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Original research article

Optimal dispatch approach for second-life batteries considering degradation with online SoH estimation

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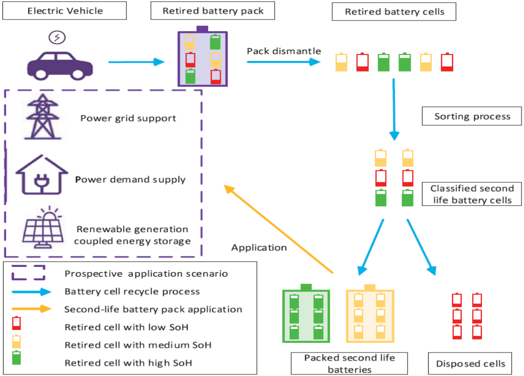
Abstract

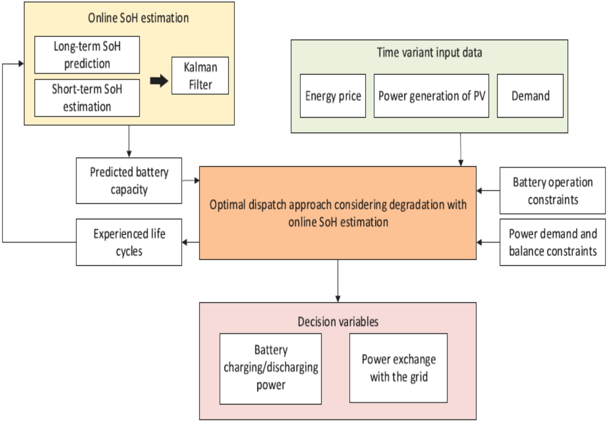


- optimal dispatch approach for recycling end-of-life electric vehicle batteries
- considering degradation with online SoH estimation

Motivation

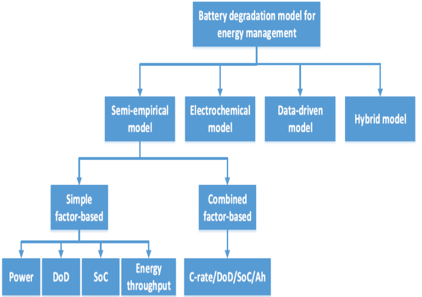
- upcoming electric vehicle (EV) battery retirement issues, second-life batteries (SLBs) have received increasing attention
  - replaced when their capacity drops to 80%
- SLBs are more vulnerable to external stress, more likely to cause combustion and explosions
  - degradation phenomenon is more prominent

Optimal dispatch approach

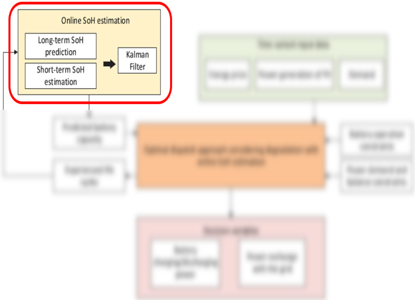


- Determining decision variables considering input data and SoH

Battery degradation models



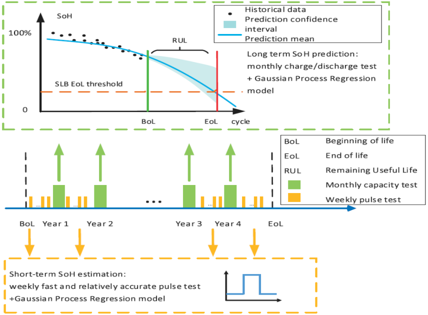
[Fig 1. Conventional models]



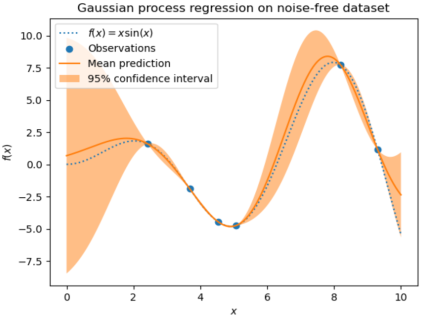
[Fig 2. Oneline SoH estimation]

- SLBs application strongly depends on the value of SoH
- SoH estimation is conducted from both short-term and long-term perspectives

Online SoH estimation



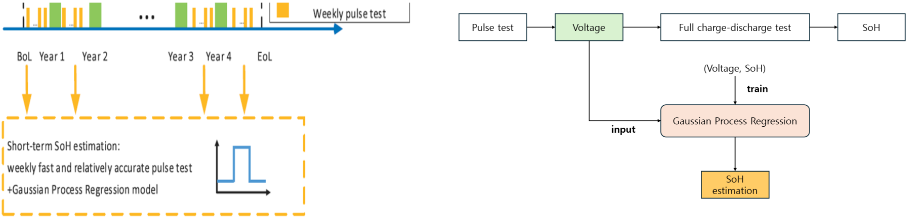
[Fig 3. Schematic of estimation]



[Fig 4. Example of GPR]

- Gaussian Process Regression (GPR) is used for both short-term and long-term SoH estimation

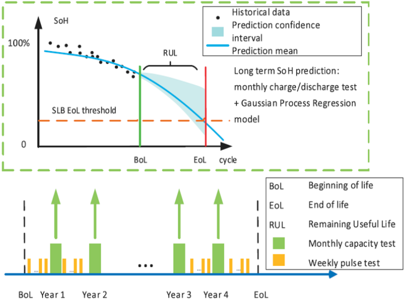
Online SoH estimation

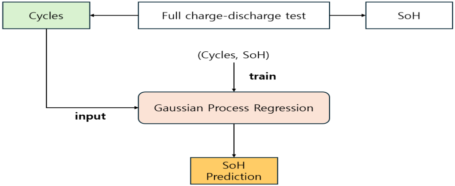


[Fig 5. Short-term SoH estimation]

- GPR model receives voltage as input to conduct short-term SoH estimation

Online SoH estimation

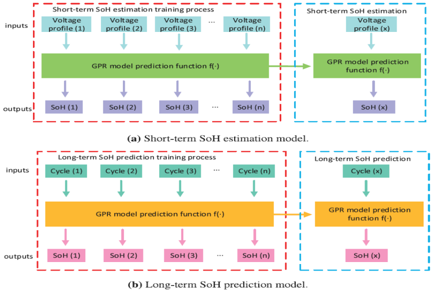




[Fig 6. Long-term SoH prediction]

- GPR model takes the accumulated number of cycles as input to conduct long-term SoH prediction

Online SoH estimation



[Fig 7. SoH estimation]

$$\mathcal{KF}\left(\mu', \sigma'^2\right) = \mathcal{GP}\left(\mu_{ST}, \sigma_{ST}^2\right) \cdot \mathcal{GP}\left(\mu_{LT}, \sigma_{LT}^2\right),$$

$$\mu' = \mu_{ST} + \frac{\sigma_{ST}^2\left(\mu_{LT} - \mu_{ST}\right)}{\sigma_{ST}^2 + \sigma_{LT}^2},$$

$$\sigma'^2 = \sigma_{ST}^2 - \frac{\sigma_{ST}^4}{\sigma_{ST}^2 + \sigma_{LT}^2}.$$

[Eqs 1. Kalman filter formulations]

- short-term estimation and long-term prediction are combined using a Kalman filter

Optimal dispatch approach

$$\min \quad \sum_{t=1}^{T} \left[c(t) \cdot P_{\mathrm{grid}}(t) + \gamma \sum_{k=1}^{N} \left(P_k^{\mathrm{ch}}(t) + P_k^{\mathrm{dis}}(t) \right) \right]$$

[Eqs 2. Objective Function]

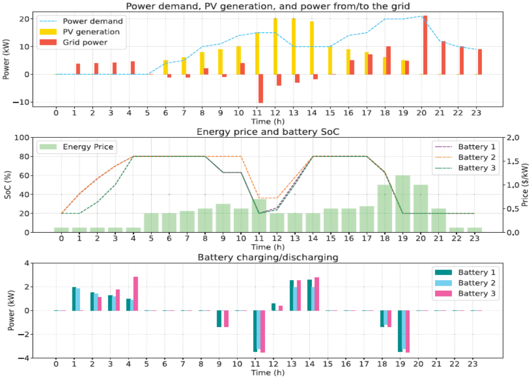
- objective is to minimize the energy cost
  - $c(t)$: Energy price
  - γ : Operation costs coefficient
  - $P(t)$: Power ouput

- objective function, along with the constraints below, is solved using a Python package (GEKKO)

$$\begin{aligned}
\text{s.t.} \quad & P_{\mathrm{grid}}(t) + P_{\mathrm{PV}}(t) = P_{\mathrm{d}}(t) + \sum_{k=1}^{N} P_k(t), \\
& E_k(t+1) = E_k(t) + P_k(t+1), \\
& P_k(t) = P_k^{\mathrm{ch}}(t) \cdot \eta_k(t) - P_k^{\mathrm{dis}}(t) \cdot \frac{1}{\eta_k(t)}, \\
& SoC_k(t) = \frac{E_k(t)}{SoH_k^{\mathrm{P}}(\tau) \cdot Q_{k,\mathrm{rated}}}, \\
& SoC_{k,\min} \leqslant SoC_k(t) \leqslant SoC_{k,\max}, \\
& \eta_k(t) = f\left(SoH_k^{\mathrm{P}}(\tau)\right), \\
& 0 \leqslant P_k^{\mathrm{ch}}(t) \leqslant g\left(SoH_k^{\mathrm{P}}(\tau)\right) \cdot P_{k,\mathrm{rated}} \cdot \lambda_k(t), \\
& 0 \leqslant P_k^{\mathrm{dis}}(t) \leqslant g\left(SoH_k^{\mathrm{P}}(\tau)\right) \cdot P_{k,\mathrm{rated}} \cdot \left(1 - \lambda_k(t)\right), \\
& SoH_k^{\mathrm{P}}(\tau) = h\left(SoH_{k,1}^{\mathrm{P}}(\tau), SoH_{k,2}^{\mathrm{P}}(\tau), \ldots, SoH_{k,m}^{\mathrm{P}}(\tau)\right),
\end{aligned}$$

$$\begin{aligned}
& SoH_{k,j}^{\mathrm{P}}(\tau) \sim \mathcal{KF}\left(\mu_{k,j}'(\tau), {\sigma_{k,j}'}^{2}(\tau)\right), \\
& cycle_{k,j}(\tau+1) = \Delta cycle_{k,j}(\tau) + cycle_{k,j}(\tau), \\
& \Delta cycle_{k,j}(\tau) = \frac{\sum_{t=168\tau}^{168(\tau+1)} P_{k,j}^{\mathrm{ch}}(t) + P_{k,j}^{\mathrm{dis}}(t)}{2 \cdot Q_{k,j,\mathrm{rated}} \cdot SoH_{k,j}^{\mathrm{P}}(\tau)}, \\
& P_{k,j}^{\mathrm{ch}}(t) = l\left(SoH_{k,j}^{\mathrm{P}}(\tau), SoH_k^{\mathrm{P}}(\tau), P_k^{\mathrm{ch}}(t)\right), \\
& P_{k,j}^{\mathrm{dis}}(t) = l\left(SoH_{k,j}^{\mathrm{P}}(\tau), SoH_k^{\mathrm{P}}(\tau), P_k^{\mathrm{dis}}(t)\right).
\end{aligned}$$

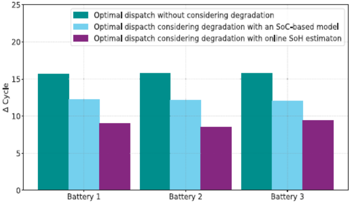
Results



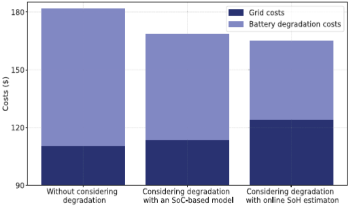
[Fig 8. Results under the optimal dispatch]

- local energy system, including power demand, PV, and ESS with 3 SLB packs, is selected

Results



(a) The experienced cycles ΔCycle.



(b) The operating costs.

[Fig 9. Experienced cycles and dispatch costs]

- least number of experienced cycles and the lowest cost

Conclusion

- consider degradation along with online SoH estimation
- extend the life-span of EV batteries, delay the need to manufacture new batteries

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"Thank you for listening"
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