Optimization of energy storage system economics and controls by incorporating battery degradation costs in REopt®

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Mass-adoption of integrated energy systems requires optimization of system economics

If you have $5M in capital to build out solar, batteries, energy efficiency improvements, or thermal storage for your organization, how do you make a sound investment?

Investments in renewable energy generation and energy storage technologies need to balance the capital costs, revenue, and maintenance costs of many technologies and services:

- Government subsidies and investment tax credits
- Electricity prices (and generation source, if optimizing tons CO$_2$ eq.)
- Intermittent generation sources
- Energy storage capital and replacement with cost learning rates
- Variable building electrical/thermal loads
Formulated as a mixed integer linear program, REopt® provides an integrated, cost-optimal energy solution.
Economics of lithium-ion energy storage systems strongly depend on battery lifetime\(^1,\)\(^2\)

Battery life is sensitive to environment and use

Control battery to maximize Net Present Value (NPV):

• Extend lifetime to avoid maintenance costs
• Charge the battery when energy costs are low
• Discharge the battery to avoid high energy costs

REopt previously assumed 10-year energy storage system lifetime.

1. Reniers, Mulder, and Howey, J. Power Sources 487 (2021) 229355
2. Thien, Axelsen, Merten, Uwe Sauer, J. Energy Storage 51 (2022) 104257
Empirical battery degradation modeling

\[ q = 1 - q_{\text{Calendar}}(t) - q_{\text{Cycling}}(EFC) - \cdots \]

\[ q_{\text{Calendar}}(t) = k_{\text{cal}}(T, SOC) \cdot t^{p_{\text{cal}}} \]

\[ q_{\text{Cycling}}(EFC) = k_{\text{cyc}}(T, SOC, DOD, C_{\text{rate}}) \cdot EFC^{p_{\text{cyc}}} \]
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Non-linear

Gasper, Collath, Hesse, Jossen, Smith, J. Electrochemical Society 169 (2022) 080518
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Non-linear

Too many variables

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Linearized degradation model

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Pick decision variables:
- Average daily state-of-charge $\overline{SOC}_{d-1}$
- Daily energy throughput $EFC_{d-1}$
- Initial battery capacity $Q_0$
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- Average daily state-of-charge \( SOC_{d-1} \)
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Linearize degradation w.r.t. decision variables:

\[ \Delta q = -(k_{\text{cal}} p_{\text{cal}} SOC_{d-1})^{p_{\text{cal}}-1} - k_{\text{cyc}} \cdot EFC_{d-1} \] for day \((d - 1): d\)

\[ q = Q/Q_0, \quad \Delta Q = \Delta q \cdot Q_0 \]
**Linearized degradation model**

\[
q = 1 - q_{\text{Calendar}}(t) - q_{\text{Cycling}}(EFC) - \cdots
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\Delta q = -\left(k_{\text{cal}} p_{\text{cal}} \overline{SOC}_{d-1} \right)^{p_{\text{cal}}-1} - k_{\text{cyc}} \cdot EFC_{d-1} \text{ for day } (d - 1): d
\]

\[
q = \frac{Q}{Q_0}, \quad \Delta Q = \Delta q \cdot Q_0
\]

**Optimizable parameters for battery type**
Parameterizing linear degradation model

1. Fit aging data with state-dependent life model, \( q = f(X) \)

\[
q = 1 - q_{\text{Loss,Cal}} - q_{\text{Loss,Cyc}}
\]

- Data
  - 30°C, Storage, 100% SOC
  - 45°C, Storage, 20% SOC
  - 45°C, Storage, 50% SOC
  - 45°C, Storage, 50% SOC
  - 45°C, Storage, 80% SOC
  - 45°C, Storage, 100% SOC
  - 55°C, Storage, 100% SOC
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 250
  - 45°C, DOD, 100% DC, 175
  - 45°C, DOD, 100% DC, 175
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Parameterizing linear degradation model

1. Fit aging data with state-dependent life model, \( q = f(X) \)
   \[
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2. Simulate 20-year lifetime with state-dependent life model
   \[
   q = \sum (\Delta q) = \sum (\frac{dq}{dt}) \cdot \Delta t
   \]
Parameterizing linear degradation model

1. Fit aging data with state-dependent life model, $q = f(X)$
   
   $$q = 1 - q_{\text{Loss,Cal}} - q_{\text{Loss,Cyc}}$$

2. Simulate 20-year lifetime with state-dependent life model
   
   $$q = \sum (\Delta q) = \sum \left[ \frac{dq}{dt} \cdot \Delta t \right]$$

3. Fit linearized life model expression to simulated aging
   
   $$\Delta q = \left( \frac{dq}{dt} \right) \cdot \Delta t$$

Overestimation of calendar fade rate at low SOCs
Costing degradation – Maintenance strategies

Augmentation (optimistic): daily replacement of lost capacity with additional capacity

$$C_{Augmentation} = \sum_{d=2}^{d=D} -\Delta Q_d \cdot C_d$$

Replacement (conservative): $N$ periodic replacements of entire BESS system, minus residual value

$$C_{Replacement} = \sum_{n=1}^{n=N} Q_0 \cdot C_{d_n} - V_{d-1}$$

Monthly SOH indicator denotes when system passes the defined replacement threshold. Ratio of sum of healthy months to analysis period determines a replacement frequency. Residual value is the fraction of remaining time until the next periodic replacement times the discount factor at the final day of the analysis period.
Example result: Large office in Palmdale, CA, PGE utility

<table>
<thead>
<tr>
<th>Inputs</th>
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</tr>
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<tbody>
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Values reported in the results table are rounded to two significant figures for clarity.

Degradation models predict fewer replacements, leading to higher NPV.

Larger battery avoids more energy and demand charges.

With fixed size, battery is utilized less to avoid degradation costs.
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Baseline LCC: $22.8M
Baseline BESS Capex: $920k
Compared to the non-linear degradation model, the linearized degradation models are overestimating degradation.

Variance in degradation rate observed across different battery types is preserved.

Example result: Large office in Palmdale, CA, PGE utility
Costing degradation forces battery SOC to be unrealistically low, as degradation increases with increasing SOC.

Low SOC is accomplished by ‘just-in-time’ charging, enabled by perfect foresight of the future electrical demand.
Sensitivity to annual average SOC constraint (Augmentation, fixed size)

An annual average SOC inequality constraint imposes more realistic battery behavior, and serves many analysis purposes:

- Quantifies resiliency cost
- Quantifies the benefit of load prediction and degradation aware controls
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Augmentation NPV: $583k
Replacement NPV: $543k
Concluding remarks

• Realistic battery degradation in REopt empowers planners and engineers to make informed decisions on energy storage system sizing and financing

• Sensitivity to scheduled replacement, augmentation, or optimized replacement maintenance strategies enables users to get confident bounds on system cost and NPV

• Average annual SOC inequality constraint enforces more realistic battery control behavior, and quantifies cost impacts of system resiliency, load prediction, and degradation aware controls

• Open-source parameters (and cost factors vs. NREL ATB) for commercial NMC-Gr, LFP-Gr and LMO-LTO lithium-ion battery systems are provided for users
Thank you!
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www.nrel.gov

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