EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

Predicting the Future Manufacturing Cost of Batteries for Plug-In Vehicles for the U.S. EPA 2017-2025 Light-Duty Greenhouse Gas Standards

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Summary

In developing the U.S. 2017-2025 Light-Duty Vehicle Greenhouse Gas Emissions Standards, the U.S. Environmental Protection Agency (EPA) modelled battery packs for future electrified vehicles to estimate their direct manufacturing costs through 2025. As part of the 2016 Midterm Evaluation of the standards for model years (MY) 2022 to 2025, the analysis was revised to account for developments in battery design since the 2012 rulemaking. This paper describes the methodology that was used for estimating battery capacity, power, and cost, and compares the projected cost estimates to other sources. An empirical equation is derived for specifying motor power as a function of target acceleration time, and conversion factors for converting cell-level costs to pack-level costs are developed.

Keywords: lithium battery, cost, prediction, vehicle performance, modeling

1 Introduction

The 2017-2025 Light-Duty Vehicle Greenhouse Gas Emissions Standards [1] were finalized in 2012 and represent a significant action to reduce greenhouse gas emissions. The rulemaking process included an accounting of the cost of meeting the standards. EPA studied the incremental cost of many advanced automotive technologies, including plug-in electric vehicles (PEVs) [2], [3], [4]. Because much of the cost of a plug-in vehicle is in the cost of the battery, it was necessary to develop a robust and transparent methodology for projecting battery costs for these vehicles. Battery costs have many drivers, and future projections derived by any methodology are subject to uncertainty. It is therefore important to consider the methodology and assumptions when assessing the validity of cost projections as conditions evolve over time.

At the time of the final rulemaking (FRM) in 2012, the task of specifying plug-in vehicle batteries for arbitrary combinations of vehicle size, power, and range was a difficult task. Few production vehicles were available at the time to either serve as a reference for the current state of technology or to suggest the rate of its future advancement. Our methodology therefore employed a wide variety of simplifying assumptions and estimation methods in order to conduct the effort in a practical way while using calculation tools that are easily accessible to external reviewers. This paper details the methodology by which we projected future battery performance specifications and costs for MY 2025, including key input assumptions derived from ongoing study of the emerging industry from 2012 through 2016.

2 Approach and Methodology

2.1 Structure of analysis

The battery cost analysis described here was only one component of a broader analysis that modelled the cost and effectiveness of many efficiency-improving technologies, including not only electrification but also advanced gasoline technologies and road load reduction, among others. Potential penetrations of these technologies were projected across 29 different vehicle types to demonstrate how a cost-minimizing compliant fleet could be achieved at various points in the timeframe of the rule and at what cost. The technology packages considered included several types of PEVs having various targets for range, power, and mass reduction. The battery cost analysis was one step in assigning cost to these vehicles through MY 2025.

As shown in Fig. 1, the battery cost analysis began by defining an array of PEVs for which battery packs would be specified and costed. This included five electrified vehicle types of various ranges (75-mile BEV (BEV75), BEV100, BEV200, PHEV20, and PHEV40), six baseline vehicle classes having different power and curb weight targets, and five levels of target curb weight reduction (0, 2, 7.5, 10, and 20 percent). This resulted in a total of 150 PEV instances. A battery sizing spreadsheet converted each vehicle's range target and mass-reduced curb weight to a target battery and motor power (kW) and a target gross battery capacity (kWh). The sizing spreadsheet was dynamically linked to ANL BatPaC [5], which provided specific energy (kWh/kg) estimates for use by the sizing algorithm and direct manufacturing costs for each battery pack.

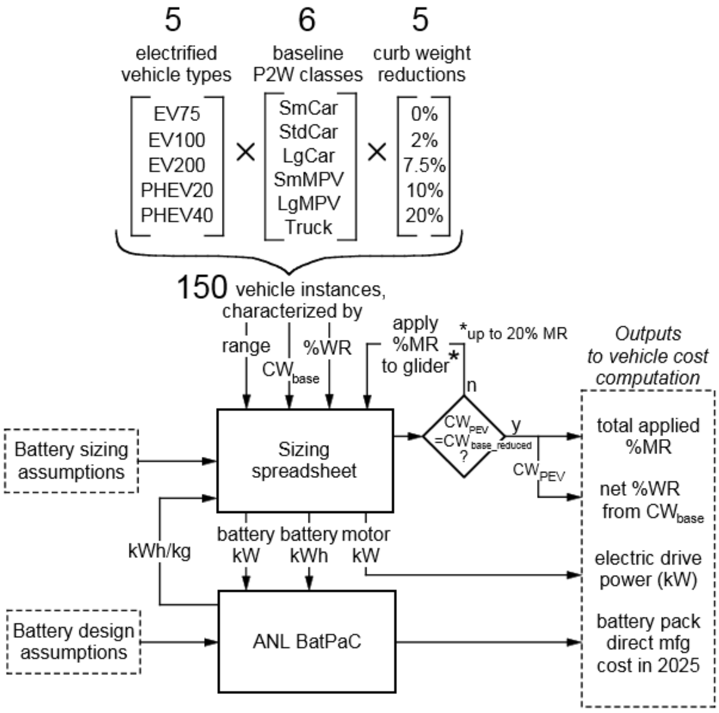

Figure 1: Analysis structure for vehicle battery sizing and cost estimation

2.2 Calculation method

2.2.1 Spreadsheet basis

The battery cost analysis is a spreadsheet-based methodology. An important first step in the analysis is to estimate battery energy capacities and power requirements for the vehicles to be modeled. Because capacity and power requirements are strongly influenced by vehicle weight, and battery weight is both a function of and a contributor to vehicle weight, sizing the battery requires an iterative solution. This problem is well suited to the iteration function available in common spreadsheet software. The use of a spreadsheet also makes the analysis easily accessible to public inspection. To this end, further detail on the choice of inputs to this analysis [3] and access to spreadsheets used in the analysis [21] are available.

2.2.2 Integration with ANL BatPaC

A core component of the methodology is BatPaC [5], a spreadsheet-based battery costing model developed by Argonne National Laboratory (ANL). BatPaC employs a rigorous, bottom-up, bill-of-materials approach to battery cost analysis. User inputs to BatPaC include performance goals (power and energy capacity), choice of battery chemistry (of several predefined chemistries), the vehicle type for which the battery is intended (HEV, PHEV, or BEV), the desired number of cells and modules and their layout in the pack, and the volume of production. BatPaC then designs the electrodes, cells, modules, and pack, and provides a complete, itemized cost breakdown. From this perspective, specifying a PEV battery pack primarily involves determining the necessary energy storage capacity (in kWh) and power capability (in kW) to provide a desired driving range and level of acceleration performance.

A basic description of the battery cost model that formed the basis of BatPaC was published in a paper presented at EVS-24 [6]. ANL later extended the model to include analysis of manufacturing costs for all types of PEVs [7]. EPA contracted an independent peer review of the BatPaC model in 2011 [8]. ANL has continued to develop the model on an ongoing basis. We used Version 3.0 of BatPac, which was provided to EPA on December 17, 2015. EPA continues to work closely with ANL to test new versions of BatPaC and to guide the development of new features.

BatPaC models stiff-pouch, laminated prismatic format cells, placed in double-seamed rigid modules. The model supports both liquid- and air-cooling, with appropriate accounting for the resultant structure, volume, cost, and heat rejection capacity. It takes into consideration the cost of capital equipment, plant area and labor for each step in the manufacturing process and places relevant limits on electrode coating thickness and other limits applicable to current and near-term manufacturing processes. It also considers annual pack production volume and economies of scale for high-volume production.

2.2.3 Basis of battery and motor power specification

An initial step was to assign targets for peak powertrain power based on desired acceleration performance. One of the most common metrics of acceleration performance is the time necessary for a vehicle to accelerate from zero to sixty miles per hour, or “0-60” time. At the time of the FRM in 2012, EPA’s annual Trends Report [20] had customarily used an equation by Malliaris et al. [9] to estimate 0-60 time as a function of the ratio of rated engine power to equivalent test weight (ETW). Because this relationship was derived from the behavior of internal combustion powertrains, we investigated its applicability to the torque-delivering behavior of electric drive by surveying the peak motor power ratings and acceleration performance of electrified vehicles present in the market between 2012 and 2016. As shown in Figure 2, comparing the empirical data for PEVs (shown by the thin orange line) to the Malliaris equation (heavy black line) showed that use of the Malliaris equation would have resulted in much higher power specification than necessary, and would have led to overestimation of the cost of the motor and the battery pack.

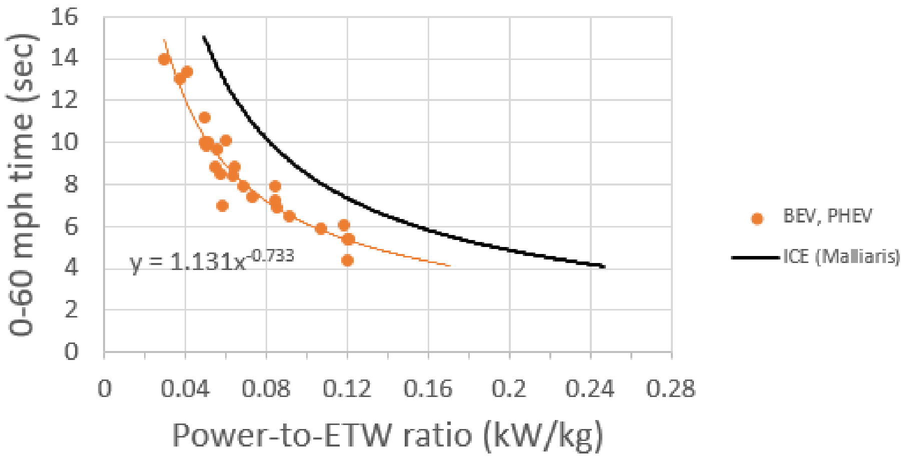

Figure 2: Relationship between peak-power-to-ETW ratio and acceleration performance for MY2012-17 PEVs

We used the empirical PEV data in Fig. 2 to derive a new equation (1) to more accurately relate the ETW and rated peak power of an electric powertrain (kW) to 0-60 time (t, in sec). While the exact relationship of rated power to acceleration would also depend on the gear ratio of the final drive, the basis of the equation on empirical data suggests that suitable ratios exist and could be chosen accordingly by the manufacturer.

$$t = 1.1321\left(\frac{kW}{kg\ ETW}\right)^{-0.733} \quad (1)$$

Motor power for each vehicle was assigned using this equation, beginning with the baseline ETW and a target 0-60 time between 8.35 and 11 seconds depending on vehicle class. As with battery capacity, motor and battery power both interact with battery and vehicle weight, and the calculation must be performed iteratively in the spreadsheet as part of the overall battery sizing process. Because PHEV20 was modeled as a blended architecture with engine assist, the motor power for these vehicles was set to half of the total required power. Battery power was derived from motor power as described later in Section 3.1.

2.2.4 Basis of battery energy capacity assignment

The next step was the specification of battery capacity needed for a given driving range. Range was modeled as a real-world, EPA-label range by applying a derating factor to an estimated 2-cycle range. For BEVs, range was considered a beginning-of-life criterion, in accordance with EPA range labeling practice. For PHEVs, however, manufacturers are likely to consider mitigating loss of electric range because it will affect the utility factor, a component in the calculation of CO_2 emissions over useful life. The PHEV sizing algorithm therefore reserves a buffer to be utilized as the battery ages, as described later in Section 3.1.

Battery capacity also depends on the vehicle energy consumption rate. This depends largely on vehicle weight, road load, component efficiencies, and other factors. To estimate energy consumption for a given PEV instance, first its curb weight was estimated as equal to the curb weight CW_{base} of the corresponding baseline conventional vehicle, modified by any applicable curb weight reduction WR_{target} (0, 2, 7.5, 10, or 20 percent), and further modified by deletion of the weight of conventional powertrain components (for BEVs) and addition of electric content (for BEVs and PHEVs), as shown in Equations (2) through (5).

$$\mathrm{WR_{target}} = \%\mathrm{WR} * \mathrm{CW_{base}} \quad (2)$$

$$\mathrm{CW_{base\_reduced}} = \mathrm{CW_{base}} - \mathrm{WR_{target}} \quad (3)$$

$$\mathrm{CW_{BEV}} = \mathrm{CW_{base\_reduced}} - \mathrm{W_{ICE\_powertrain}} + \mathrm{W_{electric\_content}} \quad (4)$$

$$\mathrm{CW_{PHEV}} = \mathrm{CW_{base\_reduced}} + \mathrm{W_{electric\_content}} \quad (5)$$

The curb weights CW_{base} of conventional baseline vehicles were assigned based on average weights for each of the 6 vehicle classes defined in the EPA baseline fleet that was generated for the broader analysis. The divisions among the classes are based in part on power-to-weight ratio and so are referred to here as “P2W class.” The P2W classes thereby establish target baseline curb weights and power requirements as inputs.

The assumed weights of the removed conventional powertrain components (called "weight delete," or $W_{ICE\_powertrain}$) varied for each of the six vehicle classes, as an approximate function of power. Electric content weight ($W_{electric\_content}$) consisted of estimated electric drive weight (motor and power electronics) and battery weight. Since the weight of this content is strongly influenced by total vehicle weight and many other variables, it is iteratively computed by the spreadsheet. Electric drive weight was based on the targets for specific power of traction motors and power electronics applicable to the 2020-2025 timeframe as published by US DRIVE [10] at 1.4 kW/kg combined. For BEVs, a gearbox weight of 50 pounds was also added.

Battery weight was computed from an estimated battery specific energy (kWh/kg). Specific energy is not a fixed value but will vary depending on the power-to-energy (P/E) ratio of the battery and its capacity. Specific energy was provided by a dynamic link to ANL BatPaC, which computes specific energy as one of its outputs.

The "raw" curb weight calculations of equations (4) and (5), if used directly, would typically generate estimated PEV curb weights that are significantly larger than the curb weights of the baseline vehicles on which they are based, because the added weight of the battery may be greater than the weight of removed components. However, the potential to save battery cost may make PEV mass reduction more cost effective. To reflect this, we chose to further constrain the iteration by forcing the projected curb weight (CW_{BEV} or

CW_{PHEV}) of each PEV to match the curb weight of the corresponding baseline vehicle ($CW_{base\_reduced}$). To do so, we solved for the percentage of mass reduction that must be applied to the glider to offset the additional curb weight. In cases where more than 20 percent mass reduction would be needed to fully offset the difference, it was capped at 20 percent and only in these cases was the curb weight of the PEV allowed to be larger than that of its baseline counterpart. The degree of applied mass reduction is tracked for each vehicle and its cost is included when estimating the total vehicle cost.

In theory, rather than constraining PEV curb weights, a similar result could have been achieved by applying the various mass reduction cases directly to the glider and allowing the curb weights to grow as they might. This would have generated a different set of mass reduction data points, with more data points representing little or no applied mass reduction. However, because we expect that manufacturers are likely to implement significant mass reduction in PEVs to save battery cost, data points representing little or no mass reduction are of limited interest. The chosen method generates a greater density of points at higher percentages of applied mass reduction that appear most likely to represent industry practice.

After determining the PEV curb weight (which in most cases was constrained to match the baseline curb weight, but now carries a specific degree of applied mass reduction in order to do so), the method then computes the loaded vehicle weight (also known as inertia weight or equivalent test weight (ETW)) by adding 300 pounds to the curb weight:

$$\mathrm{ETW}_{\mathrm{PEV}}(lb) = \mathrm{CW}_{\mathrm{PEV}}(lb) + 300 \tag{6}$$

The method then uses this test weight to develop an energy consumption estimate. First, it estimates the fuel economy (mi/gal) for a conventional light-duty vehicle of that test weight by a regression formula derived from the relationship between 2-cycle fuel economy and inertia weight. Compiled data on fuel economy vs. test weight from the EPA Trends Report [20] provided the primary data source. From this data, we derived a polynomial regression formula for fuel economy (mi/gal) as a function of ETW, as shown in equation (7).

$$FE_{conv}(mi/gal) = 0.0000005308 \times \mathrm{ETW}_{\mathrm{PEV}}{}^{2} - 0.0122335420 \times \mathrm{ETW}_{\mathrm{PEV}} + 73.4948 \tag{7}$$

This was then converted to a gross Wh/mile figure, assuming 33,700 Wh of energy per gallon of gasoline as shown in equation (8):

$$E_{gross\_FTP}(Wh/mi) = \left(\frac{1}{FE_{conv}}\right) \times 33{,}700 \tag{8}$$

This figure was then brought into electrified vehicle space by applying a series of adjustments representing assumed differences in energy losses between conventional vehicles and electrified vehicles. This required making assumptions for several powertrain efficiencies, including battery discharge efficiency, inverter and motor efficiency, transmission efficiency and other losses (such as wheel bearing, axle, and brake drag losses), and the percentage of energy delivered to the wheels that is used to overcome road loads (that is, the portion of wheel energy that is not later lost to friction braking). These efficiencies were selected based on engineering judgement and then optimized in a model calibration step so as to yield battery capacity estimates in line with the capacities seen in production PEVs of similar specifications.

PEV road loads were also adjusted relative to conventional vehicles to represent assumed reductions in aerodynamic drag and rolling resistance. PEVs were assigned a 20 percent reduction in both aerodynamic drag and rolling resistance from 2008 baseline levels. Based on simulation models used in the broader analysis, we estimated that a 20 percent reduction in each would reduce road loads to approximately 90.5 percent of baseline. The effect of reductions in curb weight were inherently represented by use of the ETW regression formula to convert curb weights into base energy consumption estimates.

The combined effect of these steps means that the estimated energy consumption of each PEV is derived from the energy consumption of a corresponding baseline conventional vehicle by applying a ratio of the road loads of the PEV ($\%Roadload_{PEV}$) to those of the baseline vehicle ($\%Roadload_{conv} = 1$) and a ratio of the assumed efficiencies (η) of the respective powertrains, as shown in equation (9).

$$E_{P/EV\_FTP}(Wh/mi) = E_{gross\_FTP} * \left(\frac{\%Roadload_{P/EV}}{\%Roadload_{conv}} * \frac{\eta_{vehicle\_conv}}{\eta_{vehicle\_P/EV}}\right) \tag{9}$$

Equation (9) yields a laboratory (unadjusted) two-cycle FTP energy consumption estimate. To represent a real-world energy consumption, the analysis applies a derating factor to convert unadjusted fuel economy to real-world fuel economy. Derating factors are discussed in a later section. Applying the derating factor (as shown with an example value of 70 percent in equation (10)) results in the PEV on-road energy consumption estimate that the method uses to determine the required battery pack capacity for the vehicle.

$$E_{onroad}(Wh/mi) = E_{P/EV\_FTP} * (\frac{1}{0.70}) \tag{10}$$

Finally, as shown by equation (11), the method determines the required battery energy capacity (BEC) as the on-road energy consumption in Wh/mile, multiplied by the desired range in miles, divided by the usable portion of the battery capacity, or usable SOC design window. The assumed usable SOC design window (*SOC%*) varied between BEVs and PHEVs and is discussed in a later section.

$$BEC(Wh) = \frac{E_{onroad}(\frac{Wh}{mi}) \times range(mi)}{SOC\%} \tag{11}$$

The iterative nature of the battery sizing problem means that all of the preceding calculations are constructed in a spreadsheet as circular references and performed iteratively by the spreadsheet software until the estimated weights, sizes, and energy consumption figures converge.

3 Selection of Primary Inputs

Fig. 1 (left of Figure) depicts the role of battery sizing assumptions and battery design assumptions in the model. Battery sizing assumptions include parameters that determine necessary battery power and capacity, such as vehicle weight, energy efficiency, usable capacity, specific energy, mass of motor and power electronics, motor power, allowances for power and capacity fade, and similar factors. Battery design assumptions include factors such as cell capacity, pack topology, cells per module, thermal medium, electrode aspect ratio and coating thickness, and manufacturing volume. These assumptions are reviewed in detail here.

3.1 Inputs influencing battery sizing

One important input to the battery sizing process is the usable SOC design window. Based on observation of existing vehicles, we chose 90 percent for BEV200 and 85 percent for other BEVs. For PHEVs, two usable SOC design windows were defined: a smaller window applicable to beginning of life (BOL) and a larger window applicable at end of life (EOL). Battery capacity was specified using the BOL figure, which effectively provides a buffer that can be utilized as the vehicle ages. PHEV20 vehicles were assigned a BOL usable SOC window of approximately 65 percent and an EOL window of 75 percent. PHEV40 was assigned a BOL window of 67 percent and an EOL window of 77 percent. These figures were chosen by engineering judgement and by considering their effect on the ability of the sizing method to reproduce battery capacities of production PHEVs.

Another important input to the battery sizing process is the required power capability of the battery. Target battery power (10s pulse) was set to 32 percent greater than the peak motor power, to account for losses in the motor (10%) and EOL power fade (20%). In the case of BEVs and many longer-range PHEVs, target capacity drove the design more than target power, such that the battery is sufficiently large that its natural power capability exceeds the target power. These batteries therefore would have enough power capability to support moderate levels of fast charging and provide a buffer against power fade.

PHEV40 was conceptualized as a range-extended electric vehicle, with a motor and battery sized to be capable of providing pure all-electric range in all driving situations. PHEV20 was modeled as a blended-operation vehicle where the motor may be assisted by the engine during the charge depletion phase. This means that PHEV40 motor power ratings in this analysis are higher than might apply to a blended-operation PHEV40. PHEVs were configured with a single propulsion motor, in contrast to some production PHEV designs that split the total power rating between two motors. Most PHEVs also include a second electric machine used primarily as a generator. The analysis does not explicitly assign a weight to this component but considers it as part of the weight of the conventional portion of the powertrain. Although a PHEV application may allow some downsizing of the conventional portion of the powertrain, the analysis did not consider potential weight reductions from this source.

The derating factor also plays a role in determining battery size. The EPA range labeling rule allows manufacturers to determine the label range value either by applying a default 70 percent derating factor to a

2-cycle range test result, or to derive a custom derating factor by an optional process. EPA certification data for MY 2012-2016 BEVs indicates that most BEV manufacturers have chosen to apply the default 70 percent derating factor in their certification tests. The same data shows that Tesla Motors has elected the optional process for its BEV200+ vehicles resulting in a factor of nearly 80 percent for the standard Model S configurations from 60 kWh to 90 kWh, and from 73 to 76 percent for higher-performance and AWD configurations of the Model S and Model X. We therefore adopted a derating factor of 75 percent for BEV200 and 70 percent for all other PEVs.

3.2 Inputs influencing battery design

We chose basic user inputs to BatPaC as follows. For performance goals, we used the power and energy requirements derived from the battery sizing analysis described in the previous section. Additional inputs include battery chemistry, cell and module layout, and production volumes. Pack voltages, electrode dimensions, cooling capacity, and cell capacity were monitored to ensure that they were consistent with current and anticipated industry practice. Warranty costs computed by BatPaC were deducted because these are accounted for elsewhere in the analysis by indirect cost multipliers (ICMs).

Chemistries were chosen due to their known characteristics and to be consistent with both publicly available information on current and near term PHEV and BEV product offerings from OEMs. We selected NMC622 for BEV and PHEV40 packs, and a blended cathode (25 percent NMC and 75 percent LMO, the BatPaC default value) for PHEV20 packs.

Pack topology for BEVs and PHEVs was optimized by choosing values for cells per module and number of modules to target a preferred cell capacity. Since the number of modules per pack must be a whole number, varying the number of cells per module allows the number of cells per pack and their capacities to be better targeted. The number of cells per module were varied between 20 and 36 as needed to achieve target pack voltages and maximum cell capacities.

BEV cells were limited to a maximum capacity of 90 A-hr. Most were significantly smaller as only the larger BEV packs approached this limit. The BMW i3 94 Ah provides an example suggesting this cell capacity can be effective in a BEV application. PHEV cells were limited to 60 A-hr. Electrode coating thickness was limited to 100 microns, which again was only approached by the largest BEV batteries. All packs were modeled with liquid glycol-water cooling. Pack voltages were limited to between approximately 300V and 400V. Electrode aspect ratio was 3:1, supported by recent developments in pack design that suggest a movement toward low-profile or “flat” floor-mounted packs. BatPaC computed costs for a range of manufacturing volumes from 50,000 to 450,000 packs per year.

4 Results

4.1 Battery sizing and cost for model year 2025

Table 1 shows projected curb weight and gross battery capacity for MY2025 vehicles for the various PEV types and P2W classes. P2W classes are distinguished by relative power and weight, with P2W Class 1 representing the smallest, least powerful vehicles. The two figures reported for each class represent the extremes of the range of values corresponding to the applied levels of weight reduction. In comparing these figures to current production vehicles, it should be noted that these future vehicles in many cases reflect improvements in road load and efficiency that may not be present in some current vehicles.

Table 2 shows the range in projected cost per kWh for each MY 2025 PEV type and P2W class at a production volume of 450,000 packs per year. It is well known that battery cost, when expressed on a cost per kWh basis, is sensitive to total pack capacity and power-to-energy (P/E) ratio. Accordingly, the costs for these packs, which are designed and costed by BatPaC, reflect these trends, with the highest cost per kWh projected for smaller PHEV20s and the lowest for larger BEV200s.

Table 1. Projected gross battery capacity for MY2025 by vehicle type, power-to-weight class, and range

	PHEV20 (25NMC/75LMO)		PHEV40 (NMC622)		BEV75 (NMC622)		BEV100 (NMC622)		BEV200 (NMC622)	
	Curb wt (lb)	Gross kWh	Curb wt (lb)	Gross kWh	Curb wt (lb)	Gross kWh	Curb wt (lb)	Gross kWh	Curb wt (lb)	Gross kWh
P2W Class 1	2571 2868	6.2 6.6	2688 2868	12.4 12.9	2295 2868	16.4 18.6	2322 2868	22.0 24.8	2506 2868	37.9 41.0
P2W Class 2	2987 3340	6.8 7.4	3137 3340	13.7 14.3	2672 3340	17.8 20.7	2703 3340	23.9 27.6	2903 3340	41.4 45.7
P2W Class 3	3231 3613	7.2 7.8	3391 3613	14.5 15.3	2891 3613	18.7 22.1	2928 3613	25.1 29.4	3138 3613	43.6 48.7
P2W Class 4	3644 4062	7.9 8.8	3851 4048	16.2 16.9	3249 4062	20.3 24.6	3292 4062	27.3 32.9	3519 4062	47.6 54.4
P2W Class 5	4377 4902	9.5 10.9	4643 4902	19.8 21.3	3934 4902	23.9 30.8	4008 4902	32.4 41.0	4325 4902	56.8 67.9

Table 2. Projected pack-level direct manufacturing costs for MY2025 by vehicle type and range ($/kWh, 2015$)

	PHEV20	PHEV40	BEV75	BEV100	BEV200
P2W Class 1	371-388	250-258	205-223	173-185	145-151
P2W Class 2	352-365	242-251	193-211	165-177	137-144
P2W Class 3	337-361	237-247	186-205	159-172	133-140
P2W Class 4	319-346	232-246	176-204	155-165	126-134
P2W Class 5	277-309	227-241	160-189	146-155	115-124

4.2 Validation of battery sizing

The effectiveness of the battery sizing methodology may be assessed by comparing the battery capacities in production vehicles to those that would be predicted by the methodology for their respective curb weights, driving ranges, and derating factors used in certification. As shown in Table 3, the methodology predicts capacities quite close to those seen in several existing BEVs.

Table 3. Comparison of projected capacities to those of selected production vehicles

Example	Range (mi)	Curb weight (lb)	Derate factor	Gross kWh	Projected gross kWh	Error
Nissan Leaf	107	3340	0.70	30	30.3	1%
Chevy Bolt	238	3580	0.70	60	61.6	3%
Model S P85D	253	4963	0.738	85	88.75	4%
Model S 60	210	4323	0.796	60	57.5	-4%
Model S 85	265	4647	0.796	85	84	-1%

One uncertainty affecting the comparison is the true usable capacity of each vehicle, as compared to our assumptions of 90 percent for BEV200 and 85 percent for other BEVs. Manufacturers do not consistently publish usable capacity and it is difficult to verify the accuracy of reported values. Another uncertainty is the true gross capacity, for which reported values may be similarly imprecise. Differences in vehicle efficiency from our assumptions may also affect the comparison.

Another perspective can be gained by looking at results in aggregate over a larger population of examples. This can be shown by normalizing the battery capacities of actual and projected vehicles to their corresponding curb weights, which removes the effect of weight differences and more clearly expresses the efficiency with which gross battery capacity is converted to label range for a given vehicle weight. In Figure 3 we compare the battery capacity per unit curb weight (kWh/kg) of comparable production BEVs against that of comparable production BEVs that were available as MY2016-17 vehicles. BEV200+ vehicles that certified for range with a derating factor different from the 75 percent that we assume in this analysis had their range adjusted in the plot to represent what their range would have been had a 75 percent factor been used. It can be seen that the battery sizing methodology predicts battery capacities for BEVs that closely follow the trend established by MY2016-2017 BEVs. Results for PHEVs were similar.

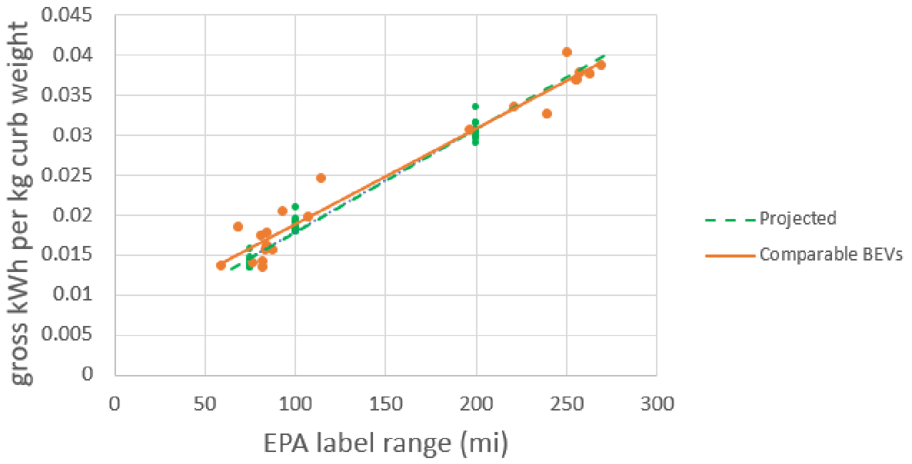

Figure 3: Projected BEV gross battery capacity per unit curb weight compared to comparable production BEVs

At shorter range points, such as BEV75, BEV100, and for PHEV20 (not shown), the projected capacity trend line runs slightly below the respective production-vehicle trend line, indicating that the methodology predicts capacities for these shorter-range vehicles that on average are somewhat smaller than found in MY2012-17 production vehicles. This is consistent with our expectation that existing shorter-range vehicles, which in the plots consist mostly of relatively low-production examples from a wide variety of manufacturers, may tend to embody a smaller degree of technology optimization than the higher-production examples from a smaller group of other manufacturers (Tesla and General Motors) that dominate the longer range points. In other words, the methodology places a slightly greater expectation of future powertrain efficiency improvement on shorter range vehicles than on longer range vehicles, relative their current state.

4.3 Validation of cost

It is important to reiterate that battery costs have many drivers and future projections are subject to uncertainty. Comparing one set of projections to those from other sources requires a full understanding of the factors considered by each source. As a first-level comparison, here we compare our projected costs to two widely reported sources that are commonly cited in similar comparisons in the literature.

4.3.1 Estimating pack costs from cell costs

One way to validate cost estimates is to compare them to examples of actual costs. Such information is rarely disclosed publicly, and is often presented in the form of cell-level costs. To compare them to the pack-level costs that we project in this analysis requires converting them to that basis using an appropriate methodology. Here we develop a basis for comparing cell costs to pack costs to facilitate such comparisons.

We collected several sources that suggest a ratio of total pack cost to constituent cell cost, or that allow such a ratio to be derived [11-17]. Further detail on our use of these sources is provided at p. 5-124 of [2]. As seen in Table 4, most of these sources suggest a ratio of about 1.25 to 1.4.

To further inform this issue, we derived pack-to-cell ratios from costs estimated by BatPaC for a pack configured similarly to that of the Chevy Bolt. The Bolt pack is 60 kWh, arranged 96S3P in 10 modules with a varying number of cells per module. Because BatPaC requires a fixed number of cells per module, we modeled 100S3P in 10 modules of 30 cells using NMC622-G chemistry at annual production of 100,000 packs and a target 10s pack power of 100 kW. Figure 4 shows the ratio of pack cost to cell cost for various pack capacities of this construction, and suggests a factor of about 1.3 would apply to a 60 kWh pack.

Table 4: Ratios of total pack cost to cell cost suggested by information in published sources

Source	Ratio
Kalhammer et al.[11]	1.24-1.4
Element Energy [12]	1.6-1.85
Konekamp [13]	1.29
USABC [14]	1.25
Tataria/Lopez [15]	1.26
Keller [16]	1.2
UBS [17]	1.32-1.44

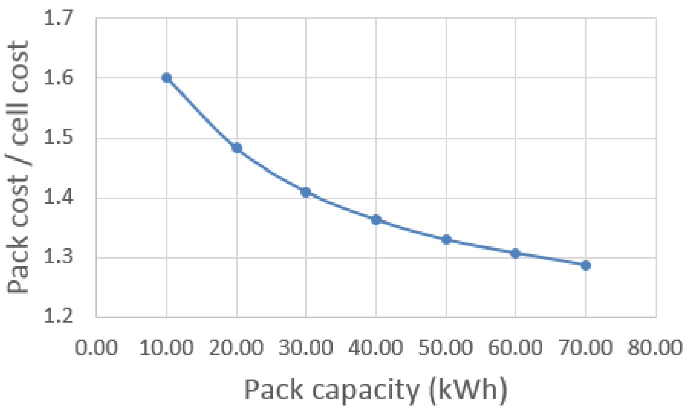

Figure 4: Ratio of pack cost to cell cost computed by BatPaC for pack topology similar to Chevy Bolt

4.3.2 Comparison of projected costs to other sources

In October 2015, General Motors publicly commented on its cell costs for the Chevy Bolt EV [19]. These costs have been widely reported in the literature and are frequently cited in comparison to future projections. GM reported a cell cost of $145 per kWh for 2015 to 2019, dropping to $120 per kWh in 2020 and to $100 per kWh in 2022. Assuming cell-to-pack factors of 1.3 and 1.5, the 2015-2019 figure would translate to $190 to $220 per kWh on a pack level, while the figures for 2020 and 2022 would translate to $156-$180 and $130-$150 per kWh, respectively. Our estimates for BEV200 pack cost, which range from approximately $120 to $150 per kWh and which we attribute to 2025, compare well to the 2022 pack-converted costs of $130-$150 per kWh.

The analysis described in this paper generated costs only for the year 2025 and only for the six P2W classes modelled. These costs acted as inputs to a downstream analysis (not described in this paper) that generated costs for intervening years by applying a reverse learning curve based on a range of production volumes, for a group of specific PEV technology packages corresponding to the 29 vehicle classes considered in the broader analysis. The yearly estimates resulting from these curves were ultimately used to project PEV vehicle costs in the broader analysis and are somewhat more conservative on a cost per kWh basis as compared to the raw 2025 costs reported in Table 2.

Figure 5 compares the yearly cost estimates for BEV200 to the pack-converted GM costs. Our estimates appear consistent with or somewhat conservative relative the trend established by the GM pack-converted cost estimates.

As a further comparison, Figure 6 plots our estimated costs for larger packs (PHEV40 to BEV200) against the survey of published future cost estimates reported by Nykvist & Nilsson [18]. Our estimated costs for these packs also lie within the range of future cost trends suggested by this survey.

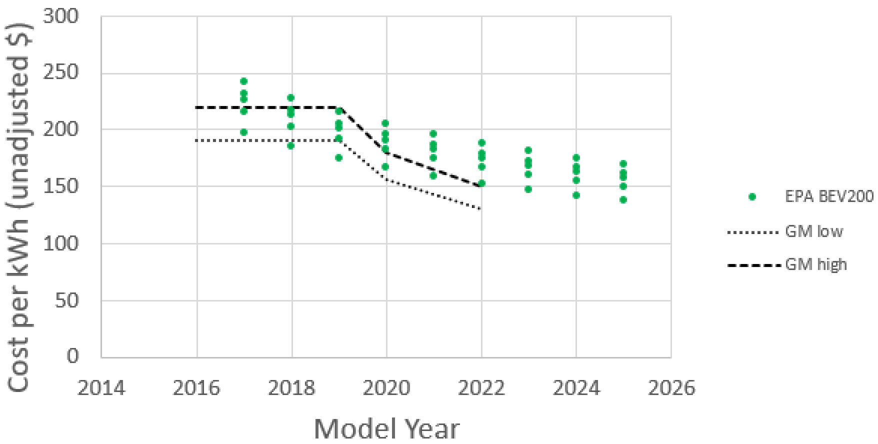

Figure 5: Comparison of Estimated Pack-Converted Chevy Bolt Costs to Post-Processed BEV200 estimates

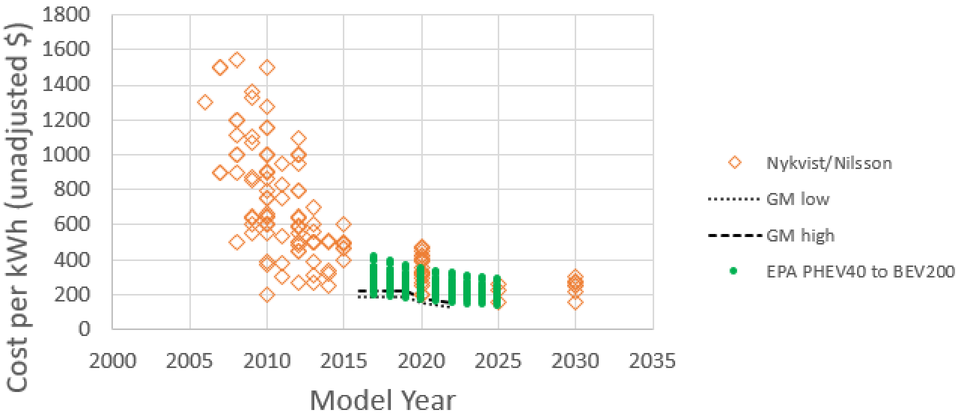

Figure 6: Comparison of Estimated Costs to Nykvist & Nilsson trends [18]

Summary

We outlined a spreadsheet-based method to project battery capacities, motor and battery power ratings, and battery costs for an array of future PEVs. A relationship between 0-60 time and electric drive motor power rating was derived from empirical data. A range of cost ratios between total pack cost and constituent cell cost was derived from published sources and BatPaC output data to assist in the comparison of cell costs to pack costs. The projected battery capacities appear to align well with trends established by production PEVs in the market. Projected costs for BEV200 appear consistent with widely cited cell costs for a production BEV, and projected costs for PHEV40 and BEVs appear consistent with trends described in the literature.

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