Learning only buys you so much: practical limits on battery price reduction

Learning only buys you so much: practical limits on battery price reduction

I-Yun Lisa Hsieh[1,+], Menghsuan Sam Pan[2,+], Yet-Ming Chiang[2], and William H. Green[1,*]

[1]Department of Chemical Engineering, Massachusetts Institute of Technology, Cambridge, MA, 02139, U.S.

[2]Department of Materials Science and Engineering, Massachusetts Institute of Technology, Cambridge, MA, 02139, U.S.

[+]These authors contribute equally

[*]whgreen@mit.edu

Highlights

- Low battery prices would facilitate transition to electro mobility.
- Essential materials costs set lower limits on electric vehicle battery prices.
- Lithium-ion NMC battery is unlikely to reach the $100/kWh price target.
- New battery chemistry is required to lower the price floor imposed by materials.

Abstract

Wide deployment of electric vehicles (EVs) would greatly facilitate global de-carbonization, but achieving the emission targets depends on future battery prices. Conventional learning curves for manufacturing costs, used in many battery projections, unrealistically predict battery prices will fall below $100/kWh by 2030, pushing EVs to hit price parity with internal combustion engine vehicles (ICEVs) in the absence of incentives. However, in reality, essential materials costs set practical lower bounds on battery prices.

Our 2-stage learning curve model projects the active material costs and NMC-based lithium-ion battery pack price with mineral and material costs as the respective price floors. The improved

model predicts NMC battery prices will fall only to about $124/kWh by 2030 – much cheaper than today, but still too expensive to truly compete with ICEVs, due primarily to the high prices of cobalt, nickel, and lithium. Our results suggest that stabilizing raw materials prices and/or stimulating R&D activities on alternative battery chemistries will be important to achieve environmentally sustainable EV-based ground transportation at an attractive price.

Keywords

Energy Science/ Battery Technology/ Energy Storage/ Energy Economics/ Electro Mobility

1. Introduction

Growing global awareness of the environmental impact of combustion is accelerating the adoption of electric vehicles (EVs), but high EV purchase prices prevent their widespread market penetration. The U.S. DOE has set a battery price target of $125/kWh by 2022 for clean transportation applications[1], suggesting that significantly lowering battery price (pack prices were $200-$300/kWh in 2016 and 2017) is a necessity to make EVs economically attractive.[2] High battery price is considered to be an important barrier to EV profitability for automakers, and $100/kWh has been estimated as a threshold for an EV to be truly cost-comparable to an internal combustion engine vehicle (ICEV).[3] Currently, EV production is mainly driven by government subsidies and mandates. The new "dual-credit scheme" mandate in China is expected to drastically increase EV adoption and correspondingly increase battery production volumes. According to the learning curve concept, as cumulative installed capacity increases, battery production costs per kWh are expected to decline as a power law owing to improved designs/manufacturing techniques and economies of scale. However, battery prices depend on both materials and manufacturing costs. Essential materials, especially expensive elements (lithium, nickel and cobalt), used in current battery technologies, will eventually constrain the declining trajectory of production cost and set practical lower bounds on battery prices.

Cobalt price, in particular, has soared over the past few years, mainly due to the projected increase in EV battery production, but also due to political factors in the world's largest cobalt producer -- Democratic Republic of Congo (DRC).[4] Even though mining companies like Glencore and ERG are exploring and developing new cobalt operations and productions, it is expected that the world cobalt supply will not keep up with the growing demand driven by EV mandates. To secure raw materials that are critical for EV batteries, GEM, a major Chinese supplier of battery chemicals, recently announced a deal with Glencore to purchase roughly one-third of its cobalt production in the next three years.[5] Further downstream, Volkswagen has recently placed $24.6 billion in battery orders with CATL, a major customer of GEM, to deliver most of the batteries for Volkswagen EVs sold to the Chinese domestic market.[6] These announcements highlight the fact that large-scale EV adoption depends on reliable supplies of battery materials and that the costs of these materials are significant.

2. Literature Review

Because battery price is a key barrier restricting EV market proliferation, several authors have modeled battery production cost reduction trajectories, typically using conventional learning curves. Learning curves are widely applied due to their advantage of depending only on two variables (cumulative production volumes and historical prices), as opposite to "bottom-up" models that require much more input parameters and data.[11] Nykvist and Nilsson reported that cost estimates for lithium ion batteries (LIBs) for EV manufacturers declined by ~14% annually between 2007 to 2014, from above $1000/kWh in 2007 to $400/kWh in 2014, with a learning rate of 6% to 9% cost reduction for each doubling of cumulative production.[7] Schmidt et al. projected future prices of 11 electrical energy storage technologies by constructing experience curves, resulting in an experience rate of 16±4% for EV LIB packs.[8] Kittner et al. conceptualized LIB costs as a function of two variables: annual production volume and cumulative patents, showing a learning rate of 16.9% for economies of scale and 2.0% decrease in prices per 100 Patent Cooperation Treaty patents.[9] Berckmans et al. predicted cost and sale prices of NMC-based batteries up to 2030 by using process-based cost modeling, which entailed individual learning curves of the material, energy, labor, and overhead costs.[10] All four of these "learning curve-based" models in the literature predict that battery prices will drop below $100/kWh by 2030, and even falling below the costs of the materials used to make them when EV's are produced in very large numbers. Conventional learning curve implicitly suggests infinite cost reductions, and thus applying it would result in too-optimistic battery price projections.

This paper, for the first time, proposes that the battery pack price should follow a 2-stage learning curve approaching a price floor dominated by the active materials costs, while the active materials costs themselves approach a price floor determined by the mineral/elemental costs. We also evaluate the techno-economic characteristics of the potential battery chemistries for EV applications, some of which are less constrained by material costs than NMC, and conclude by stating some implications of our analysis.

2. Methodology

2.1 Collection of Battery Price Data

Existing literature sometimes uses price and cost interchangeably: price paid to a battery pack supplier is a cost to the automaker purchasing the battery pack. Here, we use the term 'price' throughout this paper. The systematic review in Nykvist and Nilsson[7] serves as a key source for this paper, and we select only sources for battery packs using NMC cathodes in the references. We further incorporate new price estimates released after Ref. 7 was published, but exclude those before 2010 due to the large uncertainty in earlier price evaluations and the lack of data on total global EV battery capacity installed at that time. Price estimates are adjusted for inflation to US$ (2017) based on consumer price index data[12]. A total of 46 data points are tabulated in Table S1.

2.2 Two-Stage Learning Curve Model

Based on the battery supply chain structure (see Fig. S1), we developed a two-stage learning curve model to capture the practical limits to battery cost reduction. In the first-stage learning (material synthesis; MS), mineral costs (MinC) are considered as a floor for active materials costs (MatC); in the second-stage learning (battery pack production; BP), the active materials costs from the first-stage calculation are taken as a floor for battery pack price (BPP). The model can be found in Eq. (1) and Eq. (2).

$$\text{Stage 1: } \mathrm{MatC_t} = (\mathrm{MatC_0} - \mathrm{MinC_0})\left(\frac{V_{MS,t}}{V_{MS,0}}\right)^{b_{MS}} + \mathrm{MinC_t} \quad (1)$$

$$\text{Stage 2: } \mathrm{BPP_t} = (\mathrm{BPP_0} - \mathrm{MatC_0})\left(\frac{V_{BP,t}}{V_{BP,0}}\right)^{b_{BP}} + \mathrm{MatC_t} \quad (2)$$

By performing linear regression of the production cost and cumulative installed capacities (V_{MS} and V_{BP}), we derive learning rates (LR) for the identified two stages:

$$\text{Stage 1: } \mathrm{LR_{MS}} = 1 - 2^{b_{MS}} \quad (3)$$

$$\text{Stage 2: } \mathrm{LR_{BP}} = 1 - 2^{b_{BP}} \quad (4)$$

Details of the model parameterization are shown in SI.II. Uncertainties are reported using 95% confidence intervals based on the average (μ) and standard deviation (σ) of derived learning rates, given as $\mu \pm 2\sigma$.

2.3 Passing from Stage 1 to Stage 2 in the Model

While there are numerous different compositions of NMCs, our study focuses on four specific compositions: NMC111, NMC532, NMC622, and NMC811 (where the numbers indicate the molar ratio of Ni, Mn and Co within the cathode compounds). Increasing nickel content for higher energy density is a clear trend to satisfy the need for longer range in EV applications. This also reduces the amount of expensive cobalt required. Element requirements for a unit of energy differs across various compositions, and thus the effects of elemental prices on $/kWh active material costs are different. Therefore, different NMC variants provide the lowest material costs at different times as mineral prices fluctuate. The projected floor price for battery pack price was constructed by using the composition of NMC with the lowest projected material cost each year.

2.4 Chemical Cost of Storage and Chemical Specific Energy

Chemical cost represents a floor on the cost of the complete battery, while the chemical specific energy gives an upper bound on battery specific energy. The chemical cost and chemical specific energy for representative electrochemical couples (including electrolyte) are computed using the unit costs of the electrochemically active materials (including cathode and anode) and electrolyte, and practical capacity of active materials. Chemical specific energy is defined as the amount of energy stored in a given mass of active materials and electrolyte. Both commercially available and potential future rechargeable battery chemistries are included. Numerical values and details of the calculations are shown in SI.IV.

3. Results and Discussion

3.1 Two-Stage Learning Curve Model

One limitation of the conventional one-stage learning curve is that it implicitly suggests that cost reductions can go on forever until the cost approaches to zero. However, materials costs set a floor, which was usually ignored in the past studies of EV battery price projections using a learning curve. The mathematical model of the 2-stage learning curve is described in Eq. (1), Eq. (2), and the Supplementary Information (SI.II). Our analysis focuses on NMC-based LIBs, which are widely adopted by electric vehicle manufacturers. NMC-based LIB pack price estimates between 2010 and 2016, tabulated in Table S1, are collected from Nykvist and Nilsson[7] as well as other more recent sources. Annual battery capacity installed in EVs has grown by around 133% annually from 2010, and reached 34.5 GWh/y in 2017, with accumulated capacity of 85 GWh since the introduction of a new generation of EV batteries in 2008.[13] The learning rate, shown in Fig. 1, for active materials synthesis (LR_{MS}=3.5%) is obtained by the first-stage linear regression with the mineral cost as a floor. The second-stage fitting then depicts the learning curve of EV battery pack manufacturing (LR_{BP}=16.5±4.5%, considering uncertainty in battery price estimates) with active materials cost as a floor. Our model predicts a stronger learning effect on EV battery pack price compared to the study performed by Nykvist and Nilsson[7], but in line with more recent studies.[8,9] This suggests that our 2-stage learning curve model captures the practical limit on cost reduction and structure of the battery supply chain without sacrificing learning rate estimations. The price floors determined by materials costs play an insignificant role in historical battery prices “learning” as the materials costs accounts for only marginal amount of the total battery prices. However, as discussed below, when battery prices continue to fall in the future, the materials costs become much more important, and set practical lower bounds on battery prices.

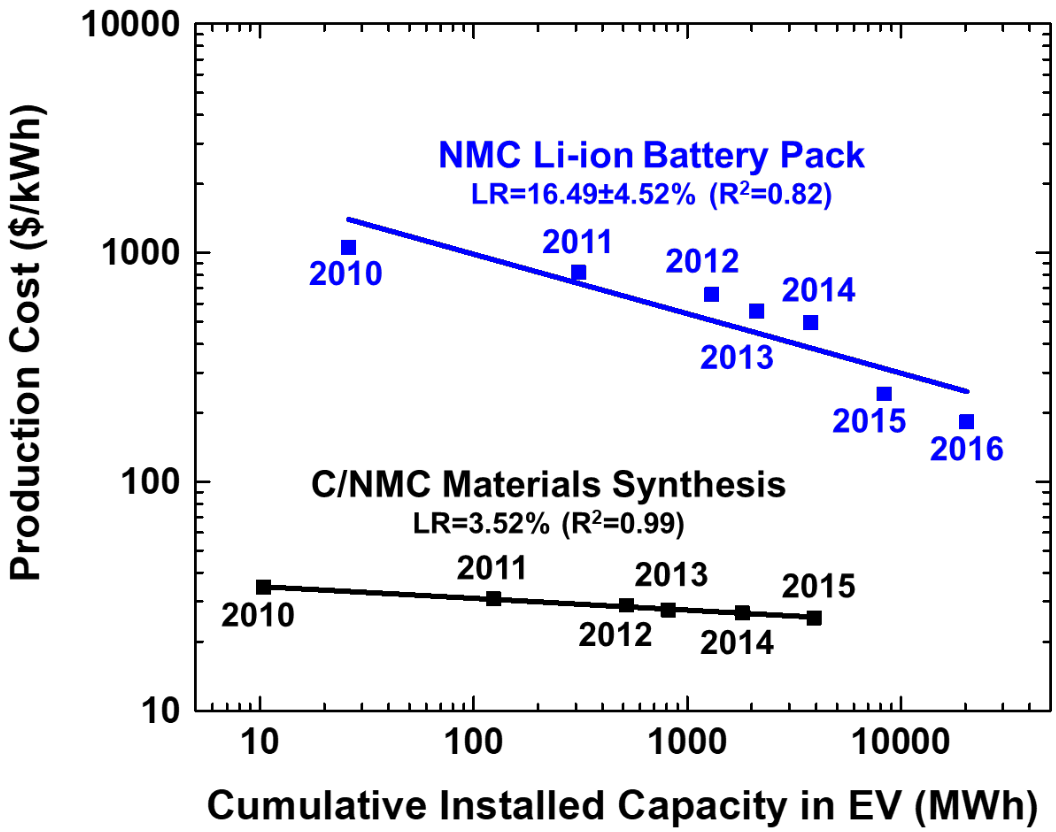

Figure 1. Two-stage learning curve model: materials synthesis and battery pack production. Learning rate (LR) is calculated by linear regression of the log of production costs and the log of estimated cumulative capacity installed, as shown in equation (1) and equation (2). Production costs during material synthesis and battery pack production are obtained by subtracting mineral costs from active materials costs, and the active materials costs from battery pack prices, respectively, see details in SI. II. NMC111 is chosen as representative for the learning rate of C/NMC material synthesis.

3.2 Future Projection for EV Battery Pack Prices

To project the future trajectory for battery prices, battery production volume and elemental costs are evaluated. Driven by strong government support, sales of new energy vehicles (NEV, including pure battery electric cars (BEVs), plug-in hybrids (PHEVs) and fuel cell models) in China rapidly grew in the past few years.[14] China has been the leading nation in total EV (BEV plus PHEV) sales since 2015, accounting for approximately50% of EVs sold worldwide in 2017, and reaching over four times the BEV sales volume of the U.S in 2017.[15] The introduction of the dual-credit system in 2017[16] further shows China's commitment to speeding up clean vehicle development and its ambitions to boost local NEV adoption. Because China dominates the EV market, it is chosen as a main driving force for global future EV market penetration. EV market penetration in China is described by fitting a Gompertz function, as shown in Fig. 2, to the historical sales market share, taken from Global EV Outlook 2017[17], and the future targets set by China's government (7% in 2020, 15% in 20205, and 40% in 2030).[18] By incorporating a China-specific passenger car ownership and sales model[19] with the derived EV penetration curve, we obtain the predicted electric passenger car sales in China between 2018 and 2030. The shifting from less expensive $LiFePO_4$ (LFP) to higher specific energy NMC in China is also considered here.[20] The detailed assumptions and methodology for battery production volumes are included in SI.III-1, and the estimated equivalent installed capacity in China and in the world toward 2030 is shown in Fig. 2.

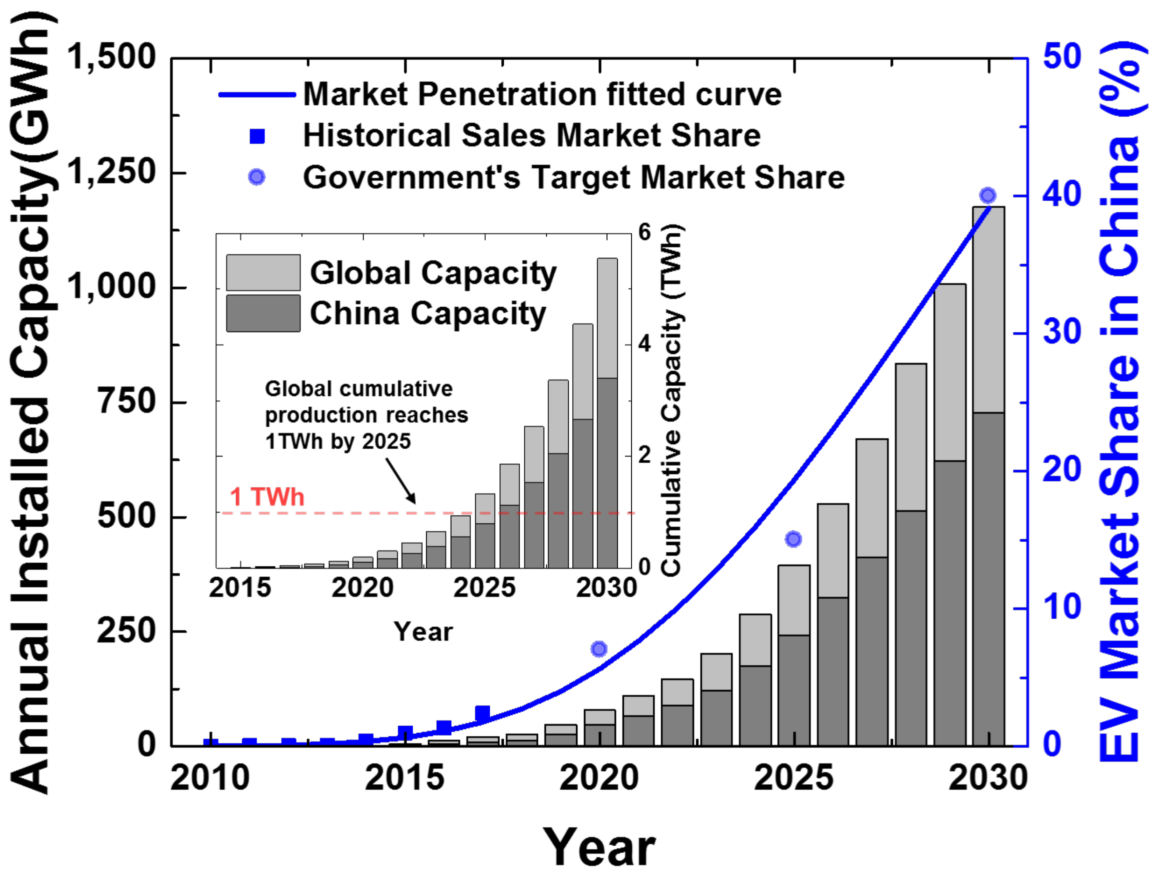

Figure 2. Projected annual NMC batteries installed capacity based on the EV sales market share in China; the inset shows the projected cumulative installed capacity, both in China and global market. Projected EV market penetration in China from fitting a Gompertz function to the historical EV sales market share and the government's targets for 2020, 2025 and 2030. Global EV production is estimated by assuming that China keeps dominating the EVs sales toward 2030.

Lithium and cobalt are experiencing price fluctuations as automakers and high-tech companies rush to lock down the supplies of critical battery materials. Lithium's price has steadily increased by about $1.9/kg/y annually for the past 7 years.[21] Cobalt's price on the London Metal Exchange (LME) surpassed $90,000/tonne in March 2018, up from $25,000/tonne in early 2016.[22] To obtain a reasonable cobalt price projection as a base case scenario, we exclude price surges that resulted from specific political events and linearly extrapolate the resulting moderately growing cobalt price trajectory in 2017, shown in Fig. S3. Given the volatility of cobalt prices, active materials costs across multiple compositions in the NMC class could have various positive or negative slopes as cobalt's price increases or decreases, depicted in Fig. S4. The model then takes the lowest active materials cost curve as a price floor for battery price projections. Our projections generally show a shift toward Ni-rich compounds with higher specific capacity and less use of the expensive cobalt in the future. SI.III details the cobalt price extrapolation and NMC composition selection by the model as the determining the floor price, followed by the battery price projections under various scenarios.

Fig. 3 depicts the projected battery pack price reductions over time along with active materials costs and mineral costs as EV technologies diffuse through the market. The downward inflection in mineral costs around 2022 corresponds to the widespread adoption of NMC811 replacing other NMC compositions. Note that the active materials costs *increase* over time; this is because the growth in mineral costs outweighs the cost benefits of greater learning in materials synthesis processes. However, strong learning effects in battery manufacturing nonetheless continue to drive total battery pack price reductions over time, approaching ~$124/kWh in 2030 in the base case, and ranging between $93/kWh to $140/kWh depending on price projections for lithium, cobalt, and nickel. The lower bound can only be reached by assuming fixed 2016 prices for the minerals, quite unlikely since the cobalt price has more than tripled since 2016. The base case value reported here is slightly lower than the bottom-up projections of NMC-based Li-ion battery pack price (~$130/kWh for Graphite/NMC622 couple) given by the US Dept of Energy Vehicle Technologies Office[23], this is because Graphite/NMC811 couple (with less usage of expensive cobalt) is expected to dominate the 2030 EVs battery market. Fig. 4 investigates the effects of mineral price fluctuations on battery pack price forecasts in 2030, showing that the cobalt commodity market greatly affects the projected battery pack price, and thus the adoption rate of EVs. The lowest and the highest price projections toward 2030 in Fig. 3 and 4 are discussed in detail in SI.III-4 as scenario 1 and 2. Overall, the unknown price trajectory of minerals leads to an uncertainty of ±$25/kWh in the battery pack price in 2030.

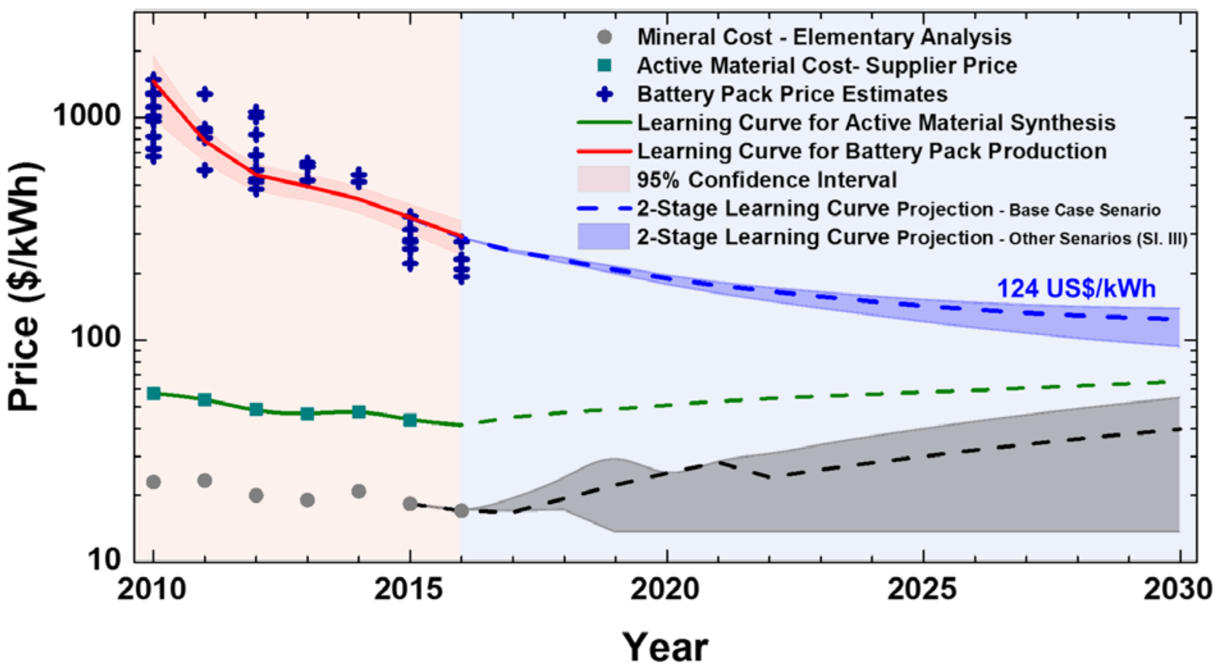

Figure 3. Past and projected price trajectory of NMC Li-ion battery pack from our 2-stage learning curve model. Base case scenario is shown in blue dash line, which approaches $124/kWh in 2030, while the light-blue shaded region represents the price range resulted from different projections of elemental costs (shown in grey shaded region). The lower bound and the upper bound of the light-blue shaded region are described as scenario 1 and scenario 2 in SI. III-4.

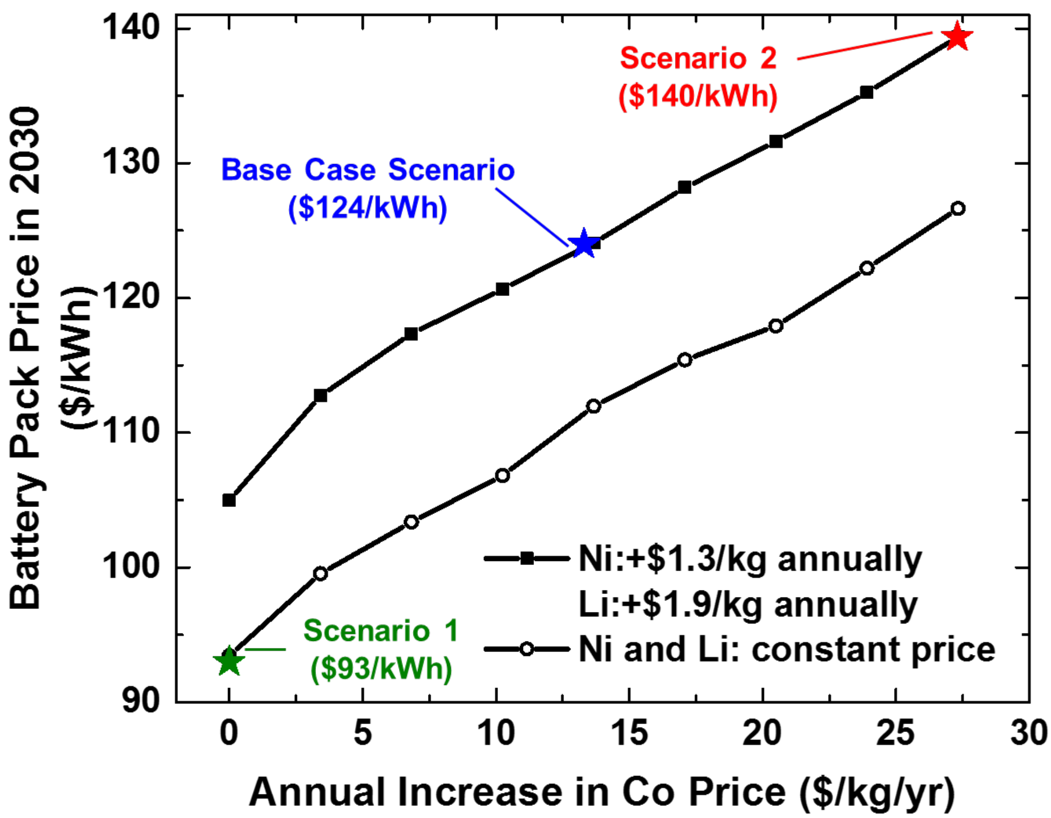

Figure 4. The effect of cobalt price fluctuations on predicted battery pack price in 2030. The base case scenario assumes that the price of cobalt will increase moderately by $13.3/kg per year after 2016; Scenario 1 infers that cobalt price keeps constant after 2016 while Scenario 2 supposes that cobalt price will annually increase by $27.3/kg.

3.3 Comparison with Existing Models

Plugging in the global EV production volumes implied by the aggressive EV targets set by China and other countries, the published "learning curve-based" models for EV battery pack price (Refs. 1-4) predict that battery pack price would fall asymptotically towards zero, falling below $100/kWh before or around 2030. Fig. 5 plots the base case scenario of our 2-stage learning analysis (blue line) which accounts for the fact that mineral costs set a floor on the price, in comparison with projections made by previous publications (circles) as well as the price projections by existing "learning curve-based" models (dashed lines) using the price data tabulated in Table S1 and capacity volume presented in Fig. 2. The conventional learning curve, also described in SI.III-1, predicts a $77/kWh battery pack price in 2030, which is 38% lower than our base case scenario. Nykvist and Nilsson[7] estimated a 8% annual price reduction probable in the future, which implies that battery pack prices would be $102/kWh in 2030 and $94/kWh in 2031. Schmidt et al.[8] predicted battery price will be around $150/kWh when the cumulative installed capacity reaches 1 TWh with no timeline specified. With our assumption of China's EV market serving as a major driving force, the global cumulative production of 1 TWh would be achieved by 2025, and that year our 2-stage learning curve model predicts a price of $143/kWh, a value consistent with that of Schmidt et al. However, if starting from $150/kWh in 2025, the experience curve model presented by Schmidt et al. would predict battery prices to drop to $106/kWh in 2030 with our production volume projection. Kittner et al.[9] estimated much lower EV battery pack price in 2015 and forecasted the price would go down to $124/kWh in 2020, just 2 years from now. By applying their two-factor learning curve model to our production volume forecasts, and following their assumption on patent activity, the battery price would fall to $33/kWh in 2030, even below our projection for active materials cost. Berckmans et al.[10] developed a process-based cost model decoupling battery costs into 4 individual learning curves (each going to zero) and predicted NMC battery pack prices of $75/kWh in 2030. Adopting their reported model parameters for 2015 with our projected production volume results in a much lower forecast of $46/kWh in 2030, less than our projected materials cost as well. In Fig. 5, we also include the projection from Bloomberg New Energy Finance (BNEF) that LIB pack prices would fall to \$73/kWh in 2030.[24]

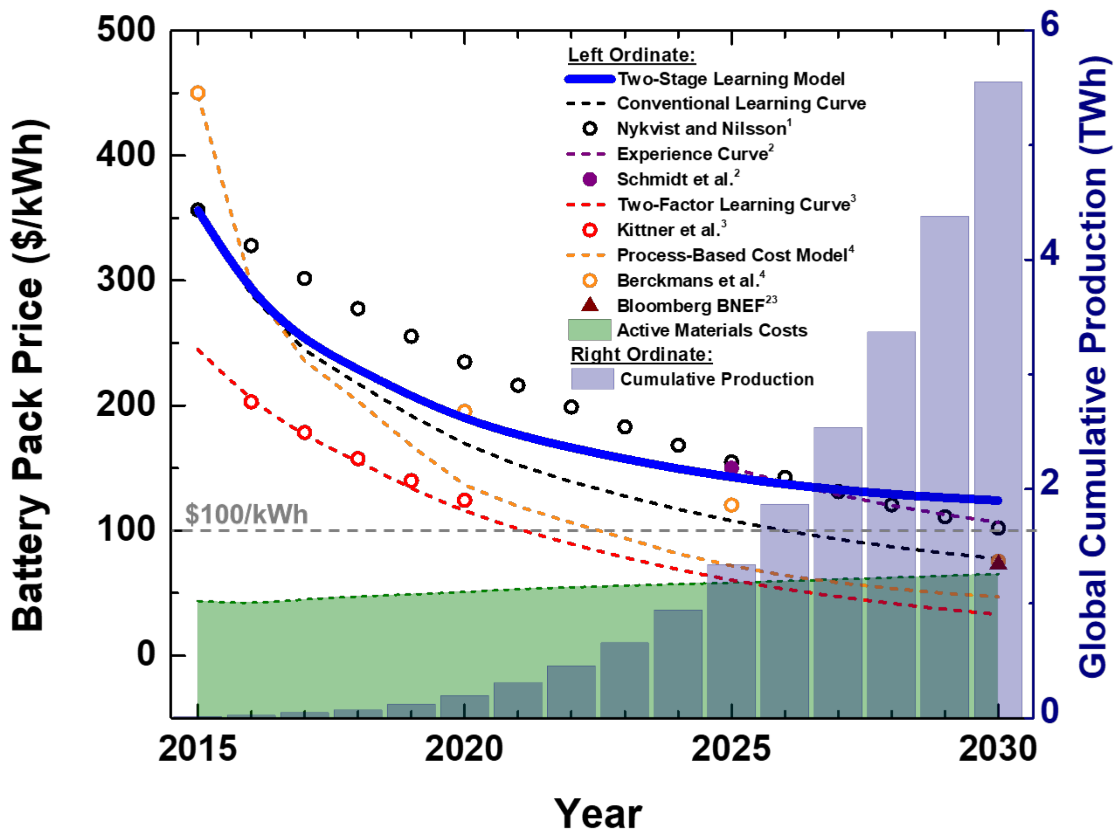

Figure 5. Comparison of battery pack price projections among various existing models. Blue line represents the projection from two-stage learning curve model presented in this study (base case scenario); black dash line is the conventional learning curve which is widely applied in previous studies; red and orange dash lines come from applying two-factor learning curve model proposed by Kittner et al. and process-based cost model developed by Berckmans et al. respectively to the projected production volume. Predicted prices from Refs. 1-4 using their projections of production volumes are shown in circles. The BNEF's

estimated 2030 price is marked in dark red triangle. \$100/kWh is considered the point where EV can compete with ICEV without subsidy. Active materials cost (base case scenario) is also shown in the figure (shaded green region) to emphasize its growing contribution to battery pack price. Our analysis suggests NMC battery pack prices are unlikely to drop as low as \$100/kWh, disagreeing with models which ignore material costs.

According to our 2-stage learning curve model, the battery price reduction will significantly slow down around 2025-30. This is due to the growing contribution of active material costs. The projected battery pack price breakdowns over time in the base case scenario are shown in Fig. 6, these emphasize the significant role that the active materials cost plays. The active materials cost corresponded to only 12% of the total battery price in 2015 (Fig 6(a)), making the projections from our model and the previous "learning curve-based" models (Refs. 1-4) close to each other in the short term. However, as active materials contribute more (about half of battery pack price in 2030 in our base case), the projected trajectories deviate as our model recognizes the practical limits on cost reductions missed in the models published previously. By comparing Fig. 6(b) and Fig. 6(c), NMC-based LIB essential elements (cobalt, nickel and lithium) and material synthesis cost are increasingly important in battery pack price contribution toward the future. In our base case scenario, total mineral costs and active materials synthesis costs comprise up to 32% and 21% of total battery pack price in 2030, starting from 5% and 7% in 2015, respectively. The former is driven by the increasing mineral prices, while material synthesis, a well-established technology, has a much lower learning rate of 3.5% when compared to that of EV battery pack production. The summation of these two costs determines a price floor of active materials costs for NMC-based LIB packs. As shown in Fig. 5, some of the existing models would predict battery pack prices in 2030 approaching or even below this floor price, which is highly unlikely. These models in prior works omitted considerations of battery market supply-chain structure and price floor governed by the materials cost in battery price projections. This results in an unrealistic underestimation (by up to 73%) of future battery pack price for NMC-based LIBs.

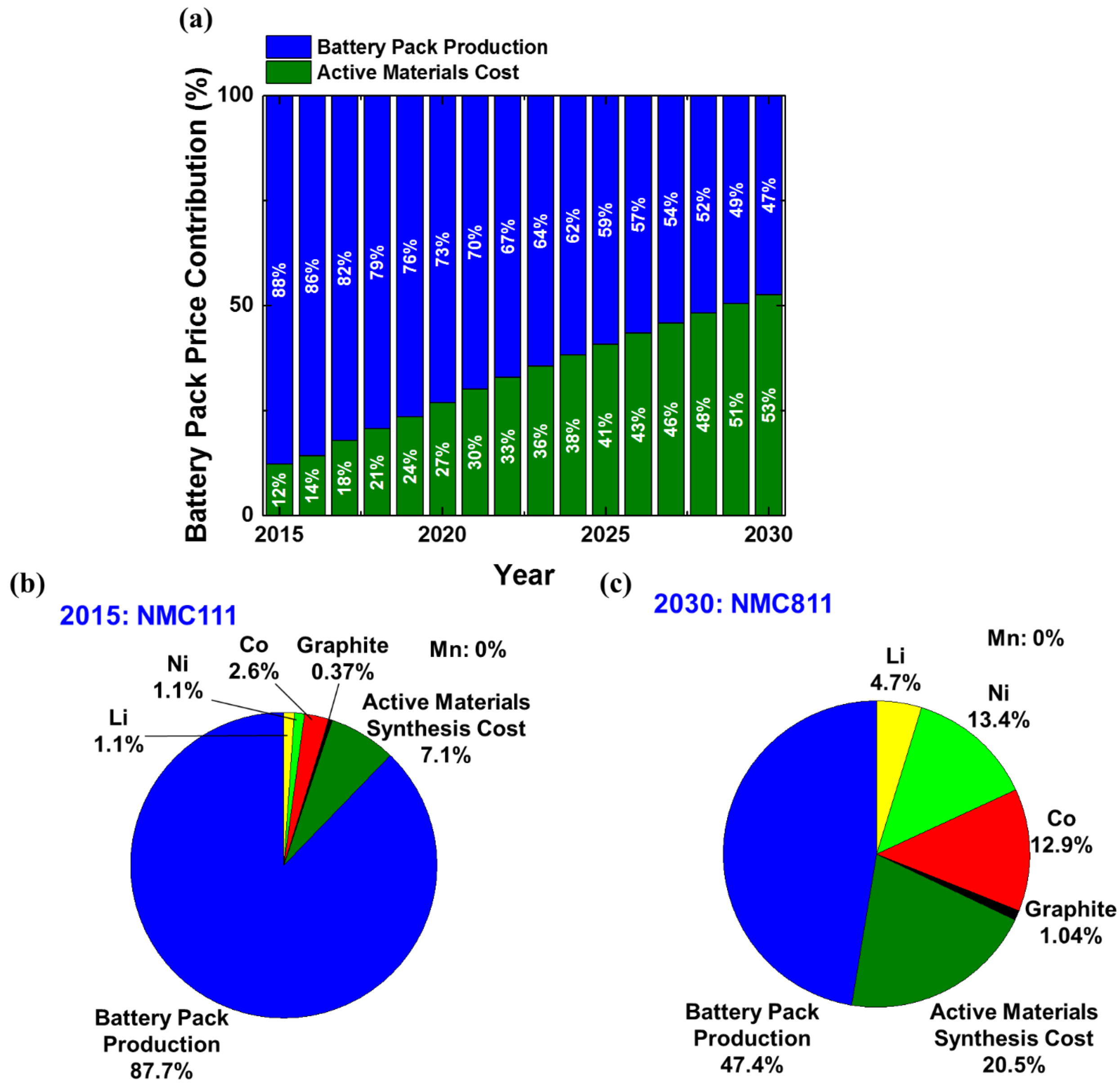

Figure 6. Battery pack price breakdowns using two-stage learning curve model (this work) in the base case scenario: (a) 2015-2030 battery pack price contribution over time of battery pack production and active materials cost; (b) and (c) 2015/ 2030 battery pack price

breakdowns among elemental prices, active materials synthesis cost and battery pack production when NMC111/ NMC811 provides lowest synthesis cost for battery pack producers, respectively. Note that in both (b) and (c), the contribution of Mn is negligible.

3.4 Promising Electrochemical Couples for EV Battery

Our battery pack price projection suggests that the current dominant NMC-based LIBs are unlikely to achieve the price targets required for widespread EV adoption. To achieve these targets, batteries made of less expensive minerals will be required. Therefore, we evaluate current techno-economic performances of emerging battery chemistries proposed for EV application. Adapting the methodology of Li et al.[25], chemical cost of storage and chemical specific energy for 24 representative and promising electrochemical couples for EV applications are calculated and shown in Fig. 7. "Chemical", here, includes cathode-active material, anode-active material, and electrolyte. Closed symbols represent commercially available batteries, while open symbols are chemistries under development. The numerical results in Fig. 7, calculation methods, and reference sources are shown in Table S3 and in SI.IV. Commercial LIBs, denoted as closed black squares in Fig. 7, currently dominate the battery market. China's EV battery producers, who previously focused on less expensive $LiFePO_4$ (LFP) for their cathode active material, are now also shifting towards higher specific energy $LiNi_xMn_yCo_{1-x-y}O_2$ (NMC).[20] Two main materials approaches are identified to reduce the chemical costs and enhance the energy density of LIBs. Ni-rich NMC provides higher specific capacity by enhancing the ratio of extractable Li, illustrated in Fig. S12, and thus higher specific energy. Currently, LIB using NMC811 ($57.2/kWh) incurs a higher chemical cost than that of NMC111 ($53.6/kWh), NMC532 ($56.1/kWh), or NMC622 ($52.8/kWh) due to lower technology maturity, but this is expected to reverse with continued development. Such shift toward Ni-rich NMC is also captured in our 2-stage learning curve as discussed earlier. LIBs with NMC111, NMC532, and NMC622 are already commercial realities, while NMC811 will join them in the near future. On the other hand, Li-rich intercalation compounds such as $0.3Li_2MnO_3$-$0.7LiMn_{0.5}Ni_{0.5}O_2$ (LRMO-LNMO) enhance the specific capacity by increasing the number of Li per transition metal atom. Another potential pathway receiving significant attention is the lithium metal battery, which replaces a graphite anode with Li metal foil (assuming 50% Li utilization here). Other widely recognized candidates for EVs including Na-ion, multivalent-based, and Li-sulfur batteries are also included in Fig. 7. Most notably, the Li-S battery, utilizing a conversion cathode capable of storing multiple electrons per host atom, can provide >1,500 Wh/kg_{c+e} at a very low chemical cost of $14/kWh, but currently suffers severe capacity fading. It should be noted that the chemistries presented here are in various stages of maturity, so many of their costs are expected to decrease, while the specific capacities are expected to increase as exemplified by the history of $LiCoO_2$, shown in Fig. S13.

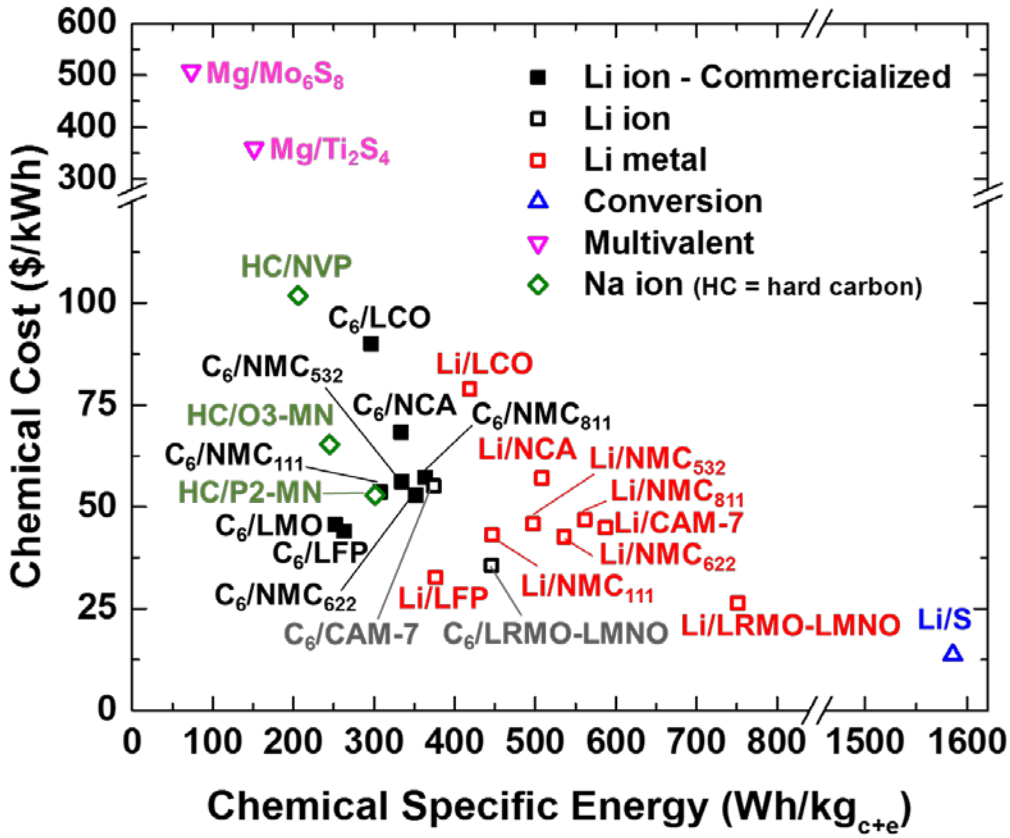

Figure 7. Chemical cost of storage ($/kWh) and chemical specific energy (Wh/kg$_{c+e}$) at present for representative electrochemical couples for EV applications, categorized into 6 groups. "Chemical" is defined to be made of cathode-active materials, anode-active materials, and electrolytes in typical combinations. Solid symbols represent commercialized chemistries.

4. Conclusions

This paper tackles the limits of the conventional learning curve and upgrades it by incorporating floor costs set by materials into our 2-stage learning curve model. Fig. 5 points out that existing models based on a learning curve without consideration of the floor set by materials costs predict an unrealistically low lithium-ion battery pack prices <\$100/kWh, suggesting that EV will soon become economically competitive with conventional vehicles. On the other hand, our 2-stage learning curve model, taking into account supply chain structure and materials costs, shows that continued maturation of the existing NMC-based lithium-ion battery technology platform alone is unlikely to reach the \$100/kWh price target. Our results show that omitting the materials costs of batteries could lead to an incorrect assessment of whether EV incentives should be extended and how soon the transition to e-mobility will occur.

While NMC battery prices are dropping rapidly now, this process will slow in the medium-term (~10 years) as materials will make up an ever increasing fraction of the total battery price. Out to and beyond 2030, it is improbable that EVs using lithium-ion NMC batteries will dominate the world vehicle market unless they are supported by significant government interventions such as high fuel taxes, subsidies, or mandates. Instead, accelerating battery chemistry innovations and stabilizing raw materials supply, amongst other actions, will be necessary before widespread electrification of transportation becomes attractive in most markets without EV-related financial incentives or high gasoline taxes. Our base case scenario shows that 2030 global cobalt demand from EVs batteries (NMC811) will reach approximately 80% of the world's total 2016 cobalt mine production [21], which suggests that automakers may need to move to different battery chemistries even less reliant on cobalt to avoid raw materials shortages and price spikes. A report given by Vehicle Technologies Office, DOE (Ref. 23) and Fig. 7 in this paper highlight some of the potential alternative battery chemistries, such as lithium-metal, lithium-sulfur, magnesium-ion batteries, and so on, that could further lower battery pack prices for EV applications.

5. Conflicts of interest

There are no conflicts to declare.

6. Acknowledgements

This work was supported through the MIT Energy Initiative's Mobility of the Future study. We thank Prof. Linsen Li at Shanghai Jiao Tong University for helpful discussion.

7. References

[1] Chu S, Cui Y, Liu N. The path towards sustainable energy. Nat Mater 2017;16:16–22. doi:10.1038/nmat4834.

[2] Dodge E. The Case for Electric Vehicles, Part 2: EV Costs. Break Energy n.d. https://breakingenergy.com/2014/10/02/the-case-for-electric-vehicles-part-2-ev-costs/ (accessed February 1, 2018).

[3] Knupfer SM, Hensley R, Hertzke P, Schaufuss P, Laverty N, Kramer N. Electrifying insights: How automakers can drive electrified vehicle sales and profitability. McKinsey Co 2017. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/electrifying-insights-how-automakers-can-drive-electrified-vehicle-sales-and-profitability.

[4] Clowes W, Wilson T. Congo May More Than Double Tax on Critical Cobalt Supply. BloombergCom 2018. https://www.bloomberg.com/news/articles/2018-01-10/congo-may-more-than-double-tax-on-critical-global-cobalt-supply.

[5] China's GEM Locks Up Large Share of Hot Commodity: Cobalt. Electron Des 2018. http://www.electronicdesign.com/automotive/china-s-gem-locks-large-share-hot-commodity-cobalt (accessed March 30, 2018).

[6] Cremer A. VW assigns 20 billion euros in battery orders in electric car drive. Reuters 2018. https://uk.reuters.com/article/uk-volkswagen-results/vw-assigns-20-billion-euros-in-battery-orders-speeds-ev-push-idUKKCN1GP12L (accessed April 2, 2018).

[7] Nykvist B, Nilsson M. Rapidly falling costs of battery packs for electric vehicles. Nat Clim Change 2015;5:329. doi: 10.1038/nclimate2564.

[8] Schmidt O, Hawkes A, Gambhir A, Staffell I. The future cost of electrical energy storage based on experience rates. Nat Energy 2017;2:17110. doi: 10.1038/nenergy.2017.110.

[9] Kittner N, Lill F, Kammen DM. Energy storage deployment and innovation for the clean energy transition. Nat Energy 2017;2:17125. doi: 10.1038/nenergy.2017.125.

[10] Berckmans G, Messagie M, Smekens J, Omar N, Vanhaverbeke L, Van Mierlo J. Cost Projection of State of the Art Lithium-Ion Batteries for Electric Vehicles Up to 2030. Energies 2017;10:1314. doi:10.3390/en10091314.

[11] Ahmed S, Gallagher KG, Nelson PA, Susarla N, Dees DW. BATPAC Model Development 2016. https://www.energy.gov/sites/prod/files/2016/06/f32/es228_ahmed_2016_o_web.pdf.

[12] Consumer Price Index (CPI) Tables : U.S. Bureau of Labor Statistics n.d. https://www.bls.gov/cpi/tables/home.htm (accessed February 7, 2018).

[13] Irle R, Pontes J, Irle V. EV-Volumes - Global plug-in vehicle sales for 2017 H1 + July, August update (2017) n.d. http://www.ev-volumes.com/country/total-world-plug-in-vehicle-volumes/ (accessed December 10, 2017).

[14] Zhang X, Liang Y, Yu E, Rao R, Xie J. Review of electric vehicle policies in China: Content summary and effect analysis. Renew Sustain Energy Rev 2017;70:698–714. https://doi.org/10.1016/j.rser.2016.11.250.

[15] IEA (2018), Global EV Outlook 2018: Towards cross-modal electrification, IEA, Paris, https://doi.org/10.1787/9789264302365-en.

[16] UPDATE-China NEV sales quota system takes effect on April 1, 2018. Gasgoo n.d. http://autonews.gasgoo.com/70010270.html (accessed February 2, 2018).

[17] IEA (2017), Global EV Outlook 2017: Two million and counting, IEA, Paris, https://doi.org/10.1787/9789264278882-en.

[18] Li F. Road map outlined for new energy industry - Business - Chinadaily.com.cn 2016. http://www.chinadaily.com.cn/business/motoring/2016-10/31/content_27226277.htm (accessed February 5, 2018).
[19] Hsieh I-YL, Kishimoto PN, Green WH (2018) Incorporating Multiple Uncertainties into Projections of Chinese Private Car Sales and Stock. Transportation Research Record. doi:10.1177/0361198118791361.
[20] Starting from next year, all BYD's passenger cars will use NMC batteries 2017. http://k.sina.com.cn/article_5454155336_14517ce48001001o5v.html?from=auto&subch=iauto (accessed February 3, 2018).
[21] Ober JA. Mineral commodity summaries 2017. U.S. Geological Survey; 2017. doi:10.3133/70180197.
[22] London Metal Exchange: LME Cobalt n.d. https://www.lme.com/Metals/Minor-metals/Cobalt#tabIndex=2 (accessed March 30, 2018).
[23] Howell D. Electrochemical Energy Storage R&D Overview 2017. https://www.energy.gov/sites/prod/files/2017/06/f34/es000_howell_2017_o.pdf.
[24] Curry C. Lithium-ion Battery Costs and Market 2017. https://data.bloomberglp.com/bnef/sites/14/2017/07/BNEF-Lithium-ion-battery-costs-and-market.pdf.
[25] Li Z, Pan MS, Su L, Tsai P-C, Badel AF, Valle JM, Eiler SL, Xiang K, Brushett FR, Chiang Y-M. Air-breathing aqueous sulfur flow battery for ultralow-cost long-duration electrical storage. Joule 2017;1:306–27. https://doi.org/10.1016/j.joule.2017.08.007.