Battery Degradation in Control Algorithms for Redistribution of Benefits in a Community Energy Project

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1 Background

Community Energy (CE) projects refer to the generation, storage and trade of energy within a community of prosumers using a **Renewable Energy System (RES)**.

RES generates energy.

Store in battery.

Charge and discharge based on prosumer demand.

Such charge/discharge cycles leads to battery degradation.

Therefore, due to a shorter lifespan, batteries are key contributors to cost.

Many **Battery Energy Storage Systems (BESS)** exist, varying in degradation behaviour, battery size, chemistry, etc.

Norbu et al. (2021) proposed a "heuristic-based battery **control algorithm**" to maximize prosumer benefits that:

- Charges/discharges the battery based on power availability
- Incorporates a battery state of health model:
  - Rainflow counting algorithm determines number of regular & irregular cycles based on a battery model.
  - This is used to determine a depreciation factor (DF).
- DF, capacity, and market cost used to estimate battery cost.

2 Terminology

Depth of Discharge (DoD): proportion of a battery capacity discharged relative to its max. capacity.

State of Charge (SoC): battery charge relative to its max. capacity.

Cycle: process of discharging then charging battery from and to some arbitrary SoC.

Cycle Life: number of cycles that battery can undergo based at a certain DoD before performance deteriorates.

3 Research Question

How does the model for the battery state of health influence the control algorithm designed for redistribution of benefits in a community energy project?

4 Methodology

1. Collect degradation curves and model parameters (e.g. cycle life, efficiency, etc.) for various BESS.
2. Simulate degradation curves for algorithm by:
   - Sampling datapoints from real-world curves.
   - Cublicly interpolating between datapoints.
3. Regularise degradation curves.
4. Analyse the effect of battery chemistry on the control algorithm.
5. Analyse the effect of battery capacity on the control algorithm.

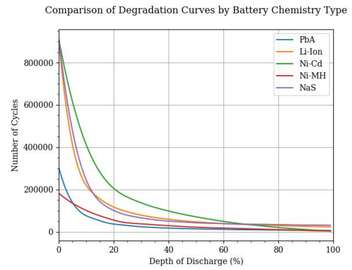

Figure 1. Comparison of simulated degradation curves by battery chemistry.

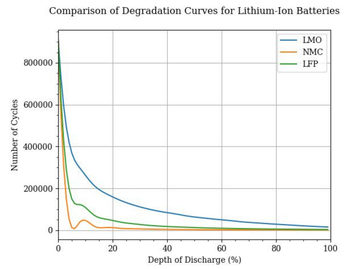

Figure 2. Comparison of simulated degradation curves by lithuim-ion battery subtype.

5 Results

- Li-ion batteries incur the lowest costs.
  - Dominates the market for grid-scale batteries.
  - LMO is the most cost-efficient li-ion subtype.
- Battries tend to incur lower costs with:
  - Higher initial no. of cycles at 1% DoD.
  - Degradation curves with negative gradients of lower magnitude.

Comparison of Cost by Chemistry		
Chemistry Type	Cost for Thames Dataset (£)	Cost for London Dataset (£)
Li-Ion	57,948.4	1,598,670
NaS	65,790	1,810,280
PbA	72,048.4	1,968,870
Ni-Cd	79,434.2	2,154,800
Ni-MH	100,885	2,725,090

Table 1. Comparison of CE costs by battery chemistry.

Comparison of Cost by Li-Ion Battery Chemistry		
Li-Ion Sub-Type	Cost for Thames Dataset (£)	Cost for London Dataset(£)
LMO	56,248.4	1,554,040
LFP	57,298.4	1,581,610
NMC	66,904.5	1,743,320

Table 2. Comparison of CE costs by lithium-ion subtype.

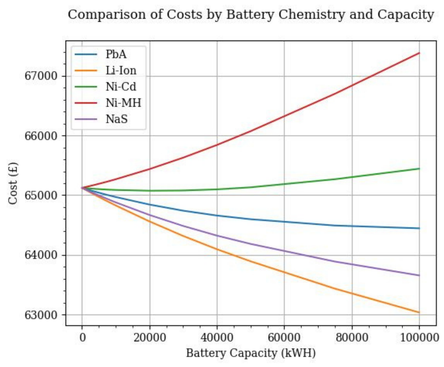

Figure 3. Cost vs. battery capacity and chemistry for Thames Valley Vision dataset.

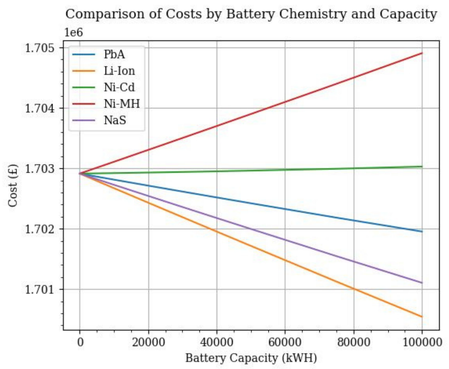

Figure 4. Cost vs. battery capacity and chemistry for Low Carbon London dataset.

- Batteries tend to decrease in cost as capacity increases.
  - Cost of li-ion batteries decreases most rapidly.
- Ni-MH batteries are an anomoly, possibly due to experiment limitations.
- Decreasing magnitude of negative gradient of trendlines and Ni-Cd results suggest there exists a minimal cost at some optimal battery capacity.
- The comparitively cost-effective chemistries exhibit longer lifetimes and lower market cost per kWh.

6 Conclusion

Limitations and Future Improvements

Lack of data on certain BESS & amount of BESS meant testing with all BESS was unfeasible. Simulate other BESS to apply model to experiment.

Data on BESS is inconsistent due to different testing environments. Explore possible improvements to the regularisation technique.

Leverage insights into the influence of the battery state of health model to improve the control algorithm.

- Key factors influencing the control algorithm include cyclic degradation, cost per kWh, cycle life, and battery lifetime.
- Costs incurred by a CE project decrease as capacity increases until a minima at some optimal capacity.
- Battery chemistry greatly influences algorithm performance due to degradation behaviour and battery parameters such as efficiency.

Norbu, S., Couraud, B., Robu, V., Andoni, M., & Flynn, D. (2021). Modelling the redistribution of benefits from joint investments in community energy projects. Applied Energy, 287. https://doi.org/10.1016/j.apenergy.2021.116575