eureqa):

$$P_{cell}^{BDS_HPPC} = f(x^{CT}, x^C) \quad (5)$$

where $P_{cell}^{BDS_HPPC}$ is the 10-sec maximum power capability of a cell calculated and x^C is the capacity of each cell in the pack in Ah. The capacity of a cell can be calculated from the decision variables listed in Table 3- 5 using the following formula:

$$x^C = a(x^{CW})^b x^{BCL} x^{CT} X^{AR} m_{cat}^{ACT} \rho_{cat} E_{NMC333}^{SPEC} \quad (6)$$

where, X^{AR} is the aspect ratio, m_{cat}^{ACT} is the mass fraction of the active material in the cathode, and is E_{NMC333}^{SPEC} the specific capacity of the cathode active material in mAh/g. For a complete list of the variables and parameters, please see Appendix A.

The energy of the battery pack is simply the product of the number of cells in the pack and the energy of each cell since all the designs considered have serially connected cells. It is also a function of the cathode chemistry, which determines the average discharge voltage of the cell (V_{NMC333}^{AVG}).

Mathematically, we have

$$E^{PACK} = x^N x^M x^C V_{NMC333}^{AVG} \quad (7)$$

Results from the cost and power performance models have been discussed in the next section.

3.7 Results and Discussion

Using the process based cost model to calculate the cost of a Li-ion battery pack of a particular design, and the performance model to determine the power capability of the battery pack, we now have the tools to design the least cost Li-ion battery pack to meet the energy and power requirements of any given electrified vehicle application. Figure 3- 2 compares the cost of a PHEV20 battery-pack design calculated using the PBCM and using ANL's BatPaC. The cost estimates have been plotted for the base case scenario along with the best case and the worst case with varying annual production volumes. The manner in which the three scenarios vary has been shown in Table 3- 7. Results from the PBCM are lower at lower production volumes compared to the estimates from ANL's BatPaC. Results from the PBCM also indicate that economies of scale with respect to manufacturing costs may be reached at about 30,000 battery packs or about 200MWh.

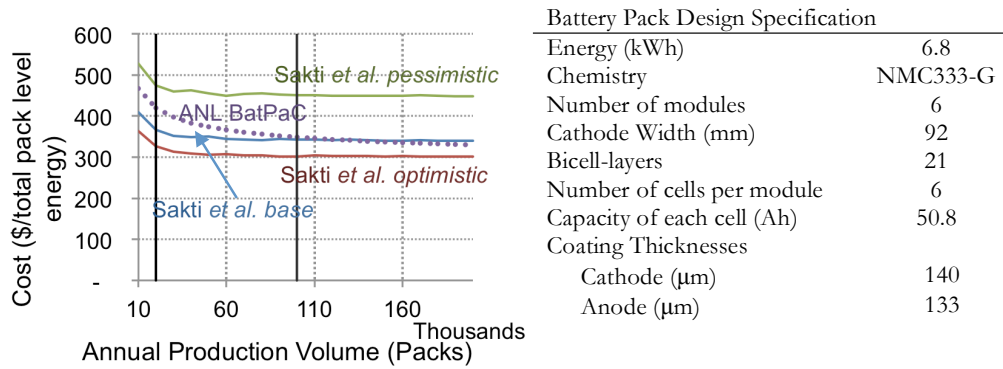


Figure 3- 2: Comparison of the results from BatPaC with the three different scenarios considered in this study for a battery pack. The battery pack design chosen will meet the requirements of a PHEV20 for a less aggressive driving cycle like the UDDS (urban dynamometer driving schedule). The requirements were calculated using PSAT. ANL BatPaC's base volume of 100,000 packs and Sakti *et al.*'s base case of 20,000 packs have been shown with the vertical lines.

Table 3- 7: The three different scenarios considered in the process based cost model.

Variable	Scenario		
	Optimistic	Base	Pessimistic
Working days/year	360	300	240
Direct Wage (w/benefits) (\$/hr)	15	18	25
Price of Building Space (\$/m ²)	1600	3000	4000
Discount Rate	6%	10%	14%
Positive Electrode Active Material Price (\$/kg)	31	31	53
Negative Electrode Active Material Price (\$/kg)	17	19	23
Separator Price (\$/m ²)	1	2	2.9
Electrolyte Price (\$/liter)	18	21.6	24.5
Scrap rates	-25%	Table 9	+25%
Yield rate	99	95	90

The cost breakdown for the base case battery reported in Figure 3- 2 above has been shown in Figure 3- 3. The cost of materials is seen to be the single largest contributor to the pack-level costs at 61%. The cost of the active material for the two electrodes comprised more than half of the total materials level cost. After the cost of the materials, the cost of equipment was seen to be the most significant. Labor (listed with “Everything Else”) in the figure was less than 5% of the total pack level costs. This shows that choosing a manufacturing location based on the labor costs will not have much of an impact on reducing the cost of the battery pack. Sensitivity analyses to identify the most significant cost drivers and the top contributors for process step parameters and materials prices have been shown in Figure 3- 4. For the process step parameters, the pack level manufacturing cost of the batteries was seen to be most sensitive to the area of dry room control required while in the case of materials, as expected, it was the price of the positive active material. The manner in which the lower and upper bound values were chosen for the sensitivity analysis has been listed in Table 3- 8 and Table 3- 9.

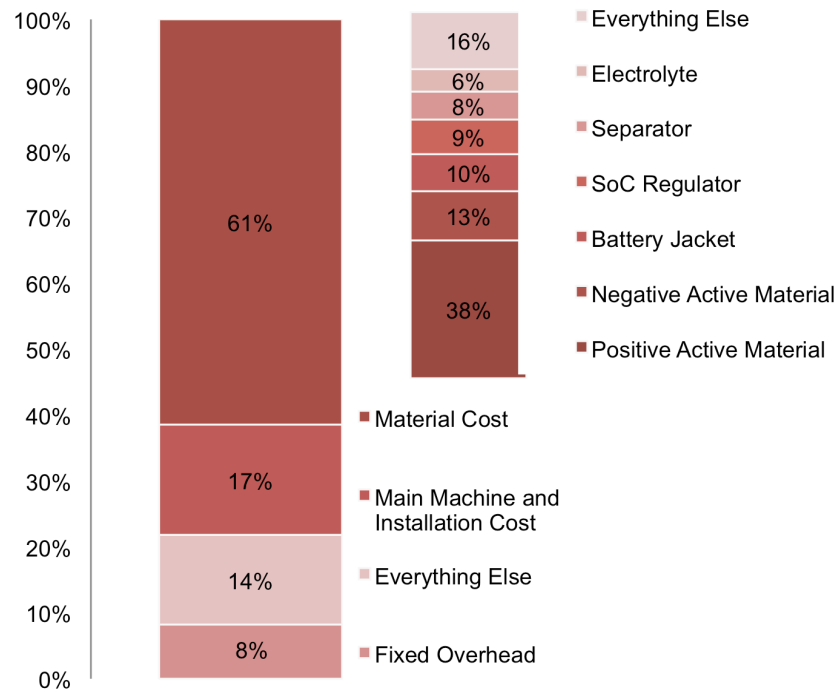


Figure 3- 3: Total and material cost breakdown of the battery pack for the base case listed in **Figure 3- 2**. An annual production volume of 20,000 battery packs was assumed.

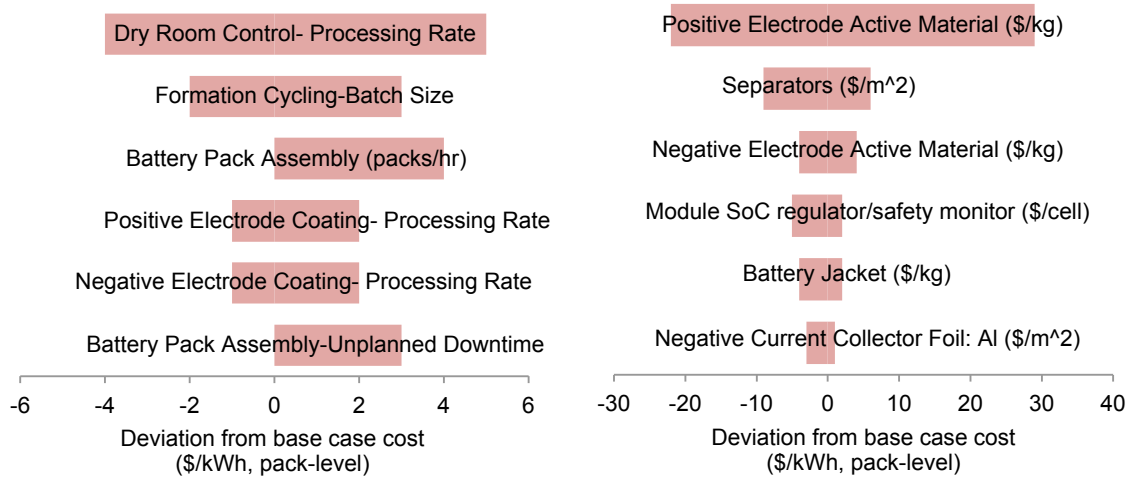


Figure 3- 4: Tornado plot showing the most sensitive process step parameters and material level costs.

Table 3- 8: Values considered for the sensitivity analysis of the process step parameters reported in **Figure 3- 4**.

Step	Process Parameter	Base Value	Lower Bound	Upper Bound	Notes
Dry-room Control (Air Locks)	Rate (m ² /m ² dry room area)	0.03	-25%	+25%	ANL's BatPaC's base rate: 100m ² for an operating areas of 3000m ²
Formation Cycling	Batch Size (cells/cycler)	500	-25%	+25%	From ANL's BatPaC. Each equipment costs about \$850K
Battery pack assembly	Processing Rate (packs/hour)	6	-25%	+25%	From ANL's BatPaC
Positive electrode coating	Processing Rate (m/min)	10	-25%	+25%	From ANL's BatPaC
Negative electrode coating	Processing Rate	10	-25%	+25%	From ANL's BatPaC
Battery Pack Assembly	Unplanned Downtime	20%	-25%	+25%	20% unplanned downtime assumed for most process steps.

Table 3- 9: Values considered for the sensitivity analysis of the materials level prices reported in **Figure 3- 4**.

Material	Base Value	Lower Bound	Upper Bound	Notes
Positive electrode active material (NMC333) (\$/kg)	31	31	53	From ANL's BatPaC
Separators (\$/m ²)	2	1	2.9	From ANL's BatPaC
Negative electrode active material (Graphite) (\$/kg)	19	17	23	From ANL's BatPaC
Module SoC regulators and safety monitors (\$/cell)	2.5	-25%	+25%	-
Battery Jacket (\$/kg)	7	-25%	+25%	-
Negative current collector foil (\$/m ²)	1.8	-25%	+25%	-

With respect to the power meta-model, Table 3- 10 lists the 10-second power capabilities of the 48 cell designs simulated using BDS that were subsequently used to build the meta-model for the power performance. These cells were all of the NMC333-G chemistry. Using Eureka Formulize, the following relationship was established between the 10-second power values and the capacity of the cell (x^C), and single side the cathode coating thickness (x^{CT}):

$$P_{cell}^{BDS_HPPC} = x^{CT} x^C / (c + d(x^{CT})^g - x^{CT}) - h x^{CT} x^C \quad (8)$$

$$P_{pack}^{BDS_HPPC} = x^N x^M P_{cell}^{BDS_HPPC} \quad (9)$$

The measures of fit for the regression analysis have been listed in Table 3- 11. Figure 3- 5 shows the residuals between the 10-sec power performance values from BDS and those predicted from the meta-model. A tight fit between the two is observed with a maximum error of 0.03kW which is between 0.02-0.04% of the peak power requirements for the applications considered in this study.

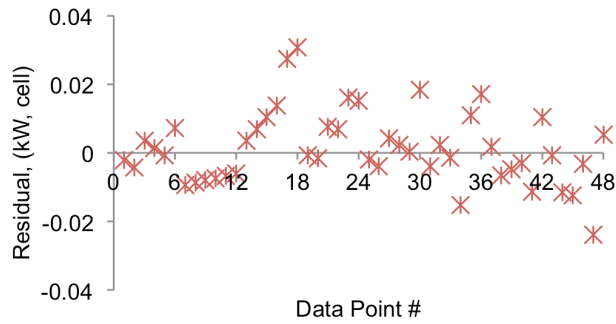


Figure 3- 5: Residuals for the cell-level power meta-model

Table 3- 10: Actual BDS results vs. meta-model predicted values for the 10s HPPC power for the 48 cell designs simulated.

x^{CT} (μm)	x^C (Ah)	BDS 10s power (kW)	Meta-model 10s power (kW)	x^{CT} (μm)	x^C (Ah)	BDS 10s power (kW)	Meta-model 10s power (kW)
25	10	0.83	0.83	125	10	0.27	0.27
25	20	1.66	1.66	125	20	0.54	0.54
25	30	2.50	2.50	125	30	0.82	0.82
25	40	3.33	3.33	125	40	1.09	1.09
25	50	4.16	4.16	125	50	1.36	1.36
25	60	5.00	4.99	125	60	1.65	1.63
50	10	0.61	0.62	150	10	0.22	0.22
50	20	1.23	1.24	150	20	0.45	0.45
50	30	1.85	1.86	150	30	0.67	0.67
50	40	2.47	2.48	150	40	0.88	0.90
50	50	3.09	3.10	150	50	1.13	1.12
50	60	3.71	3.72	150	60	1.36	1.34
75	10	0.45	0.45	175	10	0.19	0.19
75	20	0.90	0.89	175	20	0.37	0.38
75	30	1.35	1.34	175	30	0.56	0.56
75	40	1.80	1.79	175	40	0.75	0.75
75	50	2.26	2.23	175	50	0.93	0.94
75	60	2.71	2.68	175	60	1.14	1.13
100	10	0.34	0.34	200	10	0.16	0.16
100	20	0.68	0.68	200	20	0.31	0.32
100	30	1.03	1.02	200	30	0.47	0.48
100	40	1.37	1.36	200	40	0.64	0.64
100	50	1.72	1.70	200	50	0.78	0.80
100	60	2.06	2.04	200	60	0.97	0.96

Table 3- 11: Measures of fit for the power meta-model

R ² Goodness of Fit	0.99
Correlation Coefficient	0.99
Maximum Error	0.03
Mean Squared Error	0.00
Mean Absolute Error	0.01

As a separate validation, the area specific impedance (ASI) values calculated for the 48 different cell designs were used as inputs to calculate the 10-sec power capability using the equations listed in ANL's BatPaC. The ASI values were seen to be similar to those reported elsewhere by some of the authors of BatPaC [31]. **Figure 3- 6** shows the comparison of the 10-sec power results from BDS and those from the equations used in BatPaC. The curves for the power performance as a function of electrode thickness for the different capacity cells (shown with thicker to gradually thinner lines) are seen to almost overlap.

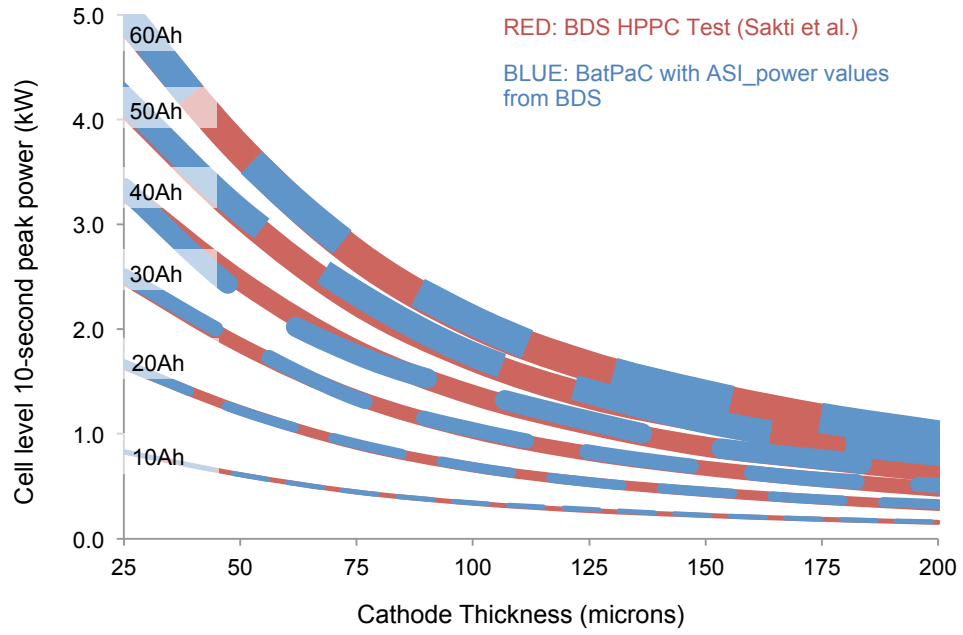


Figure 3- 6: Comparison of the 10-second power values calculated using 1) the power meta-model developed by Sakti et al. using BDS (Equation 8) and 2) BatPaC, using the ASI values from BDS. The results are seen to match up well.

Cost and power performance models developed in this section are used in the next section to estimate the optimal cost-minimizing battery design for a range of EVs.

Part II: Analysis of least cost battery pack designs for different PHEVs

3.8 Methodology

The Li-ion battery pack manufacturing process based cost model and the peak power meta-model were used in conjunction to estimate the optimal battery pack design for five different EVs: PHEV10, PHEV20, PHEV40, PHEV60 and a BEV100. The energy and power requirements of these vehicles have been listed in Table 3- 12. These values were obtained from simulations run on PSAT using the more aggressive US-06 drive cycle to calculate the power needs while the pack capacity was estimated to satisfy the EPA 5-cycle AER¹⁰. The 10-sec power requirement profile for a PHEV40 estimated from the PSAT simulations over a period of 100 minutes has been shown in Figure 3- 7. The maximum 10-sec power requirement from the simulated results was chosen to be the performance targets for the battery pack for that type of vehicle. The power-to-energy ratio for each vehicle is also listed. The power-to-energy ratio decreases as the battery size increases from a PHEV10 to a BEV. In other words, as mentioned before, the cells making up the battery pack of a PHEV10 should be able to handle more power compared to the cells making up a BEV battery pack. These energy and power values were used as the constraints while selecting the acceptable design points.

Table 3- 12: Energy and power requirements for different vehicles (calculated using ANL's Powertrain Systems Analysis Toolkit (PSAT) for the more aggressive US06 driving cycle for the power requirements while the pack capacity satisfies EPA's 5-cycle driving test for the AER.

Battery	PHEV10	PHEV20	PHEV40	PHEV60	BEV100
Size (kWh)	5	9.9	19.9	30.2	54
Power (kW, 10s)	71.5	91	103	114	128
Power/Energy ratio	14.3	9.2	5.2	3.8	2.4

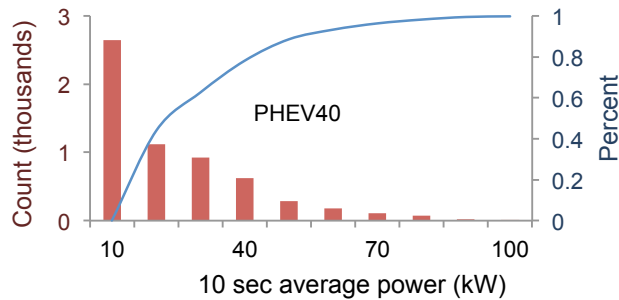


Figure 3- 7: 10-second power requirement histogram and cumulative distribution curve for a PHEV40 based on the PSAT simulations.

¹⁰ Simulations performed by Orkun Karabasoglu. For more information, please see work by Karabasoglu et al. 2013 [32]

3.9 Optimization Formulation

The following formulation was used to estimate the least cost battery pack for the five different EVs considered in this study:

Minimize the cost of the battery pack over the lifetime of the vehicle

Minimize $f(\mathbf{x}) = C_{\text{TOT}}^{\text{PACK}}$

$$\text{w.r.t } \mathbf{x} = \begin{bmatrix} x^{\text{CT}} \\ x^{\text{BCL}} \\ x^{\text{CW}} \\ x^{\text{N}} \\ x^{\text{M}} \end{bmatrix} \text{ where, } C_{\text{TOT}}^{\text{PACK}} \text{ is calculated for a set of values for } x^{\text{CT}}, x^{\text{BCL}}, x^{\text{CW}}, x^{\text{N}}, \text{ and } x^{\text{M}} \text{ using}$$

the PBCM and then interpolated linearly.

Subject to:

$$P_{\text{pack}}^{\text{BDS_HPPC}} \geq P_{\text{EV-x}}^{\text{PSAT}} \quad (10)$$

$$E^{\text{PACK}} \geq E_{\text{EV-x}}^{\text{PSAT}} \quad (11)$$

where $E^{\text{PACK}} = x^{\text{N}} x^{\text{M}} x^{\text{C}} V_{\text{NMC333}}^{\text{AVG}}$, as shown in Equation (7)

$$25 \leq x^{\text{CT}} \leq 125; x^{\text{CT}} \in \mathbf{R} \quad (12)$$

$$5 \leq x^{\text{BCL}} \leq 200; x^{\text{BCL}} \in \mathbf{Z} \quad (13)$$

$$50 \leq x^{\text{CW}} \leq 150; x^{\text{CW}} \in \mathbf{R} \quad (14)$$

$$5 \leq x^{\text{N}} \leq 50; x^{\text{N}} \in \mathbf{Z} \quad (15)$$

$$4 \leq x^{\text{M}} \leq 22; x^{\text{M}} \in \mathbf{Z} \quad (16)$$

$$10 \leq x^{\text{C}} \leq 60; x^{\text{C}} \in \mathbf{R} \quad (17)$$

where $P_{\text{EV-x}}^{\text{PSAT}}$ is the maximum 10-second power requirement and, $E_{\text{EV-x}}^{\text{PSAT}}$ is the minimum battery pack energy requirement for a EV with an AER of x miles, calculated using ANL's PSAT tool following a US-06 drive cycle.

3.10 Pack cost calculation

A design grid was constructed by varying the different design decision variables ($\mathbf{x}$) as outlined in the optimization formulation with the values shown in Table 3- 13. The cell-capacity design space of

interest is between 10Ah and 60Ah achieved by varying the cathode thickness (x^{CT}) from 25 μm to 200 μm in intervals of 25 μm , the cathode width (x^{CW}) from 50mm to 150mm in intervals of 25mm and the number of bicell-layers (x^{BCL}) from 5 to 645 in intervals of 5. However, x^{BCL} was not always varied till 645, but only to make sure that there were enough data points to interpolate in the desired design space. For the cathode width of 50mm, Figure 3- 8 shows the upper limit of the bicell-layers for which the data was collected to build the design grid for interpolation. The solid lines show the 10Ah and the 60Ah constraints. An Excel-MATLAB interface was used to input all the different values of the design decision variables in the PBCM excel spreadsheet and generate the corresponding manufacturing cost value associated with that design.

Out of the five design decision variables the number of bicell-layers (x^{BCL}), the number of cells per module (x^N), and the number of modules per pack (x^M) are integers, while the other two are real numbers. A mixed-integer non-linear programming (MINLP) based branch and bound algorithm was used on the design grid using MATLAB to interpolate the least cost design point for each of the EVs following the optimization formulation specified previously. The optimization model was run more than once with different starting points to make sure that the result was true globally.

Table 3- 13: Design decision variable values considered for the design grid.

Variable	Values	Units
x^{CT}	25:25:200	μm
x^{BCL}	5:10:645*	-
x^{CW}	50:25:250	mm
x^N	5:5:50	-
x^M	2:2:22	-

*data were not collected for all values but only enough to interpolate between 10-60Ah (please see **Figure 3- 8** for an example)

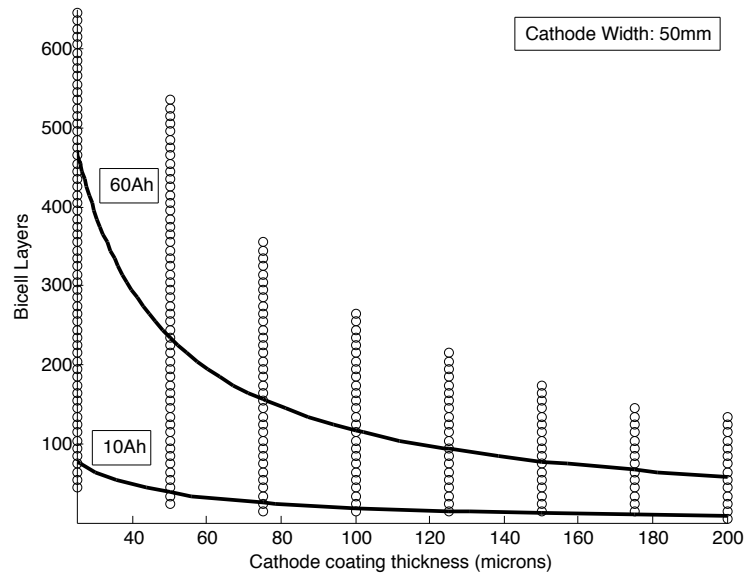


Figure 3- 8: An example of the design grid for cells of 50mm cathode width. The solid lines show the region of interest between cell capacities of 10Ah-60Ah.

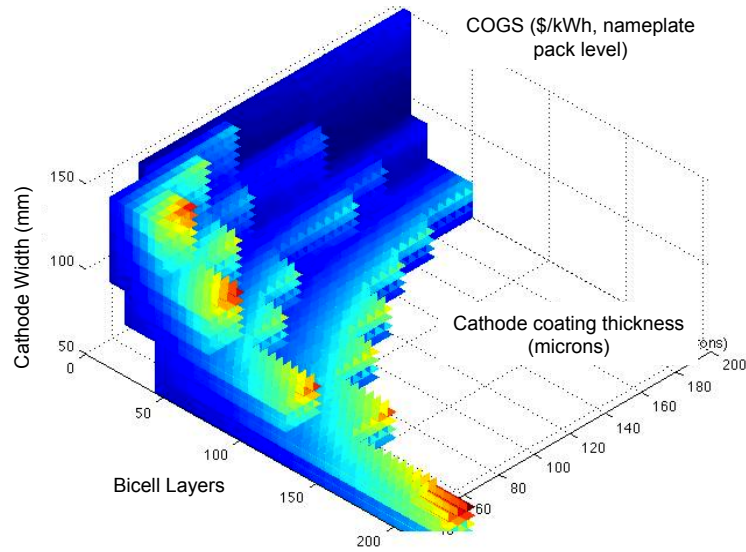


Figure 3- 9: 3D heat map resulting from interpolation of pack cost with respect to the cathode coating thickness, the number of bicell-layers, and the cathode width from the initial design grid. The design space of interest consisting of cell capacities between 10Ah and 60Ah is a subset of this space.

3.11 Sensitivity Analysis

The robustness of the results using the base case assumptions was tested with a sensitivity analysis. Table 3- 14 lists the different parameters that were varied in the sensitivity analysis and the associated lower and upper bounds that were used for the PBCM. Table 3- 15 lists the optimization constraints and their lower and upper bounds. For the power constraint the upper and lower bounds were varied by +/-25%. This was done to take into account any uncertainty that may be incorporated from the BDS power meta-model and also with respect to the PSAT simulation. Similarly, for the energy constraint the upper and lower bounds was varied by -25%, which takes into account future developments like vehicle light-weighting etc. along with the uncertainty in the PSAT simulation that calculates the required energy of the pack. Based on information from battery manufacturing experts, the base case for the maximum allowable electrode coating thickness for the cathode was considered to be 125 microns. The optimistic case was set at 200 microns while the pessimistic case was set to be 100 microns.

Table 3- 14: Process-based cost model parameters and their values for the sensitivity analysis

#	Parameter	Base	Optimistic	Pessimistic	Notes
1	Working days/year	300	360	240	Base: ANL BatPaC. Lower bound: Assumed. Upper bound: Brodd 2010.
2	Direct Wage (w/benefits) (\$/hr)	18	15	25	Upper and lower bounds: Brodd 2010, for skilled/unskilled labor. Base: ANL BatPaC
3	Price of Building Space (\$/m ²)	3000	1600	4000	Base: ANL BatPaC. Lower bound: Anderman 2011. Upper bound: Assumed.
4	Discount Rate	10%	6%	14%	Assumed
5	Positive Electrode Active Material Price (\$/kg)	31	31	53	ANL BatPaC
6	Negative Electrode Active Material Price (\$/kg)	19	17	23	ANL BatPaC
7	Separator Price (\$/m ²)	2	1	2.9	ANL BatPaC
8	Electrolyte Price (\$/liter)	21.6	18	24.5	ANL BatPaC
9	Scrap rate (%)	Table 7	-25%	+25%	Base: ANL BatPaC
10	Yield rate (%)*	95%	99%	90%	Base: ANL BatPaC

Table 3- 15: Constraints varied in the optimization as part of the sensitivity analysis

#	Constraint	Base	Optimistic	Pessimistic	Notes
1	Cathode coating thickness	125 microns	200 microns	100 microns	Based on expert opinion
2	10sec EV-x power constraint (kW)	Base	-25%	Base	Base: PSAT simulation. Lower bound addresses future improvements that may result in lower power requirements like body light-weighting etc.
3	EV-x energy constraint (kWh)	Base	-25%	Base	Base: PSAT simulation. The -25% reflects the future improvement in the mileage obtained from batteries.

Additional Scenario-yield variation as a function of electrode coating thickness and cell capacity

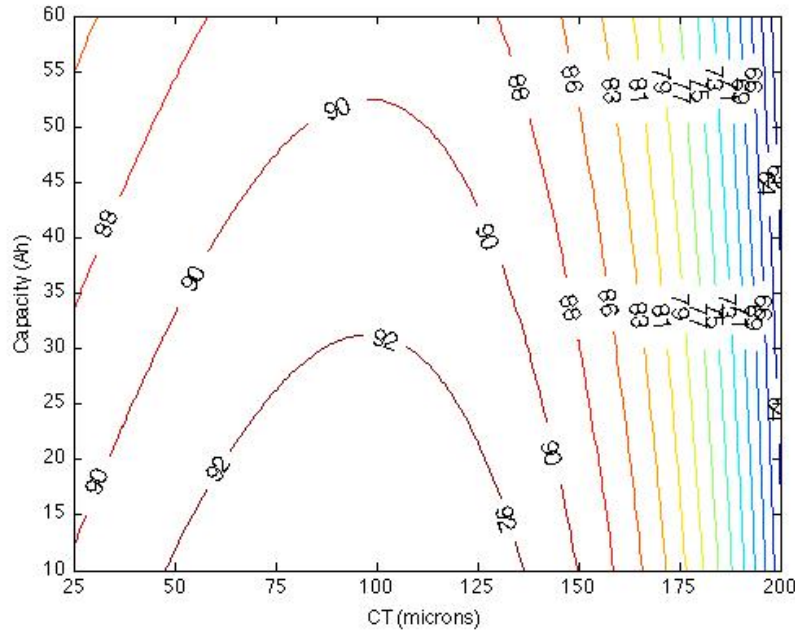


Figure 3- 10: Overall cell-level yield as a function of the cathode coating thickness (CT, microns) and the capacity of the cell (Ah)

An additional scenario is also investigated where instead of a constant cell-level manufacturing yield (as listed in Table 3- 14) across all cell designs, the yield was varied as a function of the cell-capacity (Ah) and the electrode coating thickness (microns) based on information from an industry expert. Based on information from the expert, currently battery manufacturers are able to go up to coatings of 125 microns successfully. The sweet spot with the greatest yields is for about 75-100 micron thick electrode coatings and for cell capacities of up to 40Ah. The reason behind this is that it is difficult

to make defect free electrode sheets with a very fine electrode coating on top and on the other side of the spectrum as the electrode coating thickness goes up, defects from structural integrity and drying etc. are incorporated. With respect to cell capacities, everything else being equal, for higher capacities more bicell-layers need to be stacked on top of each and with each additional bicell layer, the probability of incorporating a defect goes up. Figure 3- 10 shows a contour plot of the overall cell-level yield that we consider in the fourth scenario. These data were then used to build a meta-model of yield as a function of the cathode coating thickness and the cell capacity, using the software tool Eureqa.

3.12 Results and Discussion

The cheapest battery pack design for the different EVs were estimated to meet their power and energy requirements, as estimated using the PSAT simulations. The results have been shown in Table 3- 16 that lists the overall pack cost, the specific cost, the different design decision variables, and the resulting capacity of the optimal cell. As expected the specific cost of the optimal battery pack design is seen to decrease with the AER of the EV (from \$470/kWh in the case of the PHEV10 battery to \$239/kWh in the case of the BEV100 battery pack). To meet the power requirement, the cells for a PHEV10 and a PHEV20 are seen to have lower cathode coating thicknesses than the maximum allowable limit of 125 microns. However, for a PHEV40, PHEV60, and the BEV100, the optimal design is at the boundary of the allowable cathode coating thickness at 125 microns, indicating the possibility of decreasing manufacturing costs further if the electrode coating thickness is increased. The optimal pack designs also resulted in higher capacity cells (x^C). Design constraints allowed for cells between 10Ah and 60Ah and the optimal cell designs are seen to be within 55-60Ah. In general, the optimization results show that the cheapest design consists of higher capacity cells with the thickest electrode coatings that can still meet the power requirements of the vehicle. Once the highest possible value of the electrode coating thickness is calculated, the model then varies the number of bicell-layers (x^{BCL} , an integer) and the cathode width (x^{CW}) to result in the higher cell capacities. The number of modules per pack (x^M) was kept at the minimum possible value since according to the PBCM; additional modules resulted in additional costs associated with the SoC regulators for each module etc. The model predicts the lowest number of modules per pack since the more modules results in more costs associated with module regulators. Thus, the number of cells per module (x^N) is first increased followed by the number of modules required to provide the required energy of the pack.

Table 3- 16: Optimization results for the base case. Boundary values have been indicated with an asterisk.

Vehicle	Pack Cost (\$/pack)	Specific Cost (\$/kWh)	x^{CT} (microns)	x^{BCL}	x^{CW} (mm)	x^N	x^M	x^C (Ah)
PHEV10	2,350	470	60.9	45	100	6	4*	56
PHEV20	3,244	328	99.4	27	101	12	4*	55
PHEV40	5,246	264	125*	23	100	23	4*	58
PHEV60	7,412	245	125*	15	125	34	4*	60*
BEV100	12,733	239	125*	15	124	41	6	58

In order to relate the findings from the optimization model presented in Table 3- 16 to the real world, the optimal pack design for a PHEV40 was compared to available information for a battery pack used in the Chevy Volt. The Chevy Volt is an extended range electric vehicle (EREV) with an EPA estimated range of about 38 miles [17]. An extended range electric vehicle is a series hybrid vehicle where the internal combustion engine is used solely to charge the battery. The comparison has been shown in Table 3- 17.

Table 3- 17: Comparison of the optimal battery pack design for a PHEV40 to available information for a battery pack used in the Chevy Volt (EREV 38)

Design Specification	Sakti <i>et al.</i> PHEV40 optimal design	Chevy Volt
Pack Cost (\$/kWh)	264	500 [#]
Cell chemistry	NMC333-G*	LMO-G
Cell capacity (Ah)	58	15
Cathode coating thickness (microns)	125	-
Cell form factor	Prismatic Pouch*	Pouch
Pack voltage (V)	343	370
Cells per pack	92	288
Cells per module	23	-
Modules per pack	4	-
Cells in parallel	0*	3
Cells in series	92	96
Discharge power (kW)	103 (10s)	>125
Cooling system	Liquid*	Liquid

*A parameter and not an optimized design variable or a result of the optimization.
[#]As estimated by the National Research Council [17]

The specific cost of the battery installed in the Chevy Volt is almost higher than a factor of 2 compared to the optimal cost reported in this study. The cathode chemistry in the Chevy Volt is Mn-spinel while that in the PHEV40 is NMC333-G. LMO has a much lower energy density at 100mAh/g compared to NMC333-G at 175 mAh/g. For an EREV40, ANL reports a NMC-G battery cost to be at \$265/kWh while the same battery using LMO-G chemistry costs \$193/kWh [28]. However, most of the experts that were interviewed for the expert elicitation are of the opinion that the future chemistry (by 2018) will either be NMC333-G or a version of the chemistry. The optimal cell capacity was 58Ah while the capacity of each individual cell in Volt's battery pack is 15Ah. However, three of the cells are connected in parallel, which makes it to 45Ah. 96 of these parallel cell-groups are connected to result in a pack voltage of 370V, while the optimal battery pack estimated in this study was of 343V. The discharge power are comparable, although for the PHEV40 the cell is able to sustain that power for 10 seconds while in the case of the Volt battery similar information was unavailable. In both cases, a liquid cooling system was used. The cell form factor was similar. Chevy Volt uses a pouch cell while in the case of the PHEV40 battery, prismatic pouch cells were used. However, a likely factor contributing to the cost discrepancy is the electrode coating thickness. For the PHEV40 optimal design, the electrode thickness was 125 microns while in the case of the cells used in the Chevy Volt it is anticipated to be much less. Based on available

industry information and expert opinion, the electrode coating thickness is likely to be between 70-100 microns with the most likely estimate somewhere near the lower bound. Increasing the cathode coating thickness is likely to result in some cost reduction.

The specific costs of the cheapest designs as a function of the power-to-energy ratio of the EVs have been shown in Figure 3- 11.

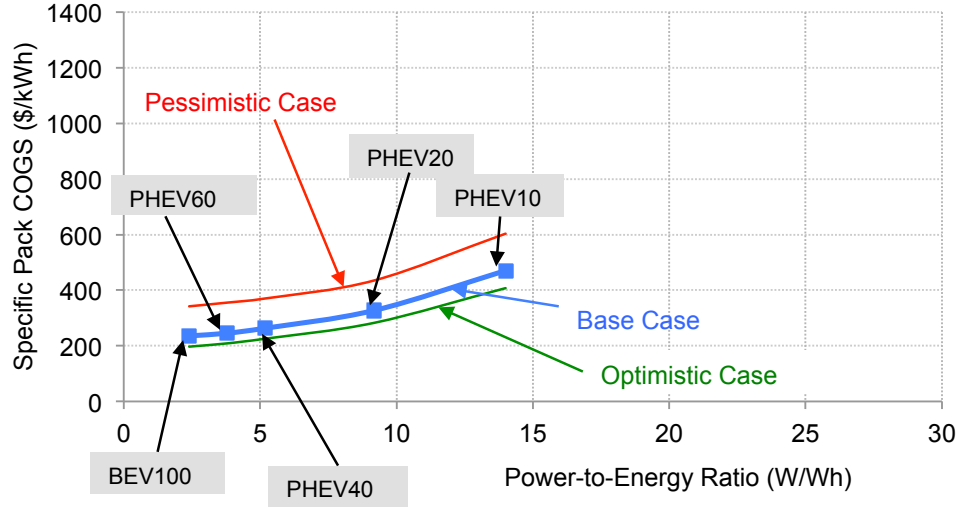


Figure 3- 11: Optimization results of the specific cost values at the pack level plotted as a function of the power-to-energy ratio of the pack.

The costs were seen to increase almost linearly. Fitting a trend line to the data points for the base case gave the following quadratic equation (coefficient of determination: 0.999):

$$C_{TOT}^{PACK} = j(X^{P/E})^k + lX^{P/E} + p \quad (21)$$

where, $X^{P/E}$ is the power-to-energy ratio of the battery. The parameters have been listed along with all the others in Appendix A.

Figure 3- 12 is a plot from a study published by Kromer and Heywood in 2008 listing the battery pack costs in a similar way for different EV applications as a function of their power-to-energy ratio. Kromer and Heywood calculate the battery costs using a generalized expression based on a base cost for a higher energy battery pack ($Cost_{High\ Energy}$) and then using a scaling factor that is a function of the battery power-to-energy ratio given by:

$$Battery\ Cost = (Cost_{High\ Energy}) \times f(Power-to-Energy\ Ratio) \quad (22)$$

In their base (current, 2008) case, they considered the cost of a higher energy battery pack to be about \$300/kWh which subsequently went down to \$250/kWh for the future base case and to

\$200/kWh for the future optimistic case. The 2008 power-to-energy scale factor was assumed to be 4.5-5, which went down to 3 in their future cases. Figure 3- 13 shows the results from this study super-imposed on the results from Kromer and Heywood. The results from this study are closer to their estimates of the costs in 2030, compared to their values in 2008. However, the energy and power requirements used in this study based on the work of Karabasoglu and Michalek, 2013 [31] (listed in Table 3- 12) are different than the energy and power requirements considered by Kromer and Heywood in their study. The power and energy values used by Kromer and Heywood have been listed in Table 3- 18. Figure 3- 14 shows the comparison between Kromer and Heywood's plot to the results from this work when the energy and power values from Table 3- 18 are used as constraints instead of the values calculated using PSAT. Costs were seen to increase by up to \$100/kWh (for a PHEV10 battery pack).

The base case cost from Figure 3- 14 was seen to follow the following linear equation (coefficient of determination: 0.999):

$$C_{\text{TOT}}^{\text{PACK}} = qX^{\text{P/E}} + r \quad (23)$$

Please see Appendix A for parameter values.

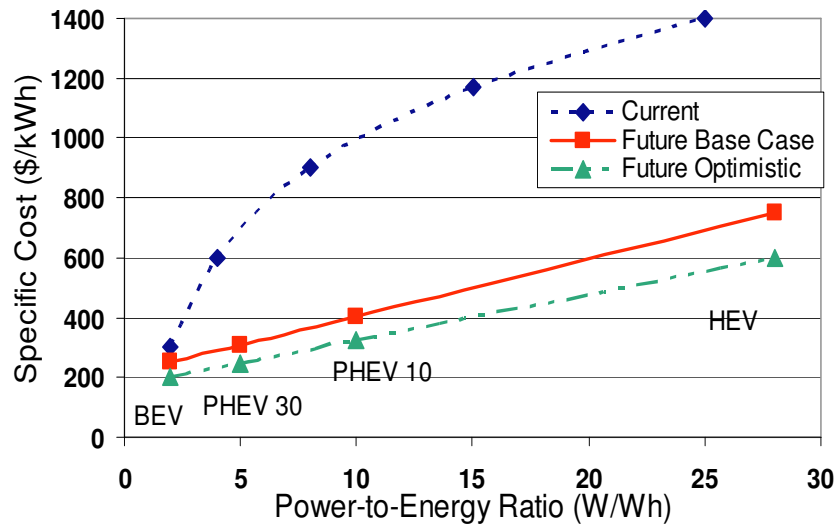


Figure 3- 12: Current and future (2030) specific costs as estimated by Kromer and Heywood (Image source: Kromer and Heywood, 2008 [12])

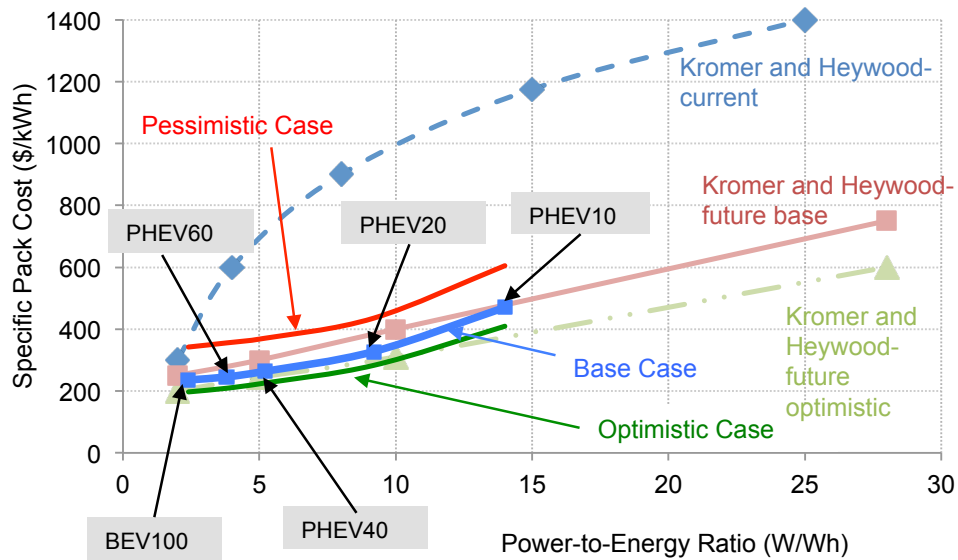


Figure 3- 13: Results from this study (Figure 3- 11) super-imposed on the results from Kromer and Heywood, 2008 (Figure 3- 12) [12]

Table 3- 18: Energy and power values used by Kromer and Heywood (compiled from Table 12 and Table 25 of the full version of Kromer and Heywood’s paper [33])

Vehicle	Battery pack energy (kWh)	Battery pack power (kW)	Power-to-energy ratio
PHEV10	3.6	48.6	13.5
PHEV30	8	44	5.5
PHEV60	16.5	47.9	2.9
BEV200	48	80	1.7

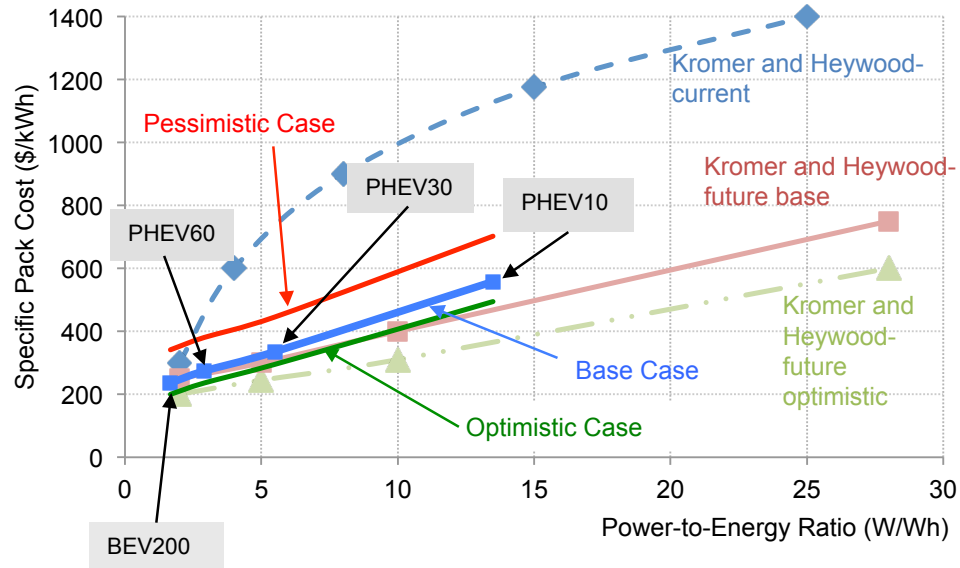


Figure 3- 14: Results from the cost and optimization model of this study using Kromer and Heywood’s energy and power requirements for different vehicles (**Table 3- 18**) super-imposed on the results from Kromer and Heywood, 2008 (**Figure 3- 12**) [12]

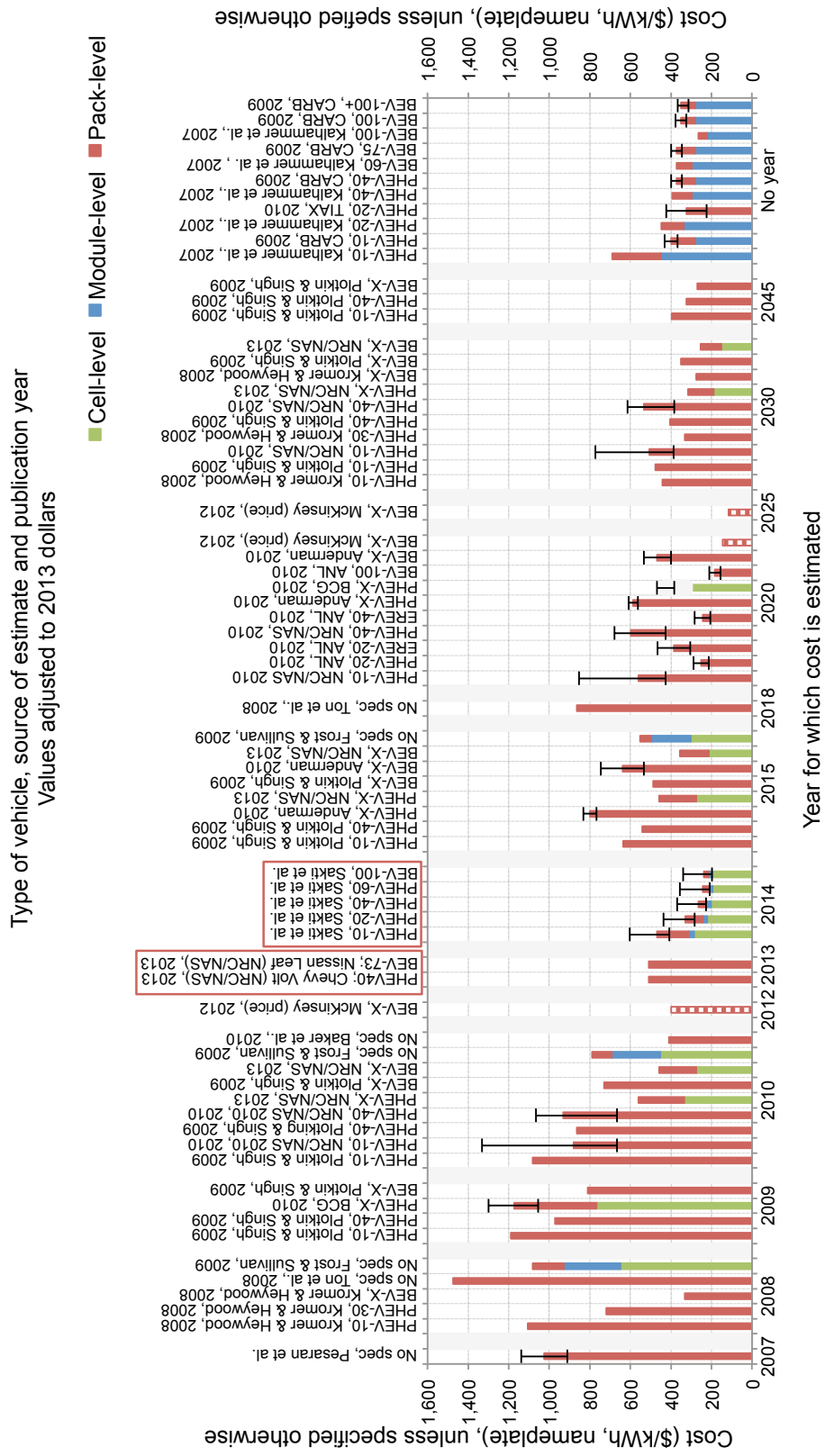


Figure 3-15: Summary of the cost estimates reported previously (**Figure 3-1**) with the cost estimates from this study added for comparison. The cost estimates from this study as well as NRC/NAS estimates for the cost of the battery pack in a Chevy Volt and a Nissan Leaf have been highlighted in red boxes.

Figure 3- 15 plots the cost estimates from this study to the summary chart presented previously Figure 3- 1. The costs are seen to be much lower than the other costs reported in the literature. This could stem from a number of reasons, the most important of which is the **electrode coating thickness**. Expert interviews as well as dissecting cells in the laboratory while validating BDS (Chapter 2) have shown that electrode coating thickness generally used by manufacturers is about 75 microns on each side of the collector. Expert opinion indicates that the manufacturers are trying to go as high as 125 microns. The optimal cathode coating thickness is about 62microns for a PHEV10, 100microns for a PHEV20, and up to the allowable limit in our model of 125 microns for a PHEV40, PHEV 60, and a BEV100. The specific cost for the PHEV10 battery pack which has cells with a 62micron thick coating is seen to be very close to the manufacturing cost of a Nissan Leaf (BEV73) and a Chevy Volt (PHEV40) battery in 2012, as assumed by the NAS/NRC report published earlier in 2013. Thus, given that our model allows much higher coating thicknesses, the costs come out to be much lower than what is reported elsewhere. Cells of lower capacities will increase the number of cells required to provide the same energy compared to if the cells were of higher capacities. This will lead to additional costs associated with monitoring these individual cells. Hence, the model predicts the highest capacity cells for the optimal design. The highest value of the electrode coating thickness that is able to deliver the power required for the application is subsequently predicted since the 10-sec power performance is a function of the cell capacity and the electrode coating thickness. Once these two variables are fixed, only a small set of combinations of the cathode width and the number of bicell-layers are feasible since the capacity depends on the amount of active material and is a function of the electrode coating thickness, the cathode width, and the number of bicell-layers, as shown in Equation (6). Whether the required amount of active material is achieved by increasing the number of bicell-layers or by increasing the width of the electrode does not seem to make much of a difference when actual numbers are tested in the PBCM. The interpolated model suggests keeping the electrode width around 100mm and varying the bicell layer accordingly as is seen from Table 3- 16.

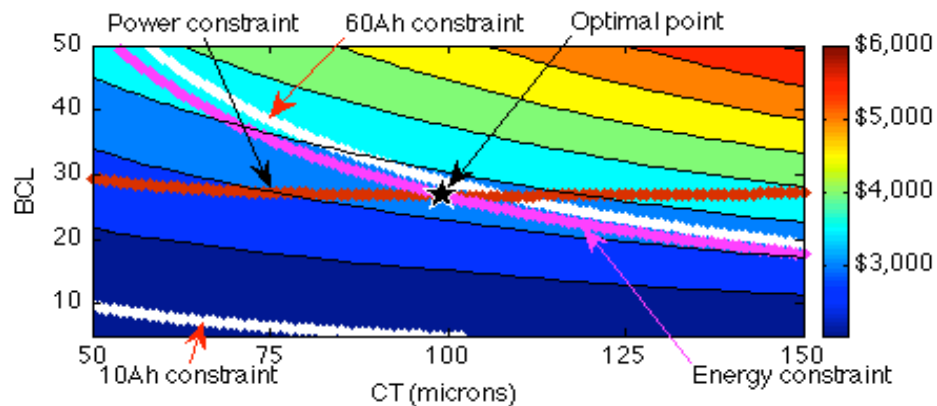


Figure 3- 16: Sample contour plot of cost as a function of the cathode coating thickness (CT) and the number of bicell-layers (BCL) for the optimal design for the PHEV20 as reported in **Table 3- 16**. The cathode width is held constant at 101mm, the cells per module at 12, and the modules per pack at 4.

A sample figure showing the design space around an optimal design point has been shown in Figure 3- 16. For the given cathode width, the white lines represent the limits for the 10 and 60Ah cells with respect to the number of bicell-layers as the cathode coating thickness is varied. The red and magenta line represents the power and energy constraints (the cells per module and the modules per pack have been assumed in this case). Given that the power is a function of the cell capacity and the cathode coating thickness, after a certain coating thickness, the capacity needs to increase to meet the power requirements and hence the power constraint curve is seen to be flat. The optimal design point is seen to be at the intersection of the energy and power constraint lines that lie between the cell capacity constraint lines.

Sensitivity Analysis

The optimal cathode coating thicknesses for the base, optimistic and the pessimistic case, listed in Table 3- 15 and the base case with varying yield (Figure 3- 10) have been shown in Figure 3- 17. It is seen that for the PHEV10 and the PHEV20, the power constraint keeps the cathode coating thickness unchanged from the base case value. For the PHEV40, the optimal coating thickness increases to ~172 microns when the constraint is relaxed to 200 microns in the optimistic case while for the PHEV60 and the BEV100, the optimal coating thickness is the maximum allowable value at 200 microns. When the yield was varied with the coating thickness and the cell capacity, as shown in Figure 3- 10, the optimal coating thickness drops to ~145-150 microns for the PHEV40, PHEV60, and the BEV100. The optimal cathode coating thickness for the PHEV10 and the PHEV20 remains unchanged indicating that thicker electrode coatings will not be able to meet the power constraint.

Sensitivity of the cost of the cheapest battery pack when the constraints with respect to the cathode coating thickness, the energy, and the power are varied have been shown in Figure 3- 18, Figure 3- 19, and Figure 3- 20 in the form of tornado plots. With respect to the cathode coating thickness (Figure 3- 18), increasing the upper limit of the cathode coating thickness to 200 microns can result in pack level savings of up to ~\$1000 for a 54kWh BEV100 battery pack. Decreasing the energy requirement of the vehicles, as calculated using PSAT, to take into account improvements in mileage resulting from vehicle light-weighting etc. in the future was seen to reduce the pack cost by up to ~\$3,000 for a 54kWh BEV100 battery pack (Figure 3- 19). Reducing the power requirement was seen to only result in small savings of up to ~\$140 for a PHEV10 (5kWh) pack and ~\$100/pack for a PHEV20 (9.9kWh) pack with no savings for a PHEV40, a PHEV60, and a BEV100 pack indicating that the energy constraint is dominant in those cases (Figure 3- 20).

A summary of the cost variation for the four different scenarios is shown in Figure 3- 21. The optimal specific cost when the yield is varied is seen to be in the range of the costs from the optimistic and the pessimistic cases. Specific costs were seen to be as high as ~\$600/kWh (for a PHEV10) decreasing to ~\$300/kWh for the BEV100, for the pessimistic case.

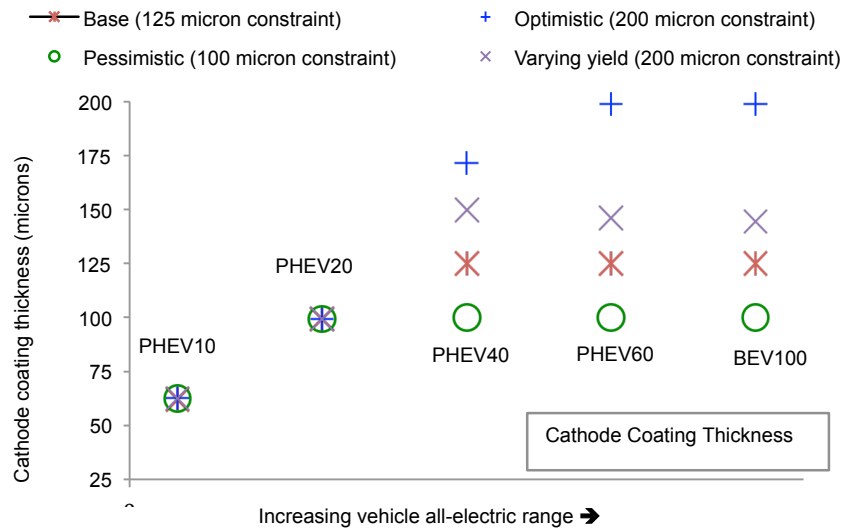


Figure 3- 17: Optimal cathode coating thickness for the four different scenarios considered. The optimal thickness for the scenario where the yields were varied as a function of the cathode coating thickness and the cell capacity was seen to lie within the range of the results from the other three scenarios.

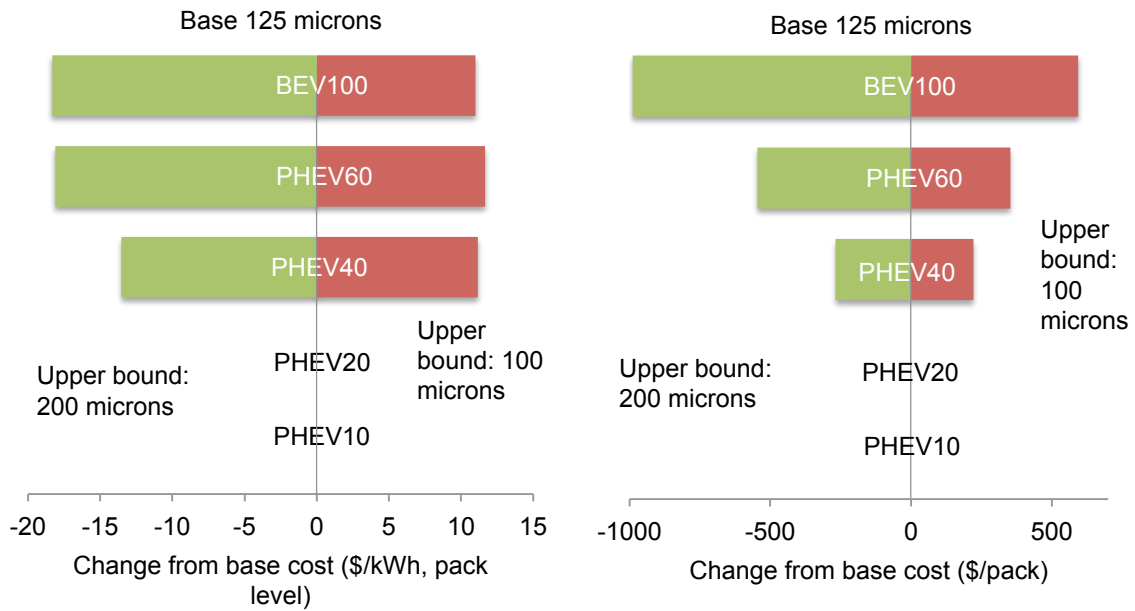


Figure 3- 18: Tornado plot of the pack cost variation with respect to the base case when the electrode coating thickness constraint is varied between 100 and 200 microns from the base case of 125 microns.

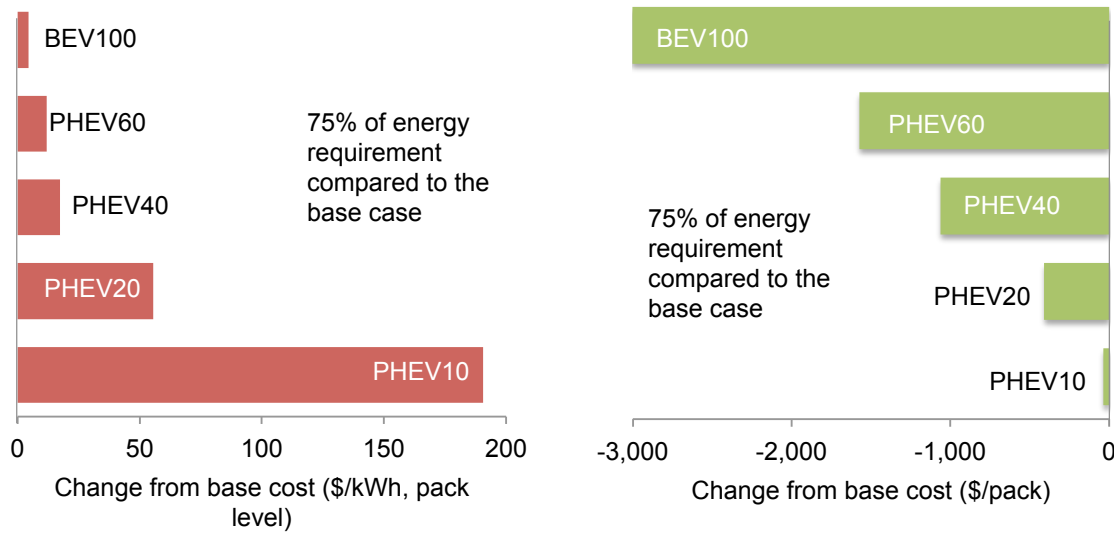


Figure 3- 19: Tornado plot of the pack cost (\$/kWh and \$/pack) variation with respect to the energy constraints when it is decreased to 75% of the calculated requirement for the base case. The pack cost decreases since the total size of the pack (kWh) decreases, but the specific cost (\$/kWh) is seen to increase.

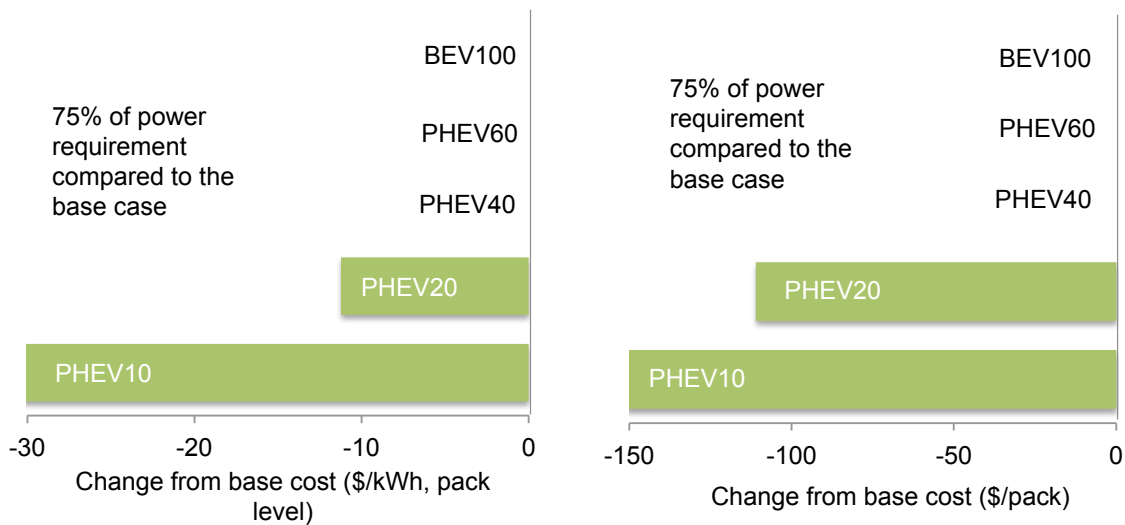


Figure 3- 20: Tornado plot of the pack cost (\$/kWh and \$/pack) variation with respect to the power constraints when it is decreased to 75% of the calculated requirement for the base case. Changing the power constraint for a PHEV40, a PHEV60, and a BEV100 does not change the pack cost or the specific cost since the energy constraint is dominant for those vehicles.

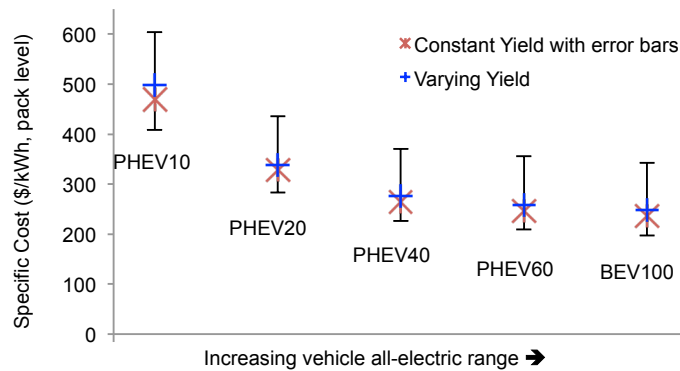


Figure 3- 21: Specific pack level cost for the different EVs calculated for the four different scenarios. The optimal cost results from the scenario in which the yield was varied as a function of the electrode coating thickness and the cell capacity is seen to lie within the range of results from the other three scenarios.

3.13 Conclusion

A techno-economic analysis was performed on Li-ion batteries and the different design decision variables of cathode coating thickness, number of bicell-layers, the cathode width, the number of cells per module, and the number of modules per pack was investigated. The power meta-model that predicts the 10sec peak power capability of a battery pack was seen to be in agreement with the approach pursued by ANL BatPaC to calculate their pack power. The results from the cost meta-model were seen to be in the range of the costs of the ANL BatPaC. The P-E ratio requirement across the different vehicles was seen to be a key factor driving costs. Optimized results indicate that the cheapest designs result from higher capacity cells that are fabricated with electrodes employing higher electrode coating thicknesses. Economies of scale was seen to be reached at an annual production volume of about 30,000 packs or ~200MWh. Optimization model results indicate that the electrode thickness is determined by the power constraint for the smaller pack cells while for the larger packs it is only manufacturing limitations that keeps the electrodes from getting thicker. Increasing the upper limit of electrode coating thickness to 200 microns can result in a decrease of the manufacturing costs at the pack-level by about 5-8%. When the yield was varied as a function of the cathode coating thickness and the cell-capacity, the optimal coating thickness was seen to only be as high as ~150 microns. Varying the yield did not seem to have any significant effect on the specific cost of the battery packs compared to the base case. Using the optimal cost results, a formula for the specific cost at the pack level as a function of the power-to-energy ratio of the battery pack was developed. The optimized costs were seen to be lower than those resulted in the literature for similar applications. A possible explanation for this is the upper limit for the electrode coating thickness considered in this study compared to what is seen in the industry indicating that it is possible to bring down the cost of battery packs for EVs through application specific designs at the cell level thus proving our initial hypothesis. Incremental developments in cell-level manufacturing whereby thicker electrode coatings can be employed for cells with lower P-E requirements was identified as a possible pathway to lower battery costs.

3.14 Limitations

The designs studied in this work do not take into account parallel cell configurations. The pack level voltage was also not taken into consideration as a design decision variable. This may result in additional costs to incorporate the battery pack into the vehicle system if the voltages are too high or too low. Additionally, this work does not account for any capacity fade that may result from using cells with thicker electrode coatings. As more information becomes available on the quantification of capacity fade resulting from thicker electrode coatings, a more informed decision on the optimal coating thickness could be made.

3.15 References

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4. An elicitation of expert assessments of current and future Li-ion battery cell and pack cost, and designs for personal vehicle electrification¹

4.1 Background

The 2014 DoE production cost goals for PHEV-40 batteries is \$300/kWh while its goal for BEV-100 and BEV-300 (EV) batteries in 2020 is between \$100-150/kWh, at the total pack level capacity [1-2] (Figure 4- 1). The United States Advanced Battery Consortium (USABC), an arm of the United States Council for Automotive Research (USCAR), which partners with different governmental agencies including the USDoE has a more detailed description of the performance requirements from the batteries for which the future cost goals are set (please see Appendix G). It's goal for a PHEV-10 is a “production price” of \$500/kWh (@100k units/year) while the goal for a PHEV40 is a “production price” of ~\$300/kWh. USABC's goal for a BEV with a 40kWh battery pack is a “selling price” of ~\$100-150/kWh (@25k units/year) [3]. Current battery prices are reported to be in the range of \$500-\$600/kWh for the entire battery pack [4]. Given that mainstream adoption of alternative powertrain technologies is necessary to achieve substantial displacement of US petroleum consumption and reduction in air emissions like greenhouse gasses, battery cost is key to addressing oil dependency and global warming in the United States. Assessment of the trajectory of the technology in the near future will help make better-informed policies with direct implications on national security and global climate.

Future cost reductions of Li-ion batteries is likely to result from a multitude of factors. Volume based cost reduction has been shown from the results of our model in the previous section (Figure 3- 2) as well has been reported in other studies [5] as well as has been where an increase in the annual production volume of the batteries brings down the cost of production. Other routes to cost reduction can involve *learning* based cost reductions resulting from declining labor hours per unit produced or, *experience* based cost reductions which is applied to the overall “cost behavior over time in a process industry” and take into account learning, specialization, investment, and scale. [6]. While information on these factors can be useful in predicting the future cost of a technology by using historical data, these approaches are also prone to issues [7] and estimating future cost reductions solely by taking into account the afore-mentioned cost reduction factors may be erroneous.

¹ Sakti, A., Azevedo, I., Fuchs, E.R.H., Michalek, J.J., Gallagher, K., Whitacre, J.F. 2014, An elicitation of expert assessments of current and future lithium-ion battery cell and pack costs, and designs for personal vehicle electrification, work in progress.

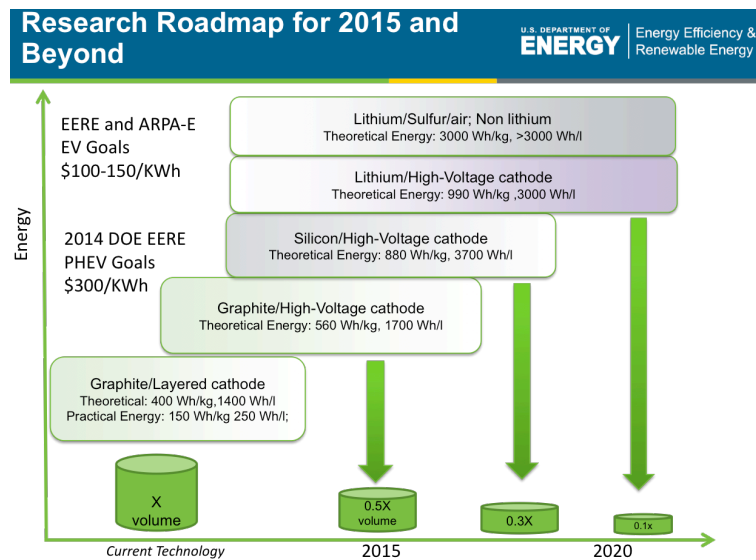


Figure 4- 1: US DoE battery production cost goals for PHEV and BEV batteries (Source: Howell 2011)

Expert elicitation, in which experts from the field are asked for their opinion on specific aspects pertaining to their field of expertise, is another tool to estimate future cost reduction. In the case of Li-ion battery pack manufacturing, experts are likely to have significantly more information on the individual process steps involved in the entire manufacturing process. Expert elicitation, too, however, is prone to errors. The errors in this case involve the subjective nature of the experts' judgments. Cognitive heuristics such as *availability*, and *adjustment and anchoring* are of particular notoriety. In the *availability* heuristic, the respondent is influenced by the ease with which he or she can recall similar instances as is being asked for in the question at hand. *Adjustment and anchoring* on the other hand, results in biases when the respondent starts off from an initial value and then adjusts that value to arrive at the final answer. It has also been shown that experts, as well as laypeople tend to show overconfidence while answering questions [8-9]. A proper protocol, which includes framing questions that limit the introduction of bias as much as possible, can help in addressing these pitfalls.

In this study we present an expert elicitation to estimate the future cost of Li-ion battery packs and cells for personal vehicle electrification. Given the systems nature of Li-ion battery pack manufacturing and the number of process steps involved, we not only elicit the overall cost of manufacturing from the experts, but also information on the most sensitive process step parameters as well as materials level cost. Such an approach of focusing on individual aspects in a systems-level problem has been shown to improve the overall quality of the results [10]. In our case, it improves the quality of our expert elicitation by adding to the robustness of our findings.

4.2 Aims and Objectives

This research aims to evaluate current and near-term (by 2018) costs and design-developments of Li-ion batteries for personal vehicle electrification by interviewing experts from the battery industry, original equipment manufacturers (OEM), and consultants. The primary objective is to identify the improvements in the design and technology that will facilitate manufacturing cost reductions in the near future based on expert opinion. A secondary objective is to use the design-specific information from the experts and use them as inputs to the process-based cost model constructed previously (Chapter 3) and compare experts' systems-level costs to what the cost model predicts.

4.3 Literature review of expert elicitations for future Li-ion battery costs

Literature is replete with projections of future Li-ion battery costs. Figure 3- 15 summarizes some of the existing cost estimates, in the context of the US, including the estimates from a study by some of the authors of this paper [11-25]. A significant amount of scatter is seen with the different estimates.

Out of the different cost estimates listed in the study, only Baker et al.'s protocol is similar to the elicitation reported in this study [22]. Baker et al. interviewed seven different experts to elicit advances in battery technologies for electrified vehicles focusing on Li-ion and li-metal batteries [22]. The elicitation was structured around five characteristics: cost, power density, specific-energy, lifetime, and recharge rate of the batteries. A total of seven experts from a mix of universities, national laboratories, and private firms were chosen. For both the technologies (Li-ion and li-metal) they started the elicitation with a question relating to the technical feasibility of the battery by eliciting the probability of the technology achieving 3000 cycles [22]. Subsequently, two different U.S. government-funding scenarios for each technology was provided to the experts and the probabilities for the technologies to achieve the high and low endpoints were elicited [22].

Bosetti *et al.* interviewed a set of 14 experts to estimate the capacity of both PHEVs and BEVs to reach commercial success in the next twenty years under three different EU public R&D funding scenarios [23]. The experts were from institutions, private sector, and academia. The authors in the paper state that their work is similar to that of Baker *et al.* (described above) but differs since the focus in this case is the EU and the elicitation also provides an assessment of future diffusion scenarios on top of the cost estimates. While Baker *et al.* elicited information only for Li-ion, and li-metal batteries, this study elicited information for Li-ion, li-metal polymer, li-sulfur, li-iron phosphate, Ni-MH, Zn-air, Pb-acid, Ni-Cd, and Zebra (molten-salt) batteries. The authors elicited information on the optimal allocation of R&D budget from 2010-2030 for different vehicular energy storage technologies, stage of R&D required for the different technologies, and the cost of different batteries in \$/kWh in 2030 under different funding scenarios. The authors finally elicited information on the potential solutions to different factors that could pose as non-technical barriers to the diffusion of electric vehicles. The factors chosen as potential non-technical barriers by the authors were: behavior changes, infrastructure, safety, lobbying/vested interests, critical mass for adoption, and rare metal supply.

In both the studies (Baker *et al.* and Bosetti *et al.*), no specification on any design aspect or the type of electrified vehicle was included in the elicitation.

4.4 Methodology

A set of ten elicitations was executed over the course of three months that involved twelve different experts from the industry (battery manufacturers, suppliers, and car OEMs), and consulting firms. Initially, the experts are free to assume any battery design that, according to them, will result in the cheapest cost battery pack in 2013 and 2018. Costs were elicited at the cell level (\$/kWh), pack level (\$/kWh), and for the battery management system (BMS) and thermal management system (TMS) contribution to the pack (\$/pack). The specific costs were elicited at the nameplate or rated capacity level (and not the usable capacity level). The experts were then asked to elaborate on what they think will result in the cost reductions by 2018. Subsequently, two different battery pack designs were specified. These designs were based on available information on two existing battery pack designs currently in use in EVs commercially available: Ford C-Max Energi and Nissan Leaf. Design1 was similar to the battery pack in Ford C-Max Energi while Design2 that of the Nissan Leaf. Table 4- 1 lists these two designs. The vehicles that these designs are representative of are only used as references and were not intended to be exact replications.

Table 4- 1: The two designs used in the elicitation based on battery pack designs in existing vehicles. Assumptions have been made and listed where information was unavailable. Items of interest, that we wish to elicit information about, have been shown in shaded boxes.

	Design1	Design2	Notes
Design reference	Ford C-Max Energi	Nissan Leaf	Selected to be representative of two different battery pack sizes.
Design reference vehicle type	PHEV-21	BEV-73	
Pack energy (kWh, total)	8	24	Data, from various sources (rounded off)
Pack power (10s, kW)	68	>90	Data, from various sources
State of charge swing window (%)	~85	~80	Data, from various sources
Cell form factor	Prismatic	Pouch	Data, from various sources
Chemistry	NMC-G	LMO-G	Data, from various sources
Cell capacity (Ah)	25	33.1	Data, from various sources
Pack cooling	Air	Air*	Data, from various sources
Cathode			
Specific capacity (mAh/g)	150	100	Data, from various sources
Single side electrode coating thickness, (μm)	60	80	Assumed based on existing knowledge
Anode			
Specific capacity (mAh/g)	330	330	Data, from various sources

*Nissan Leaf uses active air cooling for its battery pack

Once the designs were specified, the experts were asked whether they were representative of the designs by 2018 or if the designs are going to be significantly different. Subsequently, the experts were asked about their opinion on the design specifics like the cell capacities, the electrode coating thickness, specific capacities of the cathode and the anode and the state-of-charge swing. The experts were then given the opportunity to comment on what they would change to make the battery packs cheaper in the 2018 with respect to the cell form factor, the chemistry, and the type of thermal management system. Design-specific costs for the two designs, similar to what was done

previously when the experts were allowed to assume a design of their preference, was then elicited from the experts.

The elicitation was executed in two parts. Part I of the elicitation comprised of the questions described above that dealt with the systems-level costs and designs variables. In Part II of the elicitation, the expert was introduced to the manufacturing process steps and process step parameters like the active material scrap rates and the overall cell-level yield rates. The experts were then asked about the scrap rates specific to Design1 and Design2 followed by their opinion on the cumulative cell level yield and its variation as a function of the electrode coating thickness and the cell capacity (Please see the elicitation protocol, Appendix H, for more information). Once that was done, the experts were asked whether they would like to revise their previous cost estimates for Design1 and Design2. The objective behind introducing the expert elicitation in two parts was to check whether the experts changed their cost estimates after the process step parameters (scrap rates and the cumulative cell-level yield rate) were introduced to them. Finally, the experts were asked some open-ended questions with respect to Design1 and Design2, technological breakthroughs that may be disruptive to the status of Li-ion batteries by 2018, and about the protocol in general. The results of the elicitation have been presented in the next section.

4.5 Results and Discussion

Expert opinion on the cost of Li-ion batteries in 2013 and 2018, when they were free to assume any design has been summarized in Figure 4- 2. The experts have been tagged with identifiers that connect them to their respective industry: BI for battery industry, OEM for original equipment manufacturers and C for experts from the consulting industry.

Considerable scatter is seen in the experts' estimates. However, as expected, the cost values are in general agreement to what has already been reported in the literature and as summarized previously in Figure 3- 15. Expert A, who is a cell manufacturing director in a battery manufacturing company by far had the highest cost estimates for now as well as in 2018. Other than Expert L, a well known figure in the world of battery systems modeling, all other experts were of the opinion that PHEV10 batteries are the most expensive currently followed by PHEV 40 and BEV 100, with a similar trend in the cost reduction order in 2018. According to Expert L, BEV 100 batteries are more expensive currently compared to a PHEV10 or a PHEV40 battery but will see a much sharper drop in manufacturing costs by 2018 when it will be cheaper compared to a PHEV10 or a PHEV40 battery. In almost all cases the experts were of the opinion that the cost reduction from now until 2018 will result from volume and learning based reasons. Some of the experts also indicated that there is a recent push in the industry to standardize the battery designs (cell form factor etc.) and such an effort could positively impact cost reduction as well. The contribution from the battery management system (BMS) and the thermal management system (TMS) to the entire battery pack as well showed much disagreement between the experts as is seen from Figure 4- 3. Experts generally agreed that the BMS and TMS costs aren't likely to change all that much since the electronics are already mass produced and it is unlikely that there will be any volume based changes. Expert I's estimates stood out again with much higher BMS and TMS costs for a BEV and a much sharper drop by 2018 compared to the other experts.

Once Design1 and Design2 was specified all the experts who provided estimates for the costs scaled the cost for Design1, between their previous estimates for a PHEV10 and a PHEV40 given that Design1 is representative of the battery pack in a PHEV21. For Design2, experts who provided cost estimates did not change their cost estimates from the values that they provided for a BEV100 previously. The following summarizes expert opinion on the different design variables, material properties and manufacturing process step variables.

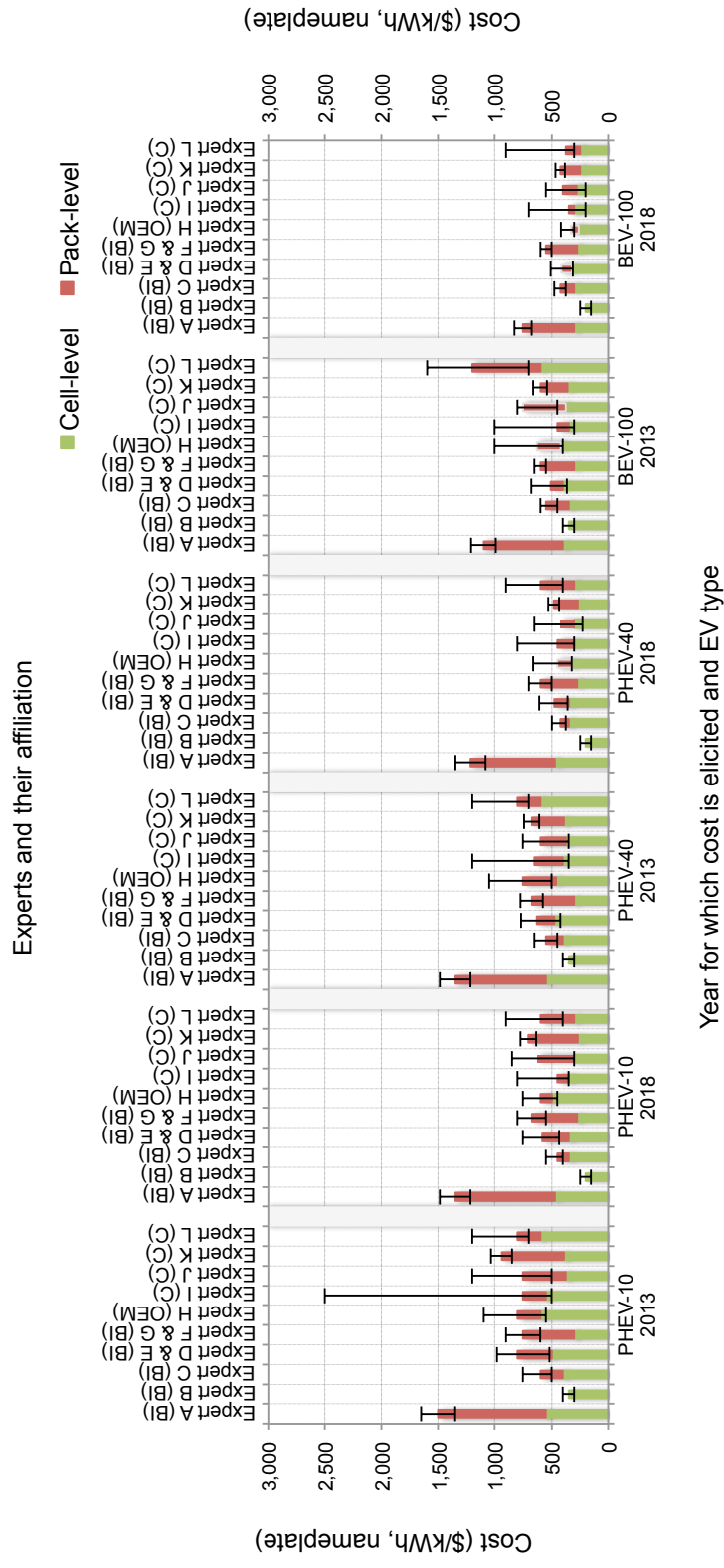


Figure 4-2: Expert opinion on current (2013) and near-future (2018) li-ion battery costs for a PHEV-10, a PHEV-40, and a BEV-100. Experts are either from the battery industry (BI), vehicle original equipment manufacturers (OEMs) or from the consulting industry (C).

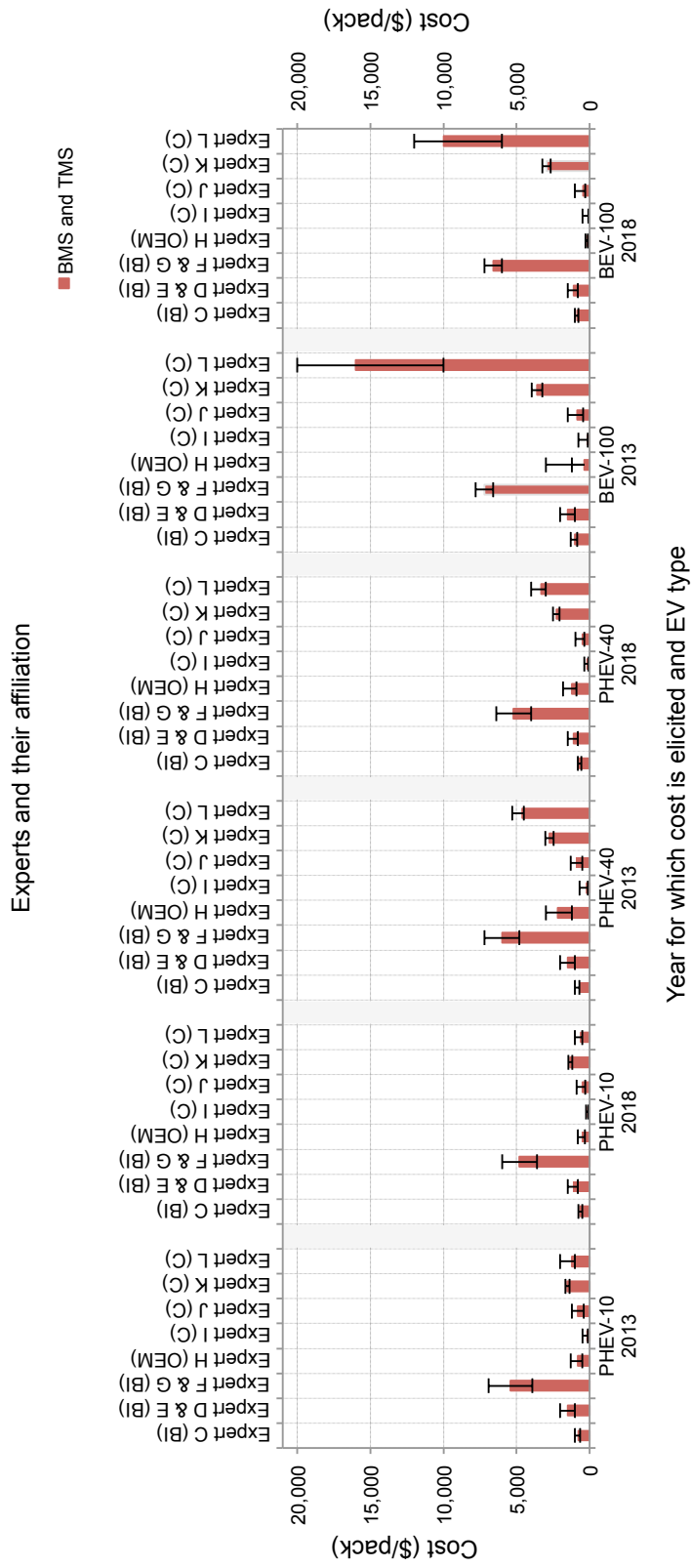


Figure 4- 3: Battery Management Systems (BMS) and Thermal Management System (TMS) contribution to the pack level cost. The active material scrap rates for the two designs, and the overall cell-level yield across all designs is also summarized. Experts are either from the battery industry (BI), vehicle original equipment manufacturers (OEMs) or from the consulting industry (C). A wide discrepancy is seen between the experts' estimates.

Cell Capacity (Ah)

Experts who commented on the cell capacities mostly either kept the base value for the two designs unchanged or increased the capacity of the cells (Figure 4- 4). For Design1 where the base value for the cells used in the battery pack was 25Ah, expert opinion suggests that cells as high as 60Ah could be used by 2018, while for Design2 where the base value of the capacity of the cells used to build the pack is 33.1Ah, expert opinion suggested that cells as high as 68-70Ah could be used by 2018. Expert G who suggested that number mentioned that currently in the Nissan Leaf (which is the reference design for Design2), the manufacturers use two 33.1Ah cells in parallel to get to a 66.2Ah which is then used in the battery pack to get to the 24kWh pack capacity. By 2018, manufacturers may instead opt for higher capacity cells without having to opt for a parallel connection to reach higher capacities.

A factor that plays a key role when deciding the capacity of the cell to be used is the overall voltage of the battery pack that has direct implications on the pack's power capability. Cells of smaller capacities will result in higher overall pack voltage when connected in series compared to a pack of the same energy using cells of higher capacities connected in series. According to Expert D beyond a pack voltage of 350V additional costs would be incurred for the pack power electronics while according to Expert J if the cells are unable to attain a certain pack voltage, a voltage booster may be needed and at that point the tradeoffs need to be considered between using lower capacity cells compared to higher capacity ones. Expert G mentioned that typically battery pack voltages are between 250V-420V. According to Expert F, concerns associated with higher voltage packs include costs associated with power electronics and other safety related issues. Expert J indicated that the demand for the battery packs is also a important factor that plays a key role in the capacity of the individual cells used in the battery pack. Manufacturers are unlikely to invest in manufacturing a new type of high capacity cell is the demand is not high enough. They would rather use cells that are already in production.

Electrode coating thickness

Very few of the experts chose to comment on the single side electrode coating thickness for the cathode and of those almost all of them kept the values unchanged from the base case (Figure 4- 4). Expert G suggested that the coating thickness could increase for these **specific** designs. Expert G also mentioned that once the electrodes are coated and they go through the formation cycling step, the electrodes swell by a factor of up to 2. The electrode thickness that we consider in this study is the thickness after the formation cycling step. According to Expert G, the electrode coating thickness during the coating step (before formation cycling and the associated swelling) can be as high as 150 microns, but that will result in very low rate cells or in other words the power performance of the cells will suffer. Expert G indicated that after the formation cycling step, the 150-micron electrode coating could swell up to a value of 300 microns. Expert H who kept the electrode coating thicknesses for Design1 and Design2 unchanged mentioned during the open-ended questions that by 2018 there would be significant manufacturing improvements and thicker electrode coatings will be seen.

Cathode specific capacity and Anode specific capacity

5 experts chose to comment on the cathode specific capacity and 6 on the anode specific capacity (Figure 4- 4). Most experts other than Expert B forecast marginal improvements. According to Expert B, the cathode specific capacity can improve by a factor of 2 for both Design1 (NMC-G) and Design2 (LMO-G) and the anode specific capacity can increase from 330mAh/g up to 500mAh/g by 2018.

State of Charge

For the state-of-charge (SoC) window, expert opinion lies on both sides of the values specified for the designs (Figure 4- 5). Of the 9 experts who commented on this question, 6 of the experts thought that the most likely SoC window for Design1 would be lower than the 85% window provided to them while defining Design1 in Table 4- 1. According to them the most likely value would be between 75-80% in 2018. Only Expert J thought that the most likely value of the SoC window for Design1 could be as high as 90% in 2018.

For Design2, the value provided to the experts for the SoC window was 80%. Two of the experts (Expert D & E) commented that the most likely value would be 75% in 2018. Two other experts (Expert H and Expert J) thought that the SoC window could be as high as 90% while Experts F & G thought it could be as high as 96% for the most likely case.

Active material scrap rate

The experts that chose to comment on the scrap rates did not vary the rates across the two different designs. The most likely value of the active material scrap rates was seen to be between 7-20% in 2013 improving to 7-15% by 2018 (Figure 4- 5).

Overall cell-level manufacturing yield

For the overall cell-level manufacturing yield, the most likely value was seen to be between 82-98% in 2013 (Figure 4- 5). Only two of the experts commented on the yield variation with respect to cells of different capacities and cells with different cathode coating thicknesses. We define the cell level manufacturing yield as the percentage of the cells entering the formation cycling step that are tested to be good cells at the end of the process step. With that definition, Expert L commented that a 40Ah cell using 100 micron cathode coating thickness will have a yield of about 99% which will go down marginally to about 98% for a 10Ah and a 60Ah cell that both have a cathode coating thickness of 25 microns. Expert L mentioned that he is unaware of electrode coating thicknesses beyond 100 microns. Expert A commented that there will not be any yield variations just in the formation cycling step across cells of different capacities and different electrode coating thicknesses. According to Expert A, yield losses, if any, will be detected in the steps leading to the formation cycling step.

When the experts were allowed to change Designs 1 and 2 with respect to three different design variables: cell form-factor, cell chemistry, and pack cooling method a split was seen between what will be more economical in 2018. Their answers have been tabulated in Table 4- 3. However, almost

every expert indicated that air-cooling would be more economical other than Expert D who commented that there would be more active cooling by 2018 and opted for liquid cooling for Design2. Most of the experts that commented on the chemistry indicated that by 2018 variations of NMC-G (NMCx-G) would be the economical choice. Most experts chose the pouch cell in the future to be the cheaper option while a handful opted for the prismatic cell packaging.

It was also seen that the experts did not change their cost estimates (for Design1 and Design2) after they were introduced to process step parameters of scrap and yield rates in Part II of the elicitation.

4.5.1 Using design specific information from the elicitation as inputs into the PBCM

Experts' cost estimates for the battery packs for Design 1 and Design 2 in 2013 were compared to the optimal costs calculated for the two designs using the cost and optimization models described in Chapter 3. The energy and power values listed in Table 4- 1 were used as constraints, similar to application specific designs and costs estimated for the five different vehicles listed in Table 3- 12. The costs calculated were found to be lower than the experts' estimates. For Design 1, the optimal pack-level cost was estimated to be ~\$470/kWh (base case) while the most-likely range from the experts was \$600-1,450/kWh while for Design 2 the numbers are ~\$320/kWh and \$450-1,200/kWh (Figure 4- 6).

For 2018, information elicited from the experts like the cathode coating thickness, yield and scrap rates etc. (listed in Table 4- 2) for the two designs were used as inputs to the PBCM developed in Chapter 3 to compare the experts systems level cost estimates for 2018 to the PBCM's estimate. The median value of the range of estimates provided by the experts was considered as the base case together with the extremes of the ranges as the low and high values. For the cell capacity, which is not an input to the PBCM, the number of bicell-layers was varied to result in the cell capacities that match the experts' opinion. All other inputs to the PBCM remained unchanged from their base case values as listed in Chapter 3 and Appendix D. The range of costs estimated using the cost model for 2018 have been shown using the blue horizontal lines in Figure 4- 6 together with the experts' estimates for the costs of Design 1 and Design 2 battery packs. Apart from one instance (Expert A, Design 1 battery pack in 2018), experts' cost projections were in ranges of costs estimated using the PBCM. The base value of the costs estimated using the PBCM however were seen to be lower than the experts' estimates.

Table 4- 2: Information elicited from the experts that was used as inputs into the PBCM. The base value was the median value of the experts' estimates while the low and the high were the absolute low and high values from all the experts. All other inputs to the PBCM were the same as that used for the techno-economic analysis (Chapter 3)

Design Variable	Base	Low	High
Design1			
Cell Capacity (Ah)	25	18	30
Coating Thickness (microns)	60	40	80
Cathode Specific Capacity (mAh/g)	160	150	300
Anode Specific Capacity (mAh/g)	338	330	500
Scrap Rate (%)	10	5	30
Yield (%)	95	60	99
Design2			
Cell Capacity (Ah)	45	20	80
Coating Thickness (microns)	80	80	100
Cathode Specific Capacity (mAh/g)	158	100	250
Anode Specific Capacity (mAh/g)	338	330	400
Scrap Rate (%)	11	5	30
Yield (%)	95	60	99

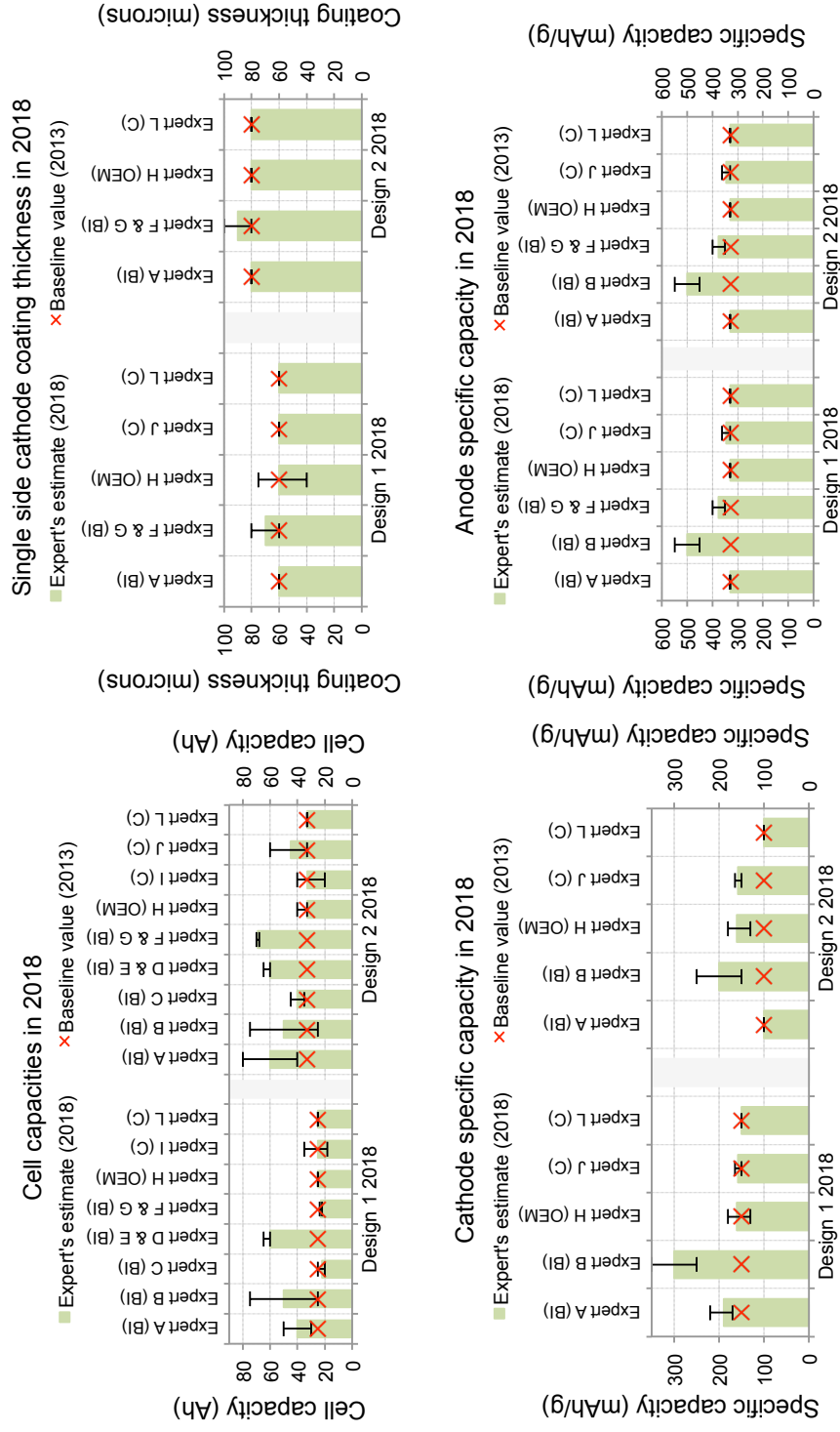


Figure 4- 4: Summary of expert opinion on how the cell capacity, single side cathode coating thickness, cathode and anode specific capacity for the two designs may change compared to the baseline values specified in **Table 4- 1** (marked by a red cross in the figures). Experts are either from the battery industry (BI), vehicle original equipment manufacturers (OEMs) or from the consulting industry (C).

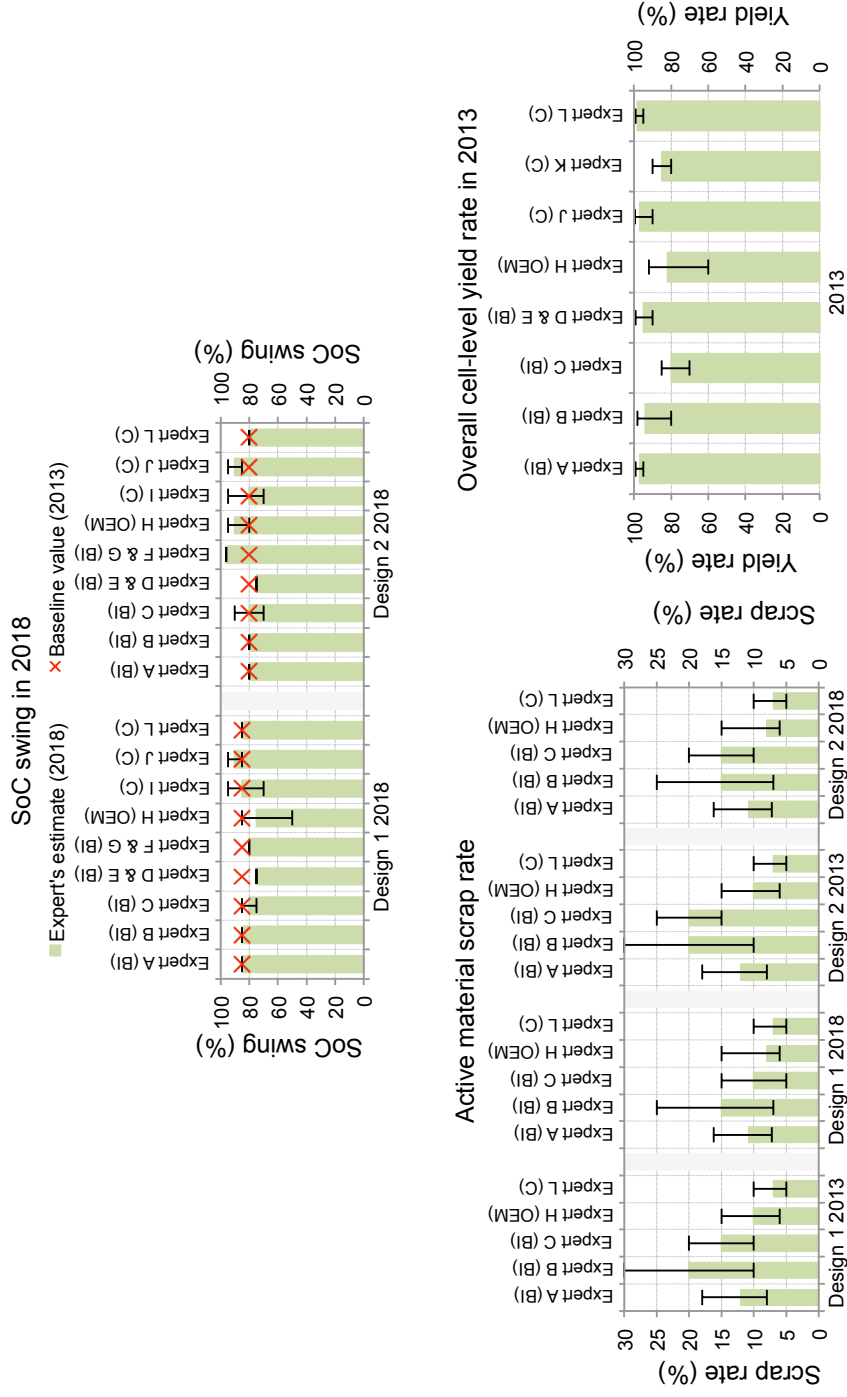


Figure 4- 5: Summary of expert opinion on how the state-of-charge swing baseline window may change for the two designs specified in Table 4- 1. The active material scrap rates for the two designs, and the overall cell-level yield across all designs is also summarized. Experts are either from the battery industry (BI), vehicle original equipment manufacturers (OEMs) or from the consulting industry (C).

Table 4- 3: Summary of expert opinion on changes in the design that may result in cheaper manufacturing costs for Design1 and Design2, specified in **Table 4- 1**, by 2018. The base value specified in the designs have been listed and the cells color coded for when the expert changed them as opposed to when the expert kept it the same. The responses to the open-ended questions at the end have also been summarized along with other notes and comments.

Expert	Design1				Design2			Notes/Comments and Responses to open ended questions
	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)		
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 (PHEV40 over PHEV10) • No technological breakthroughs before 2020. Small improvements in cell chemistry by 2018.	
D & E (BI)	Pouch/Prismatic	NMCx-G (energy), LFP-G (power)	-	Pouch/Prismatic	NMCx-G (energy), LFP-G (power)	Liquid	• Air cooling is not mainstream • More active 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	

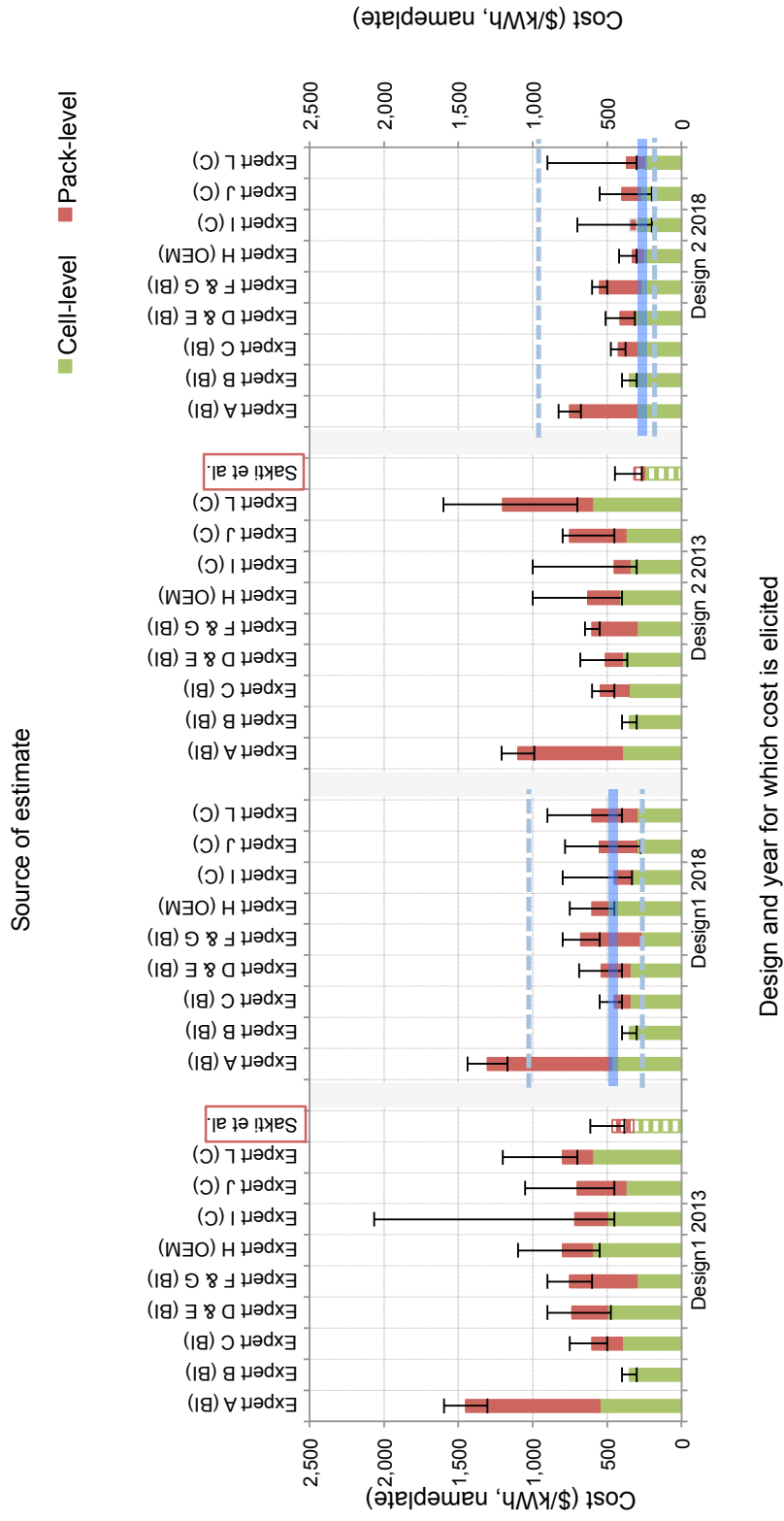


Figure 4-6: Comparison of experts' estimates for Design 1 and Design 2 battery pack costs to the costs calculated using the process based cost model developed in this study. For 2018, the design developments elicited from the experts were used as inputs to the cost model. The ranges were shown with the blue horizontal lines. The solid line represents the base value while the dotted line represents the upper and lower bounds.

4.6 Conclusion

An expert elicitation of current and future Li-ion battery cell and pack cost, and designs for personal vehicle electrification was performed. Cost estimates when the expert was free to assume any battery pack design for a PHEV10, a PHEV40, and a BEV100 was in agreement with the costs reported in the literature. Once the designs were specified the experts' cost estimates did not change. Experts' design specific costs were in some agreement with the costs calculated for the designs using the process based cost model. For the experts who provided design specific costs, for Design1; they scaled their cost estimates from PHEV10 and PHEV40, while for Design2; their cost estimates were the same as the costs for the BEV100. More experts chose the pouch cell to result in cheaper pack costs in 2018 and almost all of the experts opted for air-cooling in 2018. Expert opinion on the cheaper chemistry in 2018 seemed to lean towards versions of NMCx-G while some choosing other chemistries. Active material scrap rates varied from 7-20% in 2013 and improved to 7-15% by 2018. The overall cell-level manufacturing yield was seen to be between 82-98%. The experts agreed unanimously that no technological breakthroughs are expected by 2018 with only incremental improvements. Three of the experts indicated a shift towards higher capacity cells with one of them indicating significant manufacturing improvement resulting in cells with higher electrode coating thicknesses. It was seen that none of the experts changed their cost estimates once they were introduced to process step parameters like scrap and yield rates.

4.7 Limitations

The elicitation only includes one expert from vehicle OEMs and hence is not representative of what OEMs think about the future of Li-ion batteries may be in the near future. An effort was made to reach out to more OEMs but without success. Also, although there were about 12 experts in total, not every expert was familiar with the different questions. For instance only two experts commented on the variation of the overall cell-level manufacturing yield as a function of the cell capacity and the cathode coating thickness.

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5. Policy Implications

Results from the analysis presented in this work indicate that economies of scale for Li-ion battery manufacturing costs for prismatic pouch cells can be reached at an annual production volume of about 200MWh (~8,333 of the battery packs installed in a Nissan Leaf, each about 24kWh). In other words, at this production volume, the average cost of production of a battery pack will be equal to the marginal cost to produce an additional battery pack. Economies of scale at such a low approximate volume suggests that if true, significant volume-based cost reduction for existing Li-ion battery manufacturing may not be seen in the near future and should be kept in mind while devising strategies to incentivize and promote the adoption of electrified vehicles unless accompanied by significant improvements in the technology and the manufacturing capabilities. However, we do not account for learning effects which may result in additional cost reductions.

In the recent past, aid has been made available to some battery manufacturers in the form of federal grants. For instance, A123 systems received federal aid to the tune of around \$249 million. However, A123 systems posted losses for twelve quarters and was subsequently acquired by the Chinese company Wanxiang Group Corporation [1]. Ener1, another federal grant recipient of about \$118.5 million filed for bankruptcy earlier this year [2].

Incentives at the individual level come through the American Recovery and Reinvestment Act (ARRA) of 2009, which provides rebates for individuals who opt for certain PHEVs to alleviate to some extent the burden of the high- cost batteries. Incentives are based on the capacity of the battery installed in the vehicle as can be seen from the following excerpt:

“Section 30D provides for a credit for certain new qualified plug-in electric drive motor vehicles. The credit is equal to the sum of: (1) \$2,500, plus (2) for a vehicle which draws propulsion energy from a battery with at least 5 kilowatt hours of capacity, \$417, plus an additional \$417 for each kilowatt hour of battery capacity in excess of 5 kilowatt hours.”

-US Internal Revenue Service [3]

The findings of this dissertation with respect to the economies of scale being reached at relatively lower volumes could be one of the factors contributing towards some companies performing poorly. And if true, future investments into battery companies may not result in cost reductions beyond a certain production volume. Car manufacturer Tesla, on the other hand, who was awarded a federal loan of about \$465M was able to pay back the loan nine years ahead of schedule [4]. However, Tesla manufactures high-end cars using thousands of 18650 cells that were already being widely used commercially in laptops and other electronics. Costs of 18650 cells have come down from \$3,170/kWh in 1991 to \$200/kWh in 2011 [5]: almost a 95% drop in 20 years. While such improvements have been predicted to be likely for prismatic cells as well (NRC/NAS study), our results indicate that such reductions in cost is unlikely from volume alone without significant improvements in terms of the current state of the technology and manufacturing capabilities. Experts from the industry unanimously agreed that improvements in the next five years would be incremental and unlikely to be disruptive.

So, based on findings of this dissertation that economies of scale alone don't appear to help reduce cost beyond a relatively small production volume, and experts think that innovation won't be paradigm shifting by 2018, if policymakers want to "get over the hump" by subsidizing battery sales in order to get costs down, this will only be effective on volume grounds until about 200MWh. After that, it may be that other factors such as innovation and learning will have more influence on future costs. Previous work by Michalek et al. has shown that it may be socially more beneficial to subsidize a greater number of battery packs for HEVs and PHEV20s, given a fixed budget, than a smaller number of PHEV60s and BEV battery packs [6]. In the light of the findings from this dissertation and Michalek et al.'s findings, it seems that incentivizing smaller battery pack manufacturers to pay for the cost of capital equipment could be warranted, but that tops out at about 200MWh/year, and gains above that level will likely need to come from technology and design innovation (or possibly innovative manufacturing processes).

Furthermore, results from this dissertation have also shown how manufacturing costs may be optimized for different applications using cells of different designs, particularly by focusing on an optimal electrode coating thicknesses and cells of higher capacities. Given that economies of scale may be reached at relatively low volumes, application-specific cell designs may be one way of reducing battery pack costs by manufacturers. However, there may be issues with respect to capacity fade when thicker electrode coatings are used which have not been addressed in this work. As more information becomes available on the quantification of capacity fade resulting from thicker electrode coatings, a more informed decision on the optimal coating thickness could be made.

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Appendix A-List of abbreviations, variables, and parameter values

Abbreviations

AER	All Electric Range
ANL	Argonne National Laboratory
BDS	Battery Design Studio
BEV	Battery Electric Vehicle
DoD	Depth of Discharge
EV	Electric Vehicle
GHG	Green House Gas
HPPC	Hybrid Pulse Power Performance
LFP-G	LiFePO ₄ -Graphite
LMO-G	LiMn ₂ O ₄ -Graphite
NMC-333	LiNi _{0.33} Mn _{0.33} Co _{0.33} O ₂ -Graphite
PBCM	Process Based Cost Model
PHEV	Plug-in Hybrid Electric Vehicle
PSAT	Powertrain Systems Analysis Toolkit
SoC	State of Charge
UDDS	Urban Dynamometer Driving Cycle
USABC	United States Advanced Battery Consortium
USCAR	United States Council for Automotive Research

Variables

Variable	Description	Units
C_{TOT}^{AU}	Aggregate annual cost of production of one acceptable unit.	\$
C_{α}^{AU}	Annual cost of one acceptable unit with respect to an element α , where $\alpha \in$ (materials, labor, energy, equipment, tooling, building, and overhead)	\$
C_{TOT}^{PACK}	Aggregate annual cost of production of one acceptable battery pack.	\$
C_{α}^{ALL}	Annual cost of an element α , where $\alpha \in$ (materials, labor, energy, equipment, tooling, building, and overhead), for all units, including acceptable and unacceptable units.	\$
E_{EV-x}^{PSAT}	Minimum energy required from the battery pack of an EV-x, calculated using PSAT.	kWh
E^{PACK}	Pack energy.	kWh
E_{NMC333}^{SPEC}	Specific energy capacity of the cathode active material: NMC333	mAh/g
m_{cat}^{ACT}	Mass fraction of active material in the cathode.	-

$P_{cell}^{BDS_HPPC}$	10-sec HPPC cell power calculated using the power meta-model constructed using BDS simulations.	kW
$P_{pack}^{BDS_HPPC}$	10-sec HPPC pack power	kW
P_{EV-x}^{PSAT}	Minimum 10-sec power requirement from the battery pack for an EV-x, calculated using PSAT.	kW
V_{NMC333}^{AVG}	Average discharge voltage of NMC333	V
x^{CT}	Single side cathode coating thickness	μm
x^{BCL}	Number of bicell-layers each cell	-
x^{CW}	Width of the cathode	mm
x^N	Number of cells in a module	-
x^M	Number of modules in a pack	-
x^C	Capacity of a cell	Ah
X^{P_VOL}	Annual production volume of good and acceptable parts after all n process steps	units
$X_n^{E_VOL}$	Effective production volume of the last (n^{th}) process step.	units
$X_{i+1}^{E_VOL}$	Effective production volume of step $i+1$.	units
X^{AR}	Aspect ratio of the electrode	-
X_{ann}^{ENERGY}	Capacity of the annual number of battery packs manufactured.	kWh/year
X_{ann}^{PACKS}	Annual number of battery packs manufactured.	packs/year
$X^{P/E}$	Power-to-energy ratio of the battery pack	-
Y_i	Yield of process step i .	%
Y_n	Yield of the n th process step.	%
ρ_{cat}	Density of the cathode.	g/cc

Parameters

Parameter	Value
a	2E-9
b	2
c	149
d	0.281
g	2
b	8.98E-6
j	1.3259
k	2
l	1.6976
p	233.3
q	27.129
r	191.2

Appendix B-Additional chemistries tested using Battery Design Studio®

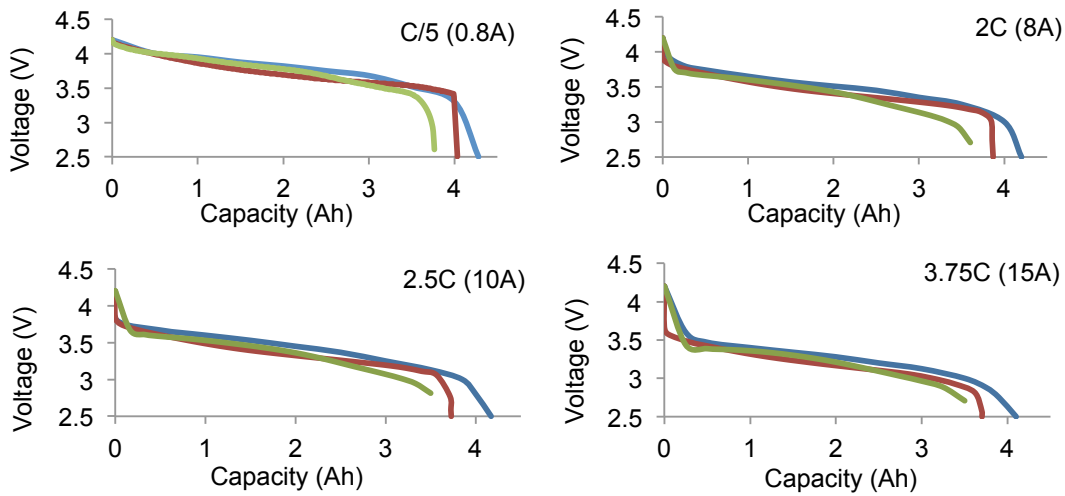
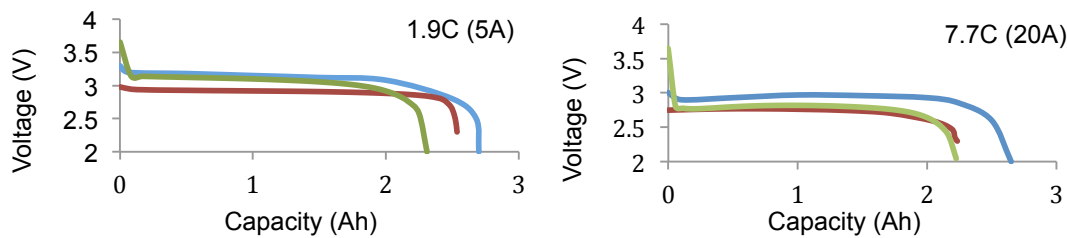


Figure B- 1: Comparison of the discharge curves at different C-rate discharges for AA Power Corporation's 4Ah LiMnNi cells. The discharge C-rates and the corresponding currents have been specified for each. The discharge rates were selected based on information in the manufacturer's data sheets to facilitate the comparison.



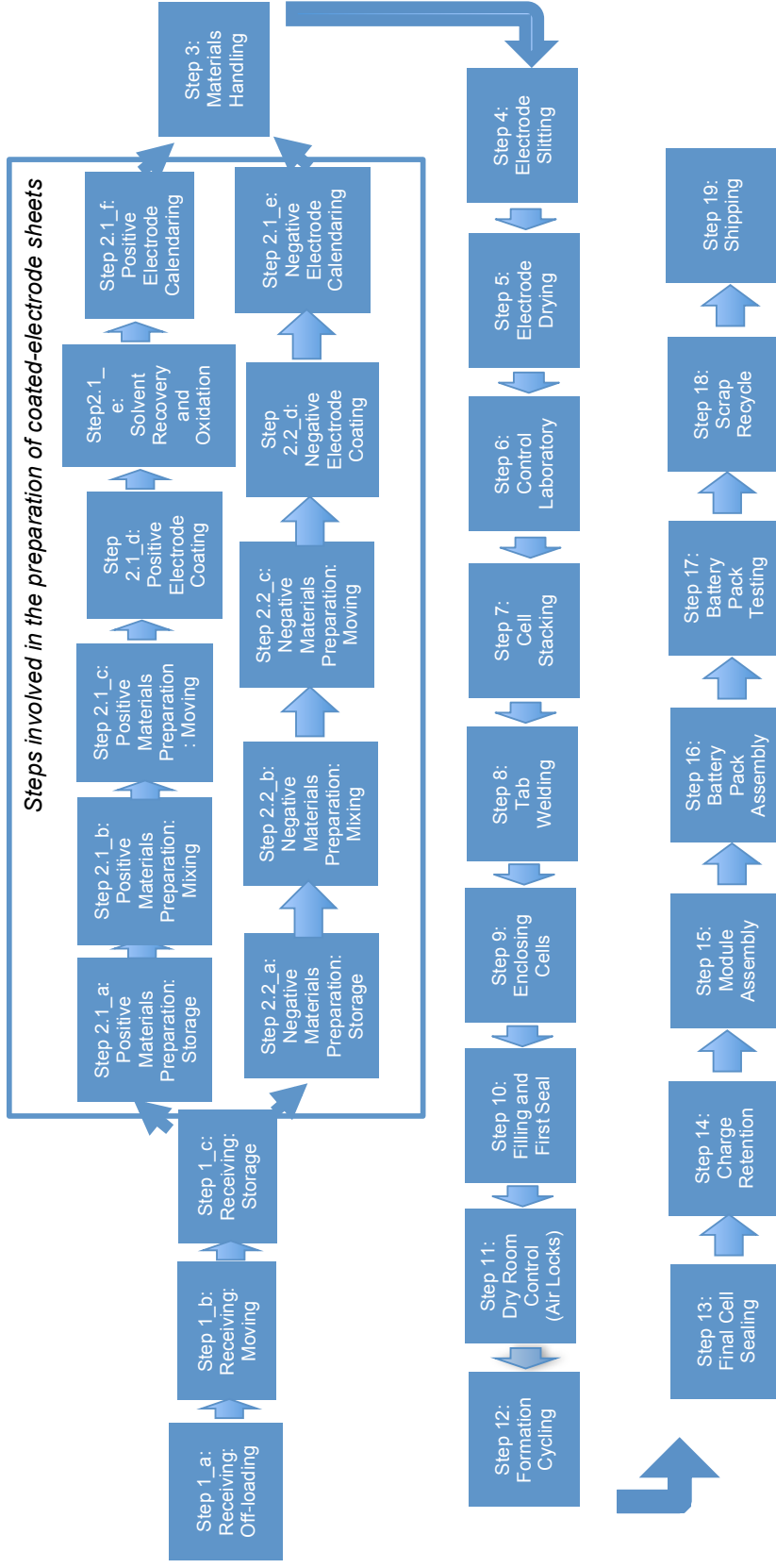
K2 Energy (obtained from AA Power Corporation) 2.6Ah LFP cells

Figure B- 2: Comparison of the discharge curves at different C-rate discharges for K2 Energy's (obtained from AA Power Corporation) LiFePO₄ cells. The discharge C-rates and the corresponding currents have been specified for each. The discharge rates were selected based on information in the manufacturer's data sheets to facilitate the comparison.

Table B- 1: The difference between the total delivered energy (Wh) calculated from integrating the discharge curves from the manufacturer, and from the laboratory as a percentage of the total delivered energy calculated from the discharge curve simulated using BDS

	Manufacturer's Specification Sheet	Laboratory Results
AA Power Corporation		
LiMnNi Cells		
C/5 (0.8A)	6.5	-5.9
2C (8A)	9.5	-7.4
2.5C (10A)	13.0	-5.7
3.75C (15A)	12.8	-4.3
K2 Energy LFP Cells		
1.9C (5A)	12.9	-4.4
7.7C (20A)	24.5	0.2

Appendix C-Li-ion battery pack manufacturing process steps



Appendix D-Li-ion battery pack manufacturing-process based cost model assumptions

Step #	Step Name	Main Machine Cost with Installation (\$)	Footprint (m^2)	Fractional Use of Labor	Processing Rate	Unplanned Downtime	Dedicated?	Notes/Comments
1_a	Receiving: Off-loading	600,000	300	1	6,667 kg/shift	20%	No	
1_b	Receiving: Moving	1,200,000	300	1	6,667 kg/shift	20%	No	
1_c	Receiving: Storage	1,800,000	300	1	6,667 kg/shift	20%	No	
2.1_a	Positive Materials Preparation: Storage	1,000,000	200	1	1,000 lit/shift	25%	Yes	
2.1_b	Positive Materials Preparation: Mixing	500,000	200	1	1,000 lit/shift	25%	Yes	
2.1_c	Positive Materials Preparation: Moving	500,000	200	0.67	1,000 lit/shift	25%	Yes	
2.1_d	Positive Electrode Coating	9,500,000	750	4	10 m/min	30%	No	Width of coater: 1.5m, Solvent evaporation rate: 11.2 s/kg, Solvent evaporation ovens: \$1,200,000
2.1_e	Solvent Recovery and Oxidation	3,000,000	225	2	212 kg/hr	20%	No	
2.1_f	Positive Electrode Calendaring	1,000,000	225	2	10 m/min	30%	No	Calendaring width: 1.5m, assumed to match the coater
2.2_a	Negative Materials Preparation: Storage	1,000,000	200	0.67	900 lit/shift	25%	Yes	
2.2_b	Negative Materials Preparation: Mixing	500,000	200	0.67	900 lit/shift	25%	Yes	
2.2_c	Negative Materials Preparation: Moving	500,000	200	0.67	900 lit/shift	25%	Yes	
2.2_d	Negative Electrode Coating	9,500,000	750	4	10 m/min	30%	No	Solvent evaporation rate: 17s/kg, Width of the coater: 1.5m, Solvent evaporation ovens: \$1,200,000
2.2_e	Negative Electrode Calendaring	1,000,000	225	1	10 m/min	30%	No	Calendaring width: 1.5m, assumed to match the coater
3	Materials Handling	1,500,000	900	4	1,135 m^2/hr	20%	No	
4	Electrode Slitting	2,000,000	300	4	1,135 m^2/hr	20%	No	
5	Electrode Drying	200,000	38	0.25	600 kg/shift	20%	Yes	
6	Control Laboratory	1,500,000	300	4	121 kWh/hr	20%	No	
7	Cell Stacking	1,000,000	150	1.25	225 bicell-layers/min	20%	Yes	
8	Tab Welding	1,000,000	150	1.25	5 cells/min	20%	Yes	
9	Enclosing Cells	750,000	150	0.75	5 cells/min	20%	Yes	
10	Filling and First Seal	1,250,000	225	1.25	5 cells/min	20%	Yes	
11	Dry Room Control (Air Locks)	20,000,000	100	2	0.03 m^2/m^2 dry room area	-	No	
12	Formation Cycling	857,143	63	0.23	See notes	20%	Yes	Batch Size: 500 cells/cycler, Cycle Time: 57,600 secs
13	Final Cell Sealing	2,000,000	450	2	15 cells/min	20%	No	
14	Charge Retention	6,333	1.2	0.004	See notes	20%	Yes	Batch Size: 500 cells, Cycle Time: 1,209,600 secs
15	Module Assembly	1,500,000	150	1.5	280 cells/hr	20%	Yes	
16	Battery Pack Assembly	1,000,000	150	1	See notes	20%	Yes	Processing rate: 6 packs/hr with 4 modules /pack
17	Battery Pack Testing	3,000,000	450	3	14 packs/hr	20%	No	
18	Scrap Recycle	2,500,000	600	5	441 kg/shift	20%	No	
19	Shipping	5,000,000	900	6	121 kWh/hr	5%	No	

Appendix E-Protocol for the Expert Elicitation

Elicitation of Expert Assessments of Current and Future Li-ion Battery Cell and Pack Costs, and Designs for Personal Vehicle Electrification

Interview Protocol

Expert: _____

Date: _____

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Outline of the Interview Protocol

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Part VIII.

Part I. Introduction

Assessments of current and future cost and performance of lithium-ion (Li-ion) batteries are scattered at best. The aim of this elicitation is to estimate the near future costs of lithium-ion batteries for different applications. We do this by first eliciting the current (2013) costs of lithium ion batteries for a PHEV-10, a PHEV-40, and a BEV-100, followed by an assessment of the costs by 2018. Subsequently, we focus on two different battery pack designs based on information available on the design of battery packs used in vehicles, currently available commercially. We will elicit information from you on improvements you foresee in their design by 2018.

Thank you for your participation.

Reference to proprietary designs

Investigators will not ask for any proprietary lithium-ion battery designs.

Report upon completion of the procedure

Upon completion of the elicitation, respondents will be provided with a report on the future costs of lithium-ion batteries. If respondents' anonymity can be protected, individual, anonymized responses from each expert will also be delivered.

Protection of respondents' anonymity

Each respondent will be assigned a number, which will then be used in the audio files and the transcriptions. Audio files will be deleted upon completion of transcription.

Part II. How will this elicitation work?

This elicitation will be conducted via Skype. The experimenter will send you part of the elicitation materials one week prior to your interview and part of it will be introduced to you during the interview. If you have any clarifying questions prior to the elicitation, please contact Apurba Sakti via email (asakti@cmu.edu).

In the following pages, we will be asking you about your expert-opinion on the current and future costs of manufacturing lithium-ion cells and packs as well as on other variables associated with li-ion battery manufacturing process for personal vehicle electrification. We'll ask you for your estimates on their present day costs as well as what you expect them to be by 2018. You are free to assume any design and we will ask you about your design assumptions. Subsequently, we will focus on two existing battery designs and ask you some design specific questions.

We will first elicit the lower bound estimate (in your judgment, what is the lowest possible value of the quantity) and then the upper bound estimate, before asking for an estimate of the 'most likely' cost, which would be your best guess. This is done to avoid some of the pitfalls of expert elicitation as discussed next. For the lower and the upper bounds and the associated range, we are interested in a 95% confidence interval.

In each of the sections, we hope to engage in substantive discussion. If you are not comfortable with a question, please do not hesitate to outline your grievances. **If you wish to interject with a note you believe to be of particular importance, please don't hesitate to do so.**

Possible issues with an elicitation of this type

Elicitations, such as these, are marred with problems of subjectivity. Experts as well as lay people show *overconfidence* while answering questions. Overconfidence means Overconfidence means that the true value of a quantity lies outside a given range for a given confidence interval more often than it should. For instance, for a range with a 98% confidence interval for a quantity, the true value of the quantity is expected to be in that range 98% of the time. If the true value lies outside of the range significantly more than 2% of the time, it indicates overconfidence.

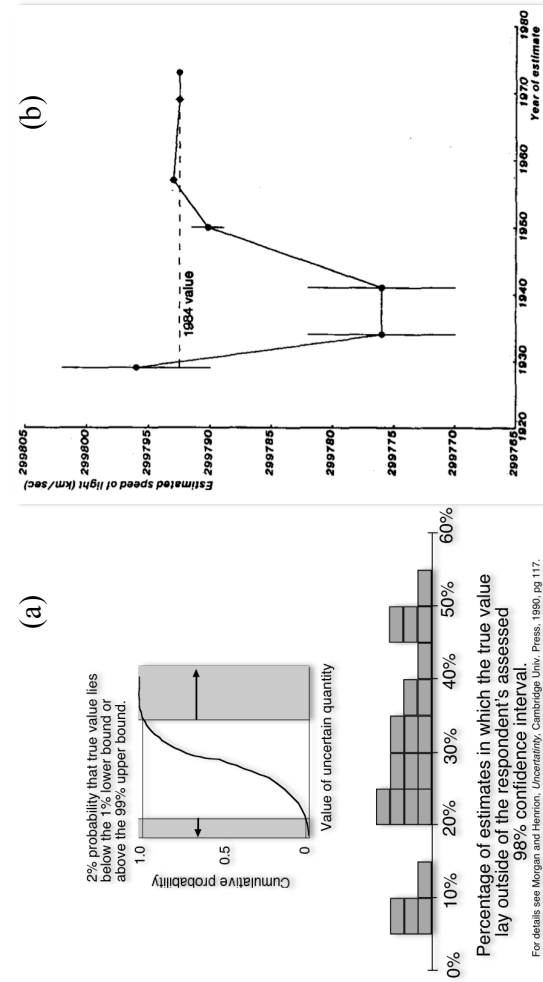
Cognitive heuristics such as *availability*, and *adjustment and anchoring* are of particular notoriety. *Availability* heuristic means that the respondent is influenced by the ease with which he or she can recall similar instances as is being asked for in the question at hand.

Adjustment and anchoring on the other hand, results in biases when the respondent starts off from an initial value and then adjusts that value to arrive at the final answer.

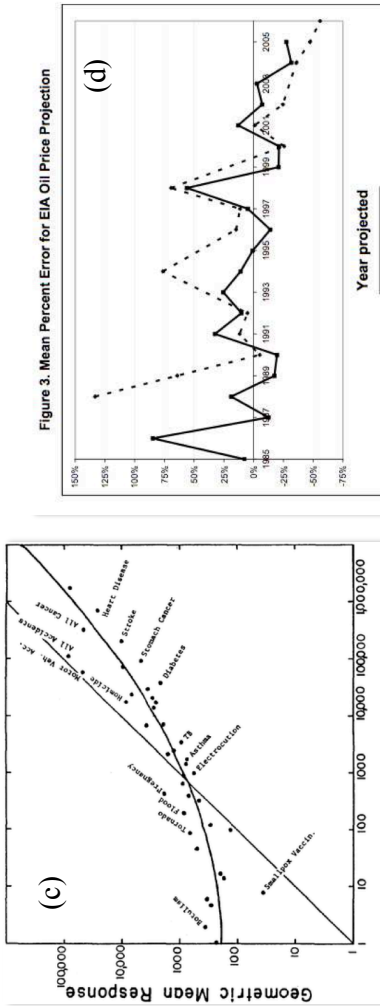
To address overconfidence, we not only elicit system level costs, but also information on the different process variables, and perform a multi-tier elicitation where the expert is allowed to revisit previous answers and modify them as the elicitation proceeds and more information is available to the expert. To address the *adjustment and anchoring* heuristic, we will first ask you for the upper and lower bounds for any quantity we elicit and then ask you for your best estimate.

In the next page we show four figures that highlight these aforesaid issues. For more information on these heuristics, please refer to *Uncertainty*, by Morgan and Henrion (1992).

Figures showing the possible issues with expert elicitation



Figures (a) and (b) Shows the problem of *overconfidence* of judgments that is often faced with elicitations. **a)** Shows the result from 21 separate studies, where well-educated people were asked to make judgments on a large number of known quantities (such as the length of the Panama Canal). 98% confidence intervals were elicited. While the percentage of times when the true value lay outside the elicited 98% confidence interval, in the perfect case, should have been 2% the figure shows the actual distribution. Each box represents a separate study, some of which had more than 1000 participants. **b)** Historical estimates of the speed of light showing the laypeople are not the only ones subject to overconfidence. (Henrion and Fischhoff, 1986) (Figure from the expert elicitation protocol in Curtright, Morgan and Keith, 2009)



Figures (c) and (d): Figures showing the heuristics of *availability*, and *adjustment and anchoring*. **c)** the availability heuristic where the occurrence of Botulism is over estimated while the occurrence of cancer underestimated due to the ease of recalling their occurrence (from Lichtenstein et al. 1978), **d)** adjustment and anchoring in EIA forecasts (from Fischer et al. RFF 2008) showing how the errors associated with the projections (both solid and dotted lines) hovers around the zero error line (Originally published in the protocol by Abdulla, Azevedo and Morgan, 2013)

Part III. Demographic Information and Expertise Level

We will now collect some basic demographic information. This information will have little bearing on our final results. We only wish to collect this information in order to highlight more accurately the sum of skills and experience we have managed to incorporate into our investigation. We also request you to provide us with a copy of your Résumé.

Title of your position:

Source of your knowledge with lithium-ion batteries:

Number of years spent in the lithium-ion battery industry:

Type of lithium-ion batteries that you have worked with:

Highest level of educational attainment:

Age:

Please indicate how you judge your level of expertise with respect to each of the following aspects:

	Not familiar with it	Only general knowledge	Highly familiar
1. Lithium-ion cell manufacturing process	0	1 2 3 4 5 6 7	
2. Lithium-ion pack manufacturing process	0	1 2 3 4 5 6 7	
3. Battery management systems	0	1 2 3 4 5 6 7	
4. Thermal management systems	0	1 2 3 4 5 6 7	

Part IV. Definitions and background information on lithium-ion battery applications under consideration in this study

For this study we are interested in lithium-ion battery cell and pack costs for three different applications: a plug-in hybrid electric vehicle (PHEV) with an all-electric range (AER) of 10 miles (**PHEV-10**), 40 miles (**PHEV-40**) and a full battery electric vehicle (**BEV**) with a 100 mile AER. We will elicit from you, the cell, and pack level manufacturing costs for each of these applications. Manufacturing costs are defined as the cost to make a complete cell or a battery pack and includes costs associated with the following: material, labor, energy, main machine and installation, building, auxiliary equipment, maintenance, and fixed overhead, in current dollars. A complete battery pack includes a battery management system and a thermal management system. You are free to assume any design that you think will be the cheapest by 2018, based on your experience.

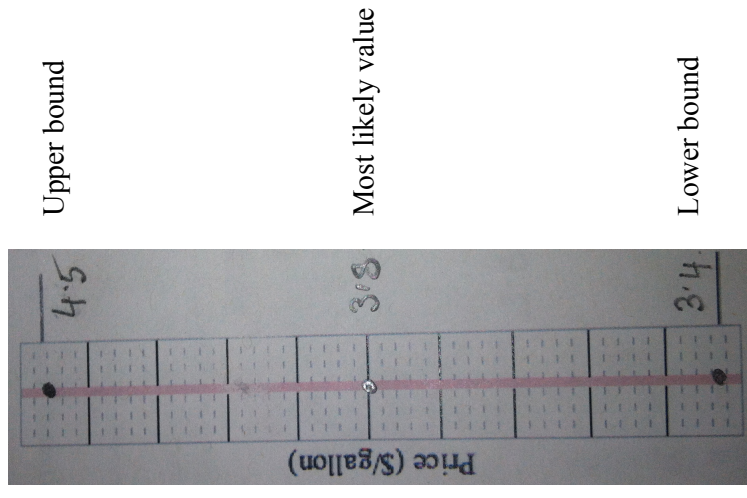
After eliciting information on the three different applications, we are also interested in looking at the near future cost and design developments of two battery pack designs based on available information on battery packs currently being used in two commercially available vehicles: an 8kWh battery pack used in the Ford C-Max Energi, and a 24kWh battery pack used in the Nissan Leaf. The design of these battery packs have been listed in detail in Part VI. Assumptions have been made wherever information was unavailable based on commonly used industry values.

Please provide all specific costs (\$/kWh) at the nameplate (or total rated capacity) level of the cell or pack, as applicable and use a 95% confidence interval for the ranges you provide us with.

Part V. Sample elicitation question for demonstration

Example: With your expert judgment, what do you expect the price of gasoline (in \$/gallon) to be in 2014?

In the following scale, please first provide us with the lower bound estimate, then the upper bound estimate, and finally the most likely value. Please provide us with a range that you expect to have a confidence interval of 95%.



Part VI-A. Eliciting cost estimates of lithium-ion batteries at the cell and pack level for a PHEV-10 in 2013 and by 2018

With your expert judgment, what is **currently (i.e., 2013)** the cost of li-ion batteries for a PHEV-10, and what is it likely to be **by 2018** at the cell, and pack level (in \$/kWh of total rated energy)?

How much of the total pack cost (in \$/pack) is contributed by the thermal and battery management systems?

PHEV-10

Cell level (\$/kWh)		Pack level (\$/kWh)		Battery Management System & Thermal Management System (\$/pack)	
2013	By 2018	2013	By 2018	2013	By 2018

☐ Do not have enough information

☐ Do not have enough information

☐ Do not have enough information

Part VI-B. Eliciting cost estimates of lithium-ion batteries at the cell and pack level for a PHEV-40 now and by 2018

With your expert judgment, what is **currently** (i.e., 2013) the cost of li-ion batteries for a PHEV-40, and what is it likely to be **by 2018** at the cell, and pack level (in \$/kWh of total rated energy)?

How much of the total pack cost (in \$/pack) is contributed by the thermal and battery management systems?

PHEV-40

Cell level (\$/kWh)		Pack level (\$/kWh)		Battery Management System & Thermal Management System (\$/pack)	
2013	By 2018	2013	By 2018	2013	By 2018

☐ Do not have enough information

☐ Do not have enough information

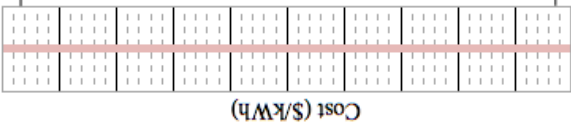
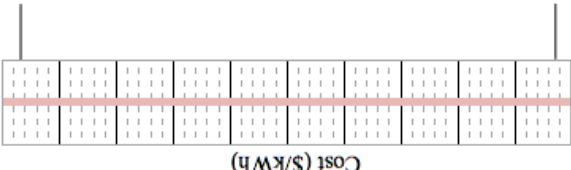
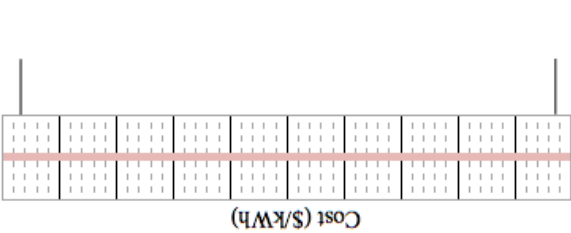
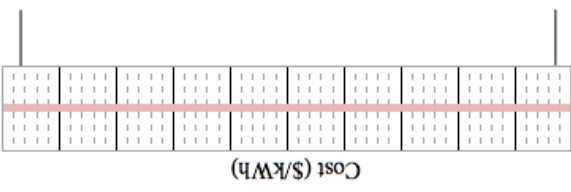
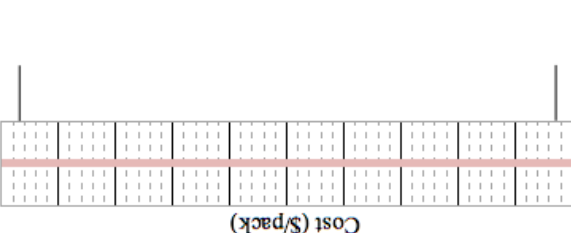
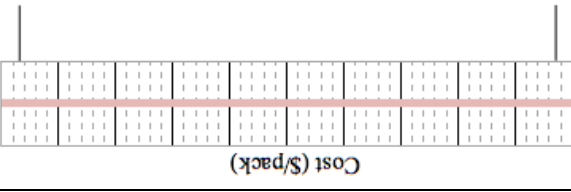
☐ Do not have enough information

Part VI-C. Eliciting cost estimates of lithium-ion batteries at the cell and pack level for a BEV-100 now and by 2018

With your expert judgment, what is **currently (i.e., 2013)** the cost of li-ion batteries for a BEV-100 today, and what is it likely to be **by 2018** at the cell, and pack level (in \$/kWh of total rated energy)?

How much of the total pack cost (in \$/pack) is contributed by the thermal and battery management systems?

BEV-100

Cell level (\$/kWh)		Pack level (\$/kWh)		Battery Management System & Thermal Management System (\$/pack)	
2013	By 2018	2013	By 2018	2013	By 2018
					

☐ Do not have enough information

☐ Do not have enough information

☐ Do not have enough information

Part VII. Design specific elicitation for near future (by 2018) developments: The designs

The following table lists the two designs that we will consider for Parts VIII to XIII. These have been selected based on the designs of battery packs currently under production for use in commercially available vehicles. Assumptions have been made and listed where information was unavailable based on existing knowledge of the industry. We are interested in the near term developments in the design of these battery packs. Items of interest, that we wish to elicit information about, have been shown in shaded boxes. The table in the following page lists some further details about the pack designs.

	Design 1	Design 2	Notes
Design reference	Ford C-Max Energi	Nissan Leaf	Selected to be representative of two different battery pack sizes.
Design reference vehicle type	PHEV-21	BEV-73	
Pack energy (kWh, total)	8	24	Data, from various sources (rounded off)
Pack power (10s, kW)	68	>90	Data, from various sources
State of charge swing window (%)	~85	~80	Data, from various sources
Cell form factor	Prismatic	Pouch	Data, from various sources
Chemistry	NMC-G	LMO-G	Data, from various sources
Cell capacity (Ah)	25	33.1	Data, from various sources
Pack cooling	Air	Air	Data, from various sources
Cathode			
Specific capacity (mAh/g)	150	100	Data, from various sources
Single side electrode coating thickness, (µm)	60	80	Assumed based on existing knowledge
Anode			
Specific capacity (mAh/g)	330	330	Data, from various sources

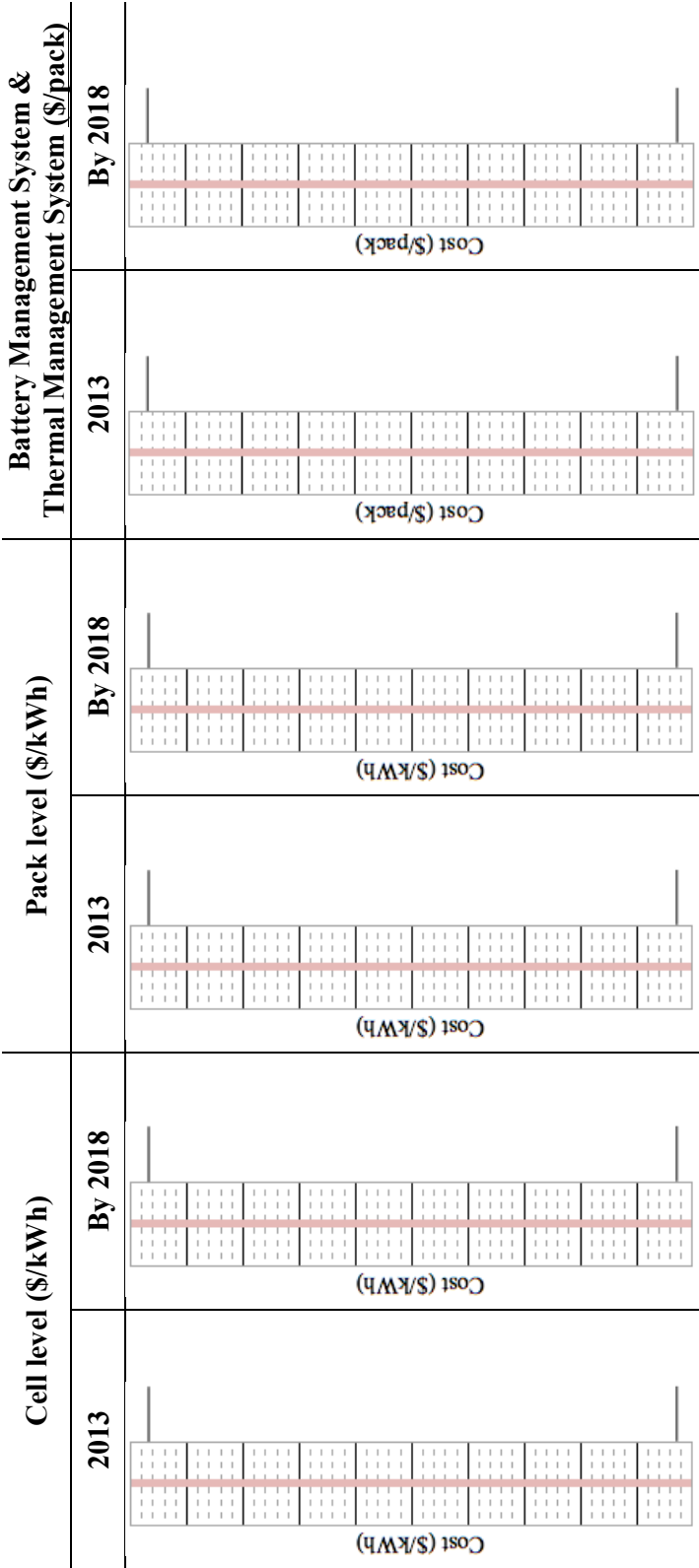
If you do not think that these designs are representative of what designs **by 2018** may be, please check the box below and provide us information on what you think the designs may be verbally or in Part XIII of this study where we ask you some open-ended questions.

☐ Designs in the table above are not representative of the main designs **by 2018**.

Part VIII-B. Eliciting current and future cost estimates of lithium-ion batteries at the cell and pack level

DESIGN 1 (8kWh pack) (similar to Ford C-Max Energi's battery pack)

What do you think is the cost of DESIGN 1 currently (i.e., 2013) and what do you expect it to be by 2018?



☐ Do not have enough information

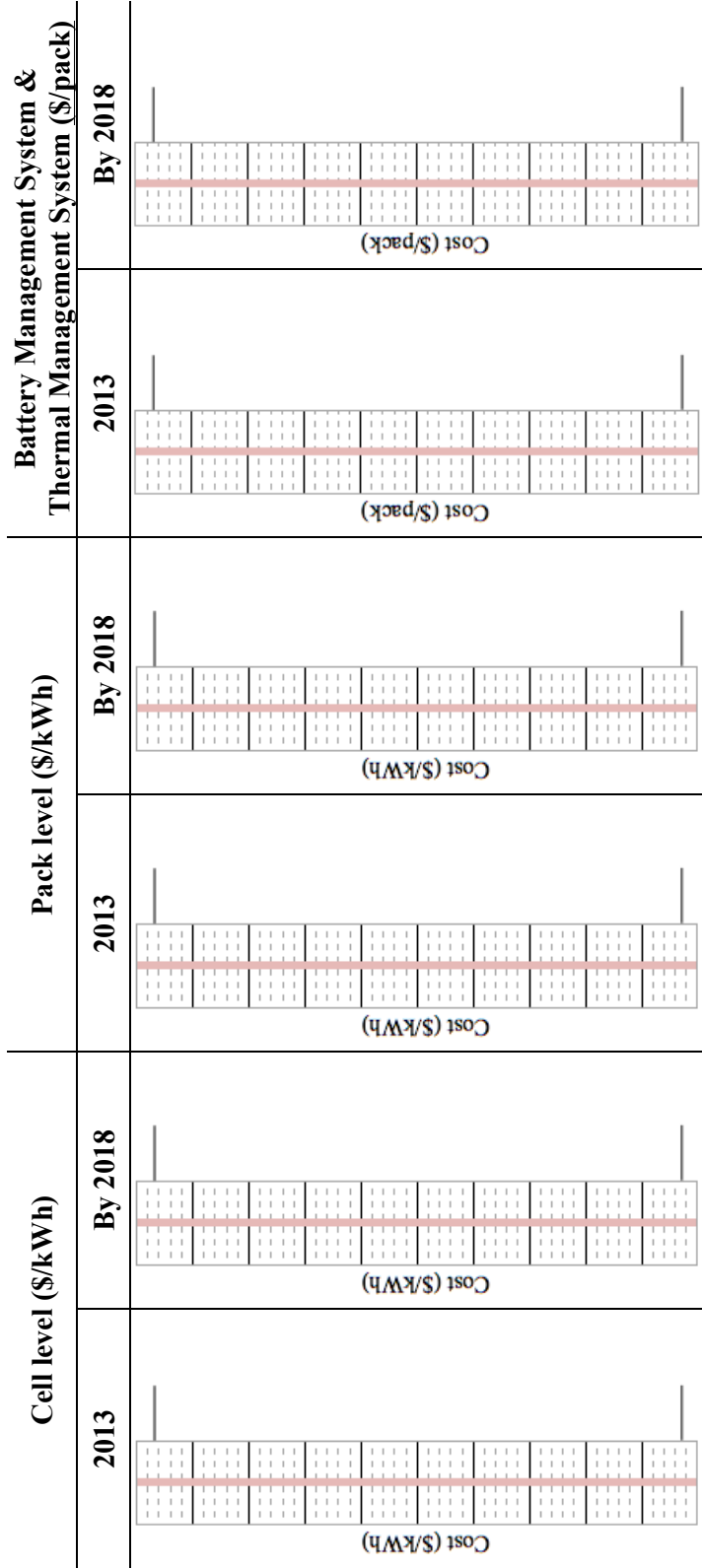
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☐ Do not have enough information

Part VIII-D. Eliciting current and future cost estimates of lithium-ion batteries at the cell and pack level

DESIGN 2 (24kWh pack) (similar to Nissan Leaf's battery pack)

What do you think is the cost of **DESIGN 2** currently (i.e., 2013) and what do you expect it to be **by 2018**?



☐ Do not have enough information

☐ Do not have enough information

☐ Do not have enough information

Elicitation of Expert Assessments of Current and Future Li-ion Battery Cell and Pack Cost and Designs for
Personal Vehicle Electrification

Interview Protocol- PART II

Expert: _____

Date: _____

Apurba Sakti

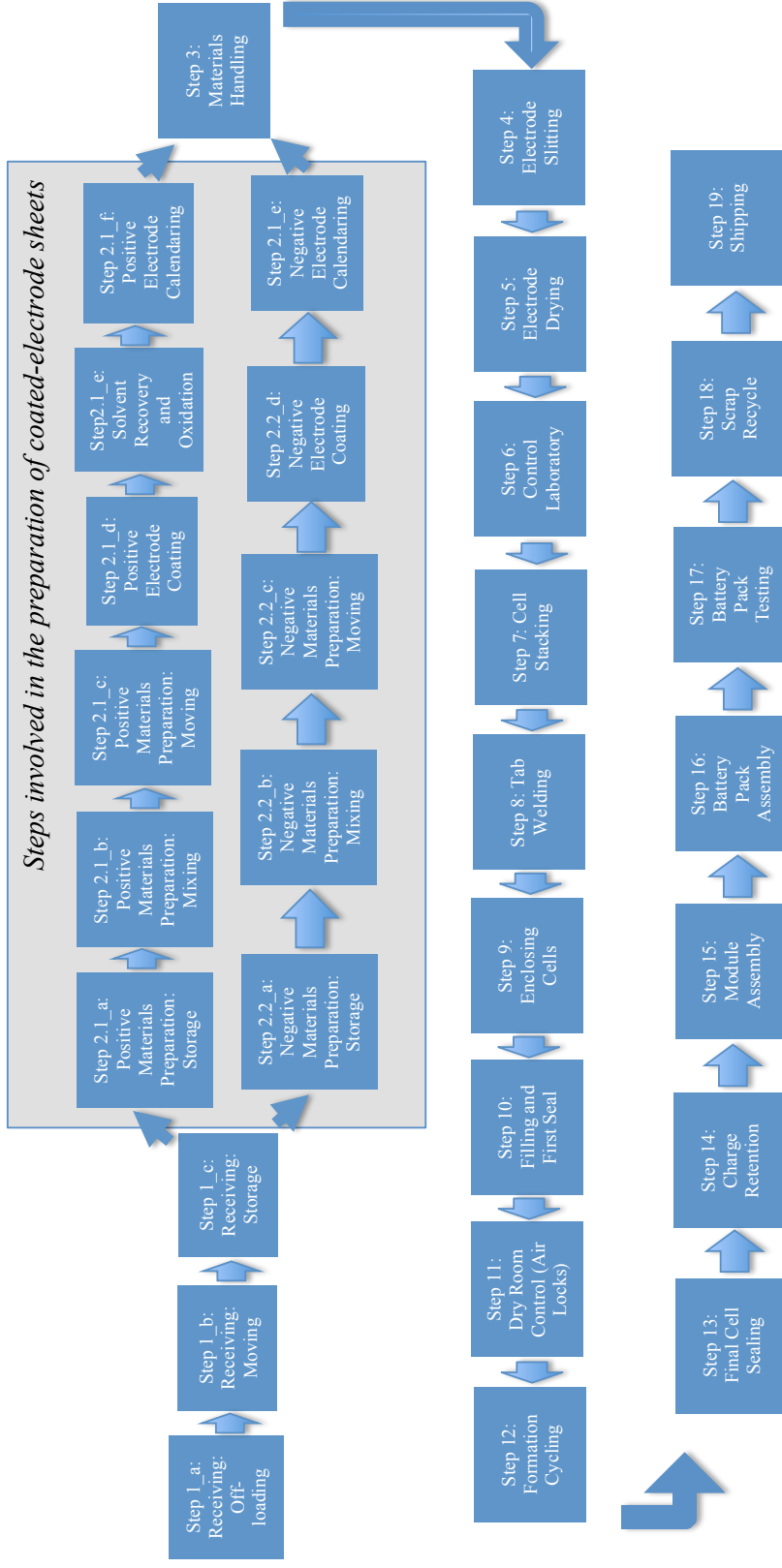
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Part IX. Flow of the steps in the manufacturing process considered in our study

The following is a flow diagram of the manufacturing process steps involved in making lithium-ion battery packs that we considered in a previous study of ours. In the following page we use this process flow to define scrap and yield rates



Part IX-A. Scrap and cumulative yield rate definitions

Scrap rates for the active materials: The scrap rate for the active material m (S_m), is defined here as the percent of positive (or negative, respectively) 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).

Mathematically,

$$S_m = 1 - \prod_{i=2.1b \text{ or } 2.2b}^7 Y_{i,m}^{\text{Material}}$$

where, $Y_{i,m}^{\text{Material}}$ is the yield of active material m in the process step i . The yield 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 $i+1$.

Cumulative yield rate (cell-level): 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 (expressed in percent) of cells entering Step 12 (shown in the figure in Part VIII above) that are confirmed at the end of Step 12 as "good cells" ($N^{\text{Cells-Good}}$).

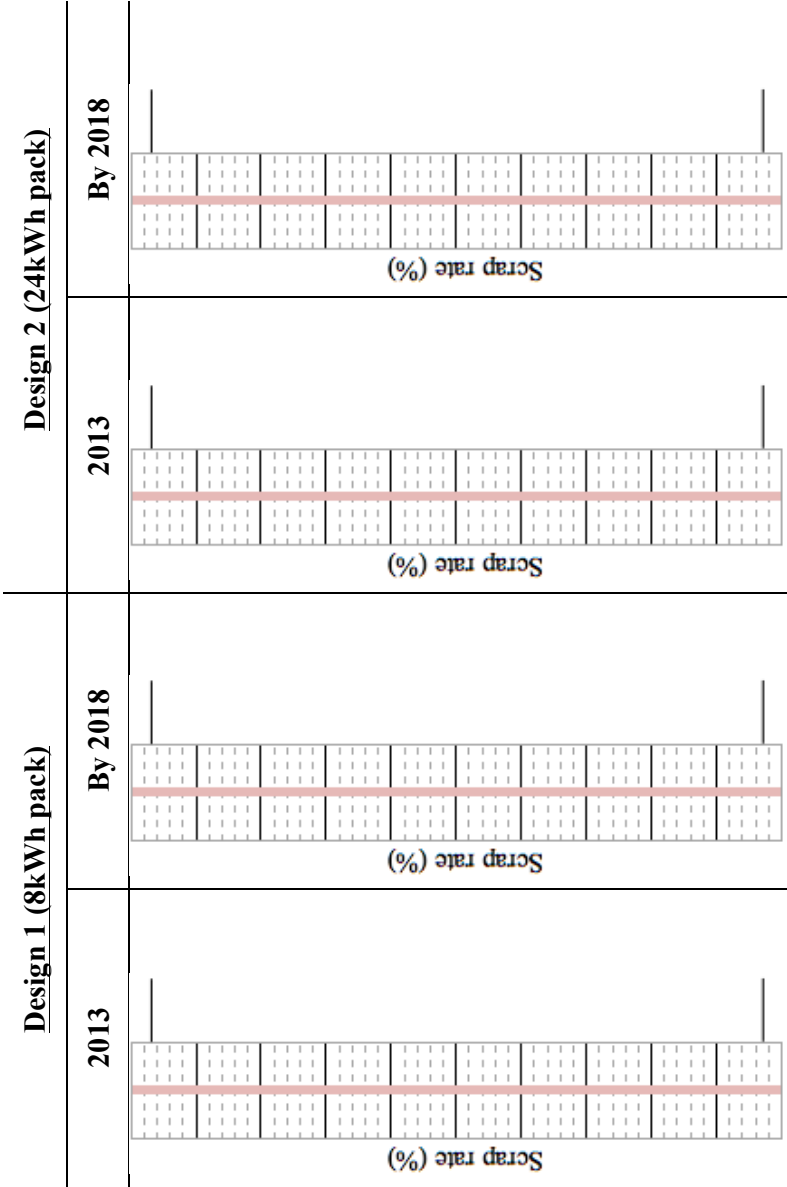
Mathematically,

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

where, $N^{\text{Cells-Total}}$ is the total number of cells entering Step 12 (shown in the figure in Part IX in the previous page).

Part X. Elicitation of the scrap rates for the active materials

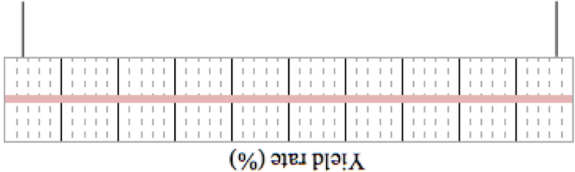
According to your knowledge, what are **currently (i.e., 2013)** the overall scrap rates for the positive and negative active materials, across all process steps in the manufacturing process, and what do you expect them to be **by 2018**? Please answer separately for the two battery designs.



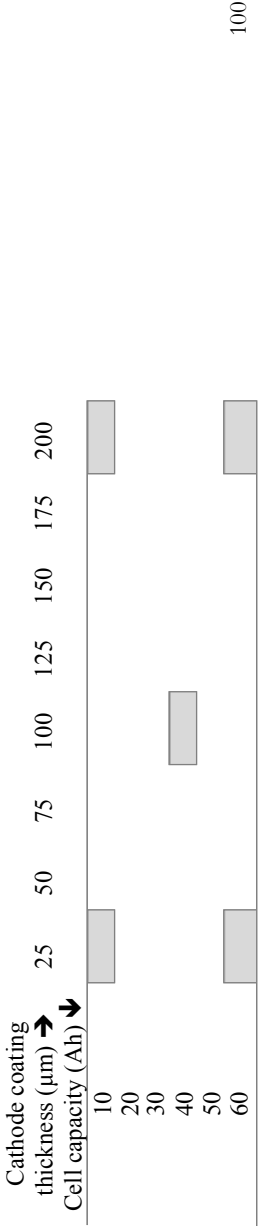
☐ I do not know enough about the process to answer this.

Part XI. Elicitation of the overall yield at the cell level

What according to your knowledge is a typical cumulative yield rate **currently** (i.e., 2013) encountered for lithium ion cell manufacturing?



Based on your experience, please provide the cumulative cell-level manufacturing yields for cells of the following coating thicknesses and capacities in the five different marked boxes that you expect **by 2018**

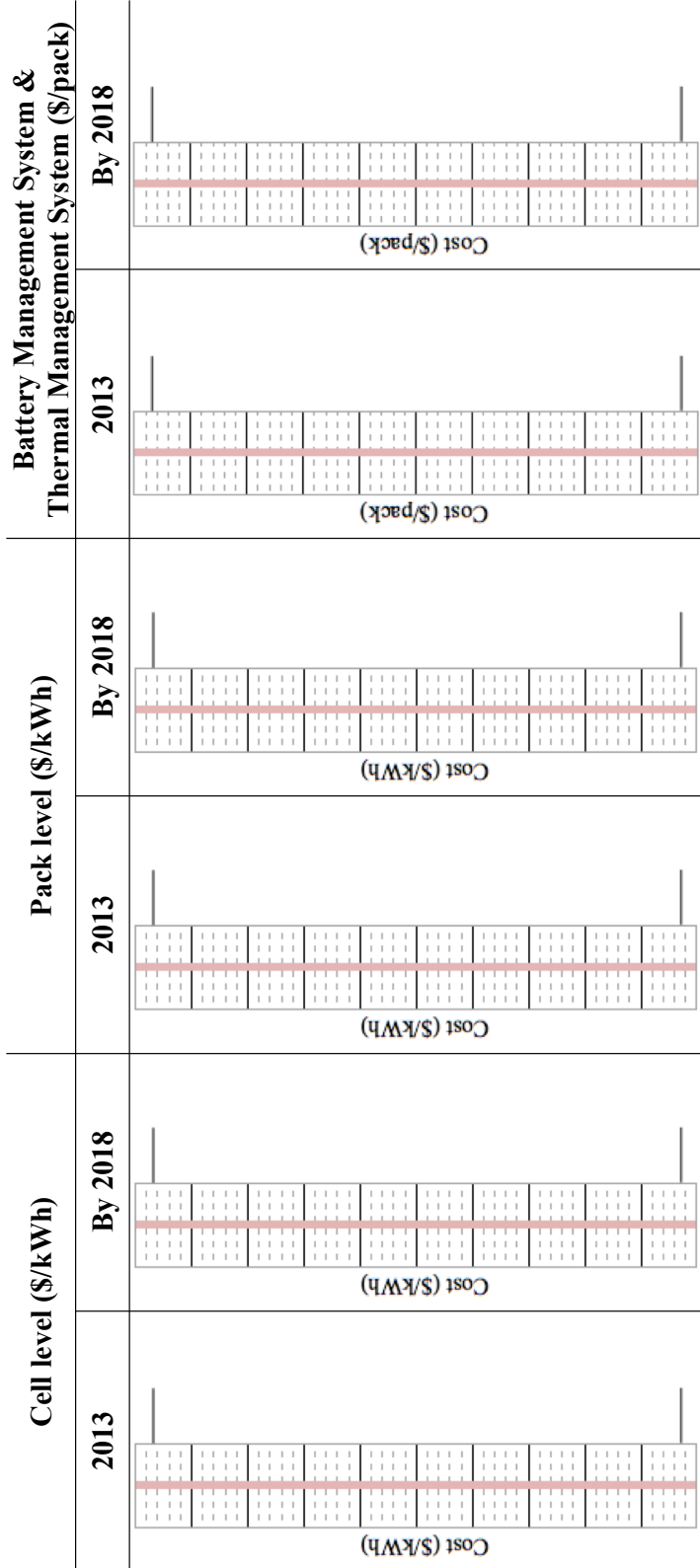


☐ I do not know enough about the process to answer this.

Part XII-A. Revisiting DESIGN 1 costs

Now that you have filled out information on the process step variables like scrap and yield rates would you like to change your previous cost estimates?

DESIGN 1 (8kWh pack) (similar to Ford C-Max Energi's battery pack)

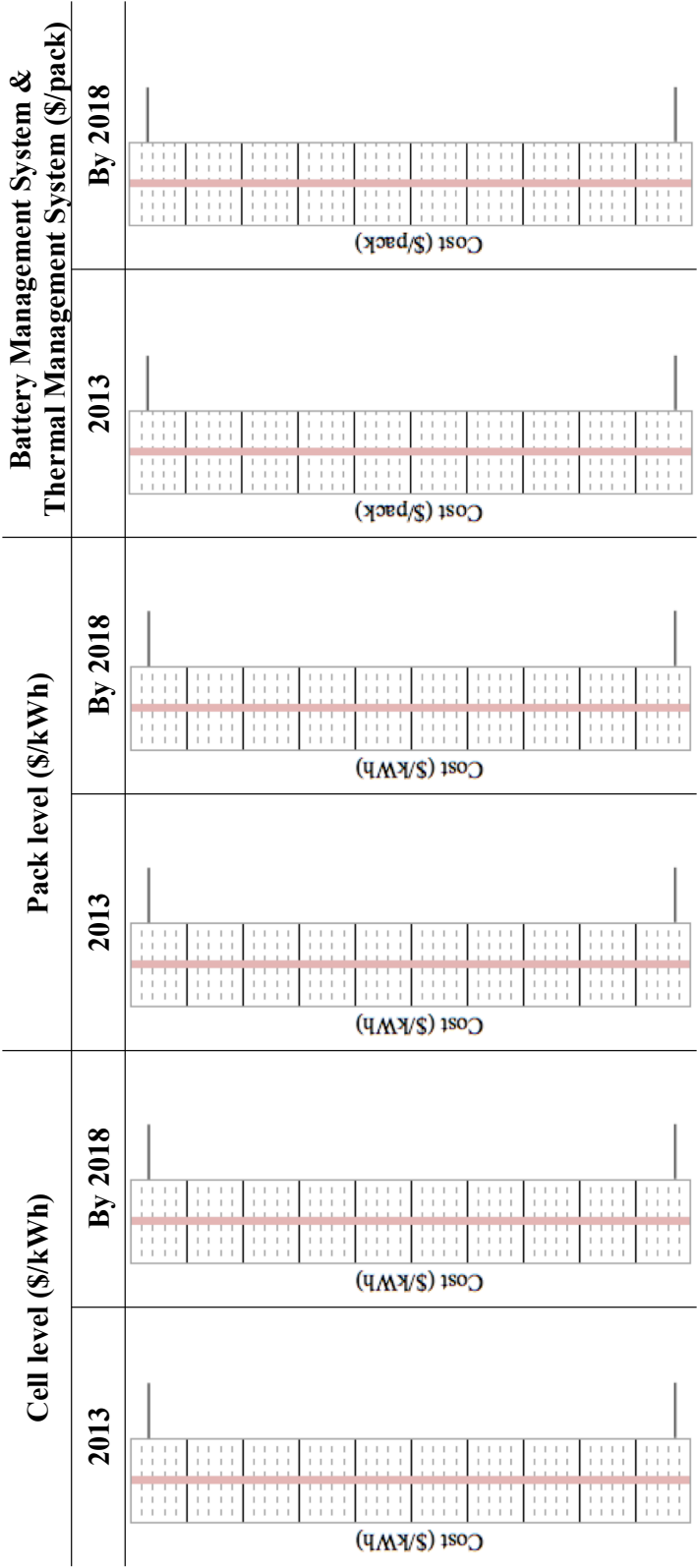


☐ No, my previous estimates remain unchanged.

Part XII-B. Revisiting DESIGN 2 costs

Now that you have filled out information on the process step variables like scrap and yield rates would you like to change your previous cost estimates?

DESIGN 2 (24kWh pack) (similar to Nissan Leaf's battery pack)



☐ No, my previous estimates remain unchanged.

Part XIII. Open-ended questions

Were the designs that we selected representative of what designs **by 2018** may be? If not, please specify.

Are there any technological breakthroughs that you foresee **by 2018** that can change things as they stand for lithium-ion batteries? If so, what are they?

What additional questions would you have liked us to ask?