Towards Energy Storage for Profitable Renewable Integration: What’s Needed and When

(Valuating Functional Loss in Energy Storage Installations)

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Motivation…

*Economically Viable* Electrochemical energy storage (EES) is enabling future power systems
What is Economic Viability?

• (of course) Depends on the application
• Low hanging fruit
  • C&I demand reduction
  • Ancillary services
• “white whale” of storage: renewable integration...
Battery Power’s Latest Plunge in Costs Threatens Coal, Gas

https://about.bnef.com/blog/battery-powers-latest-plunge-costs-threatens-coal-gas/
“Onshore wind and photovoltaic solar have also gotten cheaper, their respective benchmark LCOE reaching $50 and $57 per megawatt-hour for projects starting construction in early 2019, down 10% and 18% on the equivalent figures of a year ago.”

“. . .lithium-ion battery storage has dropped by 76% since 2012, based on recent project costs and historical battery pack prices.”
Focus on Utility Use and Economics

- “Levelized cost of stored electricity” used most commonly to valuate and inform decisions
  - Very basic/simple approach typically used: storage capX price is amortized through cycles as weighted by efficiency and discount rate
  - Does not contemplate degradation or how to valuate it over time

\[
\text{LCOE} = \left( \frac{\text{Price}}{\text{Capacity} \times \text{Cycles} \times \text{Efficiency} \times \text{Depth of Discharge}} \right) + \text{Total Ancillary Costs}
\]

*https://www.solarpowerworldonline.com/2016/12/calculating-true-cost-energy-storage/*
$LCOE = \left[ \frac{\text{Capacity \times Cycles \times Efficiency \times Depth of Discharge}}{\text{Price}} \right] + \text{Total Ancillary Costs}$

**Table 1 | Forecasted prices by using two-factor learning curve model.**

<table>
<thead>
<tr>
<th>Year</th>
<th>Forecast: consumer cells</th>
<th>EV/ES cells</th>
<th>EV/ES battery pack</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>124.15</td>
<td>155.00</td>
<td>202.88</td>
</tr>
<tr>
<td>2017</td>
<td>109.18</td>
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<tr>
<td>2018</td>
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</tbody>
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Second column represents the forecasted values. Third and fourth columns show estimations for EV/ES (electric vehicle/electric energy storage) cells (+24.85%) and for battery packs (+30.89%), respectively. Cell prices for electric vehicles and energy storage are higher due to different standards and chemistry. This model assumes the same learning across cells and battery packs. Prices are in 2015 US dollars and shown per kWh.

Testing on Tesla “Model S” Battery Cells at CMU

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<th>Cycling Protocol</th>
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<tr>
<td>Charge: constant-current Discharge: constant current</td>
<td>CC, 25 °C</td>
<td>CC, 60 °C</td>
</tr>
<tr>
<td>Charge: constant-current and constant-voltage Discharge: constant current</td>
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<td>CC-CV, 60 °C</td>
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The Materials Science of Battery Aging...
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Capacity = \( f(\text{cycles}, \text{depth of discharge}, \text{temperature}) \)

- In General – as DoD and Cycles are increased, \( \text{Capacity decreases} \)
- Fewer actual cycles the more you use the pack
  - \( \sim 1000 \) Full cycles or less for EV packs
  - \( \text{NOT a problem for cars. . .} \)
  - \( \text{HUGE problem for 4 hour stationary storage} \)
LCOE = \left( \frac{\text{Price}}{\text{Capacity x Cycles x Efficiency x Depth of Discharge}} \right) + \text{Total Ancillary Costs}

“Based on a ten-year project lifetime, and in the optimal case assuming a full charge–discharge cycle on a daily basis ignoring losses, \( \text{LCOE at current prices is US$0.15 kWh}^{-1} \) \text{ at residential scale and US$0.10 kWh}^{-1} \text{ at utility scale} ”

Baseload Renewables Coming Soon??

• No. These LCOE values are off by at least a factor of 2
• The relationship between cycle life and DoD is not captured properly in these common market assessments
• What is actually needed (to get to a place where subsidies might work):
  • LCOE adder for storage is less than the cost of the primary energy (~$5/MWh)
    • Energy storage with installed capital costs of < $75/kWh, with at least 2000 100% cycles of known non-fading capacity
    • NO known battery can do this – some long term projects seeking solution

The Present Reality

• Like other installed capital assets, batteries have more value earlier in their life, and less value as they age

• Use/dispatch decisions should be based on the evolving present value of the assets, and weighed against the use case value proposition

Our Solution:

Create A dispatch decision model that incorporates incremental battery degradation to determine the true value and the optimal dispatch for different use cases of the storage asset
An intertemporal decision framework for electrochemical energy storage management

Guannan He\textsuperscript{1,2}, Qixin Chen\textsuperscript{3}, Panayiotis Moutis\textsuperscript{4}, Soummya Kar\textsuperscript{4} and Jay F. Whitacre\textsuperscript{1,2,5*}
Why Intertemporal?

• **Intertemporal choice/decision** is used when choices at one time influence the possibilities available at other points in time

• **Short-term operational decision is necessary**
  – Accurate forecasting information is only available in day/hour-ahead

• **The degradation/usage of battery has long-term constraint and effects**
  – The incremental degradation accumulates and affects future profitability
  – The total degradation/usage of battery has a life-cycle limit

• **The short-term profit opportunities vary significantly in long term**
  – Weekday v.s. Weekend/Holiday, Summer v.s. Winter
  – Increasing penetration of renewables

• **Battery owner has time preference in battery revenues**
New Metrics/Concepts Introduced.

**Marginal Benefit of Usage**

- **Definition:** The maximum benefit that can be achieved with an incremental unit of battery usage/ degradation
- **Derivation:** A necessary optimality condition for long-term optimization problem that maximizes the life-cycle benefit:

\[
\frac{\partial}{\partial \text{Degradation}_t} \text{Short-term Benefit}_t = \frac{\text{MBU}}{\text{Discount Factor}_t}
\]

**Average Benefit/Cost of Usage**

- **Average Benefit of Usage (ABU):**
  The average life-cycle benefit per unit of battery usage/ degradation
  \[
  \text{ABU} = \frac{\text{LB}_{\text{max}}}{\text{D}}
  \]

- **Average Cost of Degradation (ACD):**
  The average capital cost per unit of battery degradation
  \[
  \text{ACD} = \frac{\text{CAPEX}}{\text{D}}
  \]
### Case Study: Energy Arbitrage

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Power capacity</td>
<td>50 MW</td>
</tr>
<tr>
<td>Energy capacity</td>
<td>200 MWh</td>
</tr>
</tbody>
</table>
| **Cycle life**         | 3000 cycles-100% DOD  
                        | 30000 cycles-10% DOD  |
| Calendar degradation   | 0.5% capacity loss/year |
| Capital Cost           | $200-300/kWh     |
| Charge/discharge efficiency | 90%              |

Price scenario: California ISO 2016 market prices

~3X better than most data suggests
Optimal Decisions - Year 1

DMBU = (1 + 7\%)^1 \cdot 5 \ $/MWh-throughput
Optimal Decisions - Year 2

DMBU = (1 + 7\%)^2 \cdot 5 \$/\text{MWh-throughput}
DMBU = \((1 + 7\%)^3 \cdot 5\) $/MWh-throughput
Optimal Decisions - Year 4

$$DMBU = (1 + 7\%)^4 \cdot 5 \ $/\text{MWh-throughput}$$
Optimal Decisions - Year 5

DMBU = (1 + 7\%)^5 \cdot 5 \ $/MWh-throughput
DMBU = (1 + 7\%)^6 \cdot 5 \text{ $/MWh-throughput}$
Optimal Decisions - Year 7

$$DMBU = (1 + 7\%)^7 \cdot 5 \text{ \$/MWh-throughput}$$
DMBU = \((1 + 7\%)^8 \cdot 5\) $/MWh-throughput
DMBU = (1 + 7\%)^9 \cdot 5 \ $/MWh-throughput
Optimal Decisions - Year 10

DMBU = \((1 + 7\%)^{10} \cdot 5\) $/MWh-throughput
Optimal Decisions - Year 11

DMBU = \((1 + 7\%)^{11} \cdot 5\) \$/MWh-throughput
Decreasing Value Analysis
## Valuation & Subsidy

<table>
<thead>
<tr>
<th></th>
<th>Energy Arbitrage</th>
<th>Energy Arbitrage + Frequency Regulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total profit ($ million 2016)</td>
<td>8</td>
<td>37</td>
</tr>
<tr>
<td>Optimal MBU ($/MWh-throughput)</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>ABU ($/MWh-throughput)</td>
<td>7</td>
<td>35</td>
</tr>
<tr>
<td>Unit capacity capital cost ($/kWh)</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Average cost of degradation ($/MWh-throughput)</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td><strong>Break-even capital cost ($/kWh)</strong></td>
<td><strong>40</strong></td>
<td><strong>210</strong></td>
</tr>
<tr>
<td>Required subsidy ($/MWh-throughput)</td>
<td>26</td>
<td>0</td>
</tr>
</tbody>
</table>
Summary

• Current energy storage technology is not tenable for making renewable + Battery power economically competitive.
  • capacity fade + capX are both issues

• An intertemporal framework for quantitatively assessing values and costs, and determining the optimal dispatch of electrochemical energy storage has been developed

• We introduce new usage/degradation metrics (ABU & ACD) for economic assessment, subsidy design and technology learning study of battery storage.

• The only viable use case calls on multiple income streams, some of which are limited in market size.
Long-term Decision

Numerically optimize the life-cycle MBU based on historical and forecast information

Arbitrarily setting the unit cost of degradation in short-term operational decisions could cause great life-cycle benefit loss.