Paper No: 25PESGM0614

State-of-Health Estimation for Lithium-ion Batteries via Ensemble Learning of Random Partial Discharging Curves

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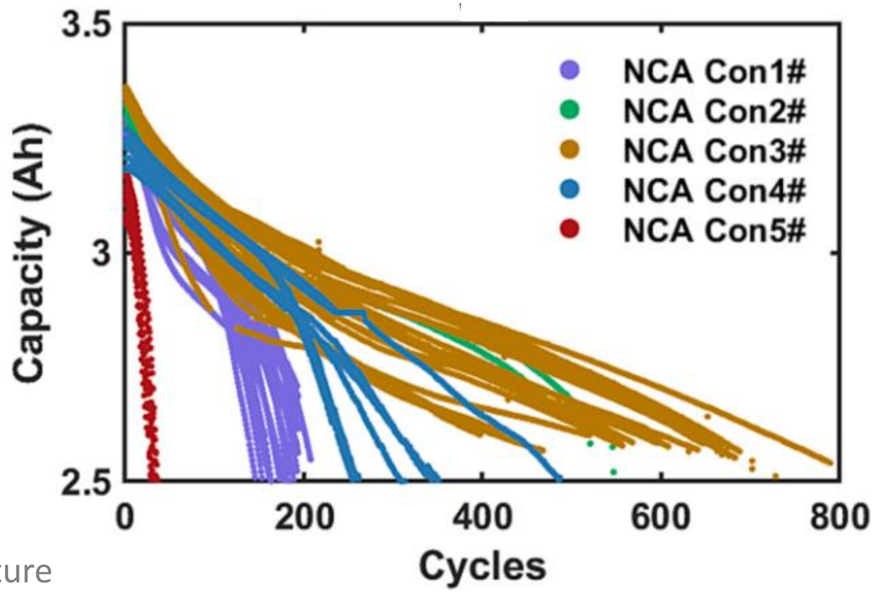
Background

- Widespread applications of Lithium-ion battery energy storage systems
- Battery degradation is inevitable, which leads to capacity and power decrease
- State-of-health (SOH) estimation is a crucial function of battery management system
- SOH is defined as the ratio of present capacity to the nominal capacity

$$SOH = \frac{C_{now}}{C_{nominal}} \times 100\%$$

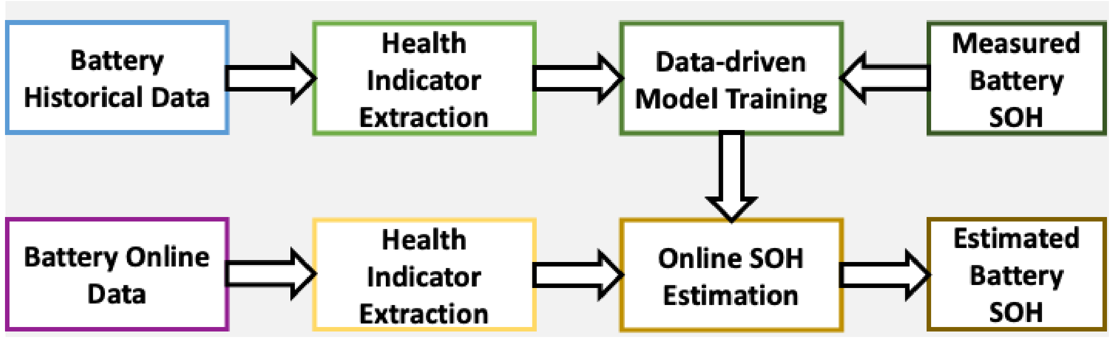


Fu, Shiyi, et al(2024)

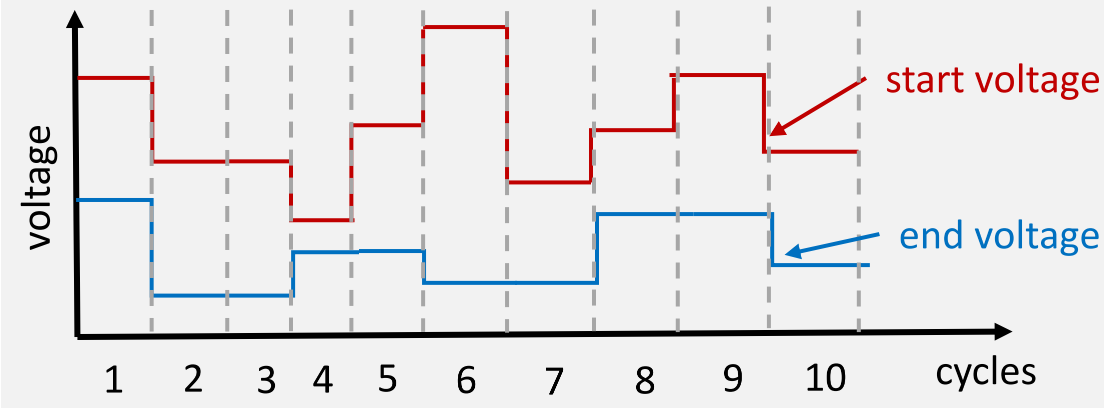
Fu, Shiyi, et al. "Data-driven capacity estimation for lithium-ion batteries with feature matching based transfer learning method." Applied Energy 353 (2024): 121991.

Introduction

Data-Driven methods for Lithium-ion battery SOH estimation



Challenges brought by **random partial discharging curves**



the discharging curve of each cycle starts and ends at random voltages, so it is **impossible** to **predefine a voltage window** that is consistently covered by all cycles for **HI extraction**

Existing problems of data-driven methods:

- Data-driven methods often extract HIs from predefined voltage windows, which fail during **random partial discharging process**
- Existing **unscaled health indicator** (HI) is sensitive to cell-to-cell variation

Solution – a new **ensemble learning** method is proposed

- **Scaled HI** is extracted to alleviate the negative impact of cell-to-cell variation on SOH estimation
- Multiple Gaussian process regression (GPR) based SOH estimator are constructed over **different voltage windows**
- SOH is estimated by aggregating estimators within actual discharging voltage range via **product of experts** (PoE) method

Methodology

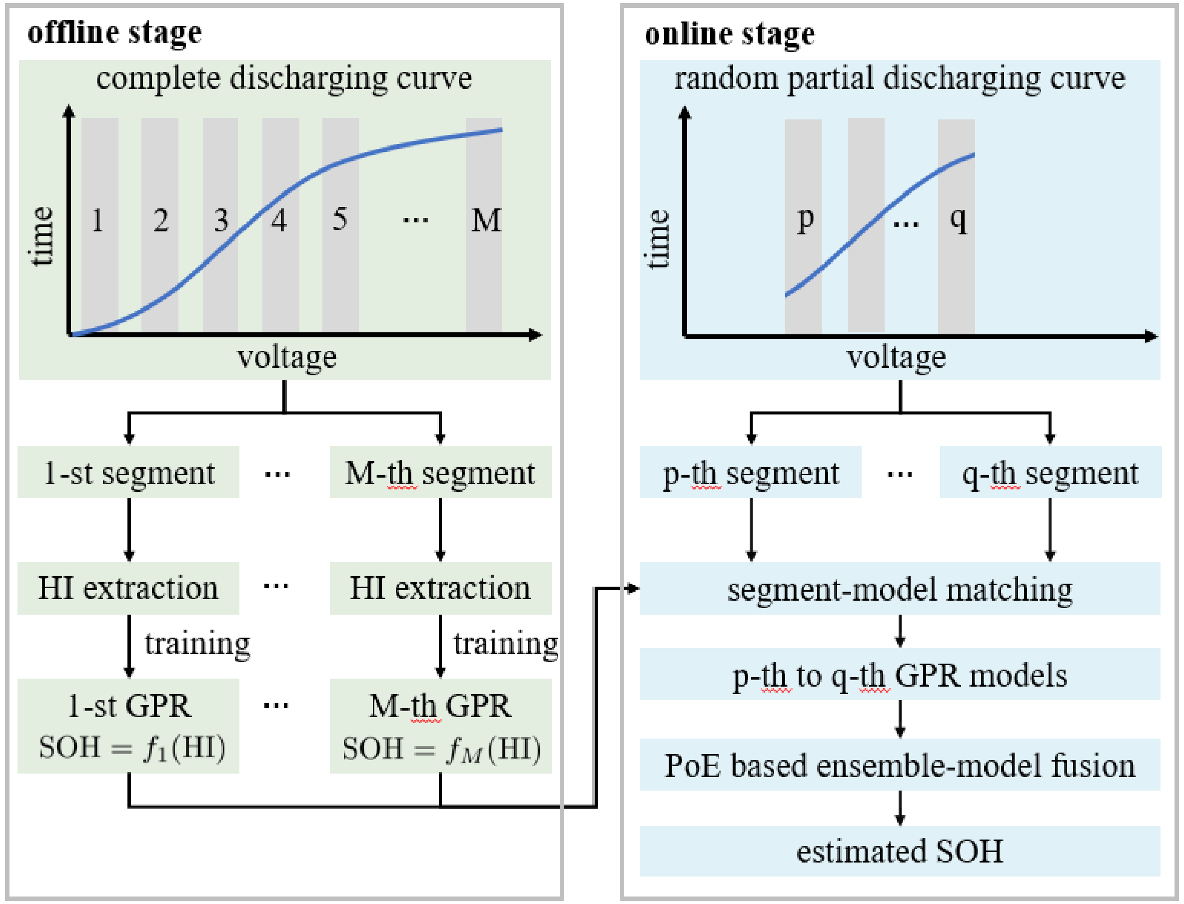
Framework of the proposed method

Offline stage:

- Collect complete discharging curves
- Split each curve into M segments
- Extract scaled HI from each segment
- Construct an individual GPR-based SOH estimator for each segment

Online stage:

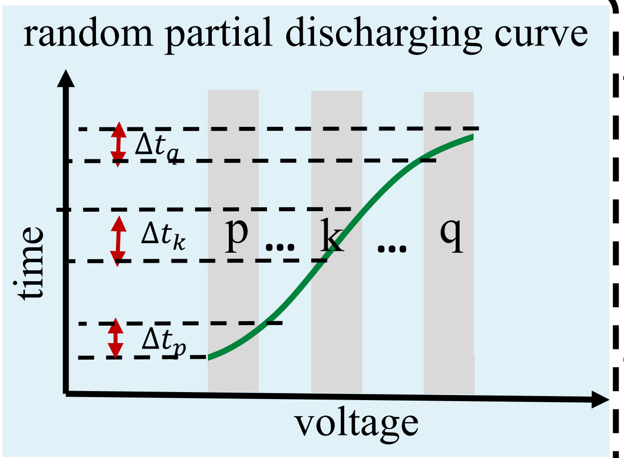
- Collect a random partial discharging curve
- Activate GPR models within the partial curve via segment-model matching
- Estimate SOH by aggregating activated GPR models via PoE



Methodology

Online ensemble-model fusion

Scaled HI extraction



$HI_p = \Delta Q_p / \Delta Q_p^1,\ \Delta Q_p = I\Delta t_p$

⋮

$HI_k = \Delta Q_k / \Delta Q_k^1,\ \Delta Q_k = I\Delta t_k$

⋮

$HI_q = \Delta Q_q / \Delta Q_q^1,\ \Delta Q_q = I\Delta t_q$

ΔQ_i^1 (i= p,…,q) is the charging capacity ΔQ_i at 1-th cycle

HI_p ⋮ HI_k ⋮ HI_q

Activate q-p+1 GPR models

p-th GPR: $P(SOH|D_p) = \mathcal{N}(\mu_p, \sigma_p^2)$

D_p: training data of p-th GPR

Estimated SOH: μ_p | Uncertainty: σ_p^2

⋮

k-th GPR: $P(SOH|D_k) = \mathcal{N}(\mu_k, \sigma_k^2)$

D_k: training data of k-th GPR

Estimated SOH: μ_k | Uncertainty: σ_k^2

⋮

q-th GPR: $P(SOH|D_q) = \mathcal{N}(\mu_q, \sigma_q^2)$

D_q: training data of q-th GPR

Estimated SOH: μ_q | Uncertainty: σ_q^2

$\{\mu_i\}_{i=p}^q$

$\{\sigma_i^2\}_{i=p}^q$

Aggregate q-p+1 GPR models

Product of experts (PoE):

$$P(SOH|D) = \prod_{i=p}^{q} P(SOH|D_i)$$

$$P(SOH|D) = \mathcal{N}(\mu, \sigma^2)$$

$D = \{D_i\}_{i=p}^q$: training data of activated GPR models

Final SOH estimate: $\mu = \sum_{i=p}^q w_i \mu_i$

Weight: $w_i = \frac{\sigma_i^{-2}}{\sum_{j=p}^q \sigma_j^{-2}}$

Decrease the weights of SOH estimates with great uncertainty

Results

Case 1: comparison with R^2 based multi-model fusion

Table. 1 Comparison of **mean** RMSE across testing batteries

methods	Oxford data	NASA data
proposed method	**0.72%**	**1.25%**
R^2 based multi-model fusion	1.10%	1.64%

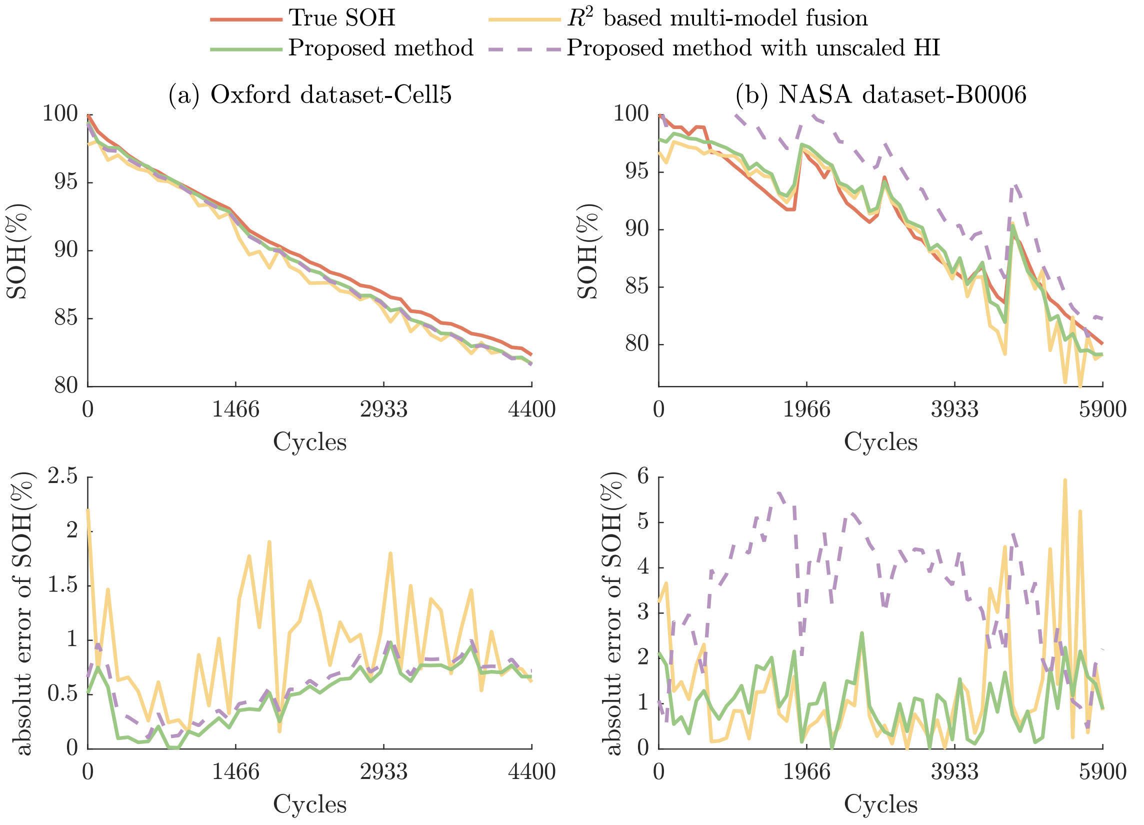
- The proposed method achieves **35%** and **24%** lower mean RMSE on two datasets

Case 2: comparison with unscaled HI

Table. 2 Comparison of **mean**, standard deviation (**std**), and **maximum** of RMSE across testing batteries

methods	Oxford data			NASA data		
	mean	std	max	mean	std	max
proposed HI	**0.72%**	**0.29%**	**1.30%**	**1.25%**	**0.03%**	**1.28%**
unscaled HI	0.91%	0.57%	1.91 %	2.16%	1.35%	3.71%

- The proposed HI achieves **21%** and **42%** lower mean RMSE on two datasets
- The proposed HI achieves more **consistent estimation**, demonstrated by smaller std and maximum of RMSE



SOH estimation results on Oxford dataset (a) and NASA dataset (b)

Conclusions

Conclusions:

- This paper proposes a new ensemble learning method to estimate SOH from random partial discharging curves.
- A scaled HI is proposed to effectively reduce the negative impact of cell-to-cell variation on SOH estimation.

Future work:

- The future research aims to extend the proposed method to dynamic working conditions, necessitating extracting reliable HI from dynamic working conditions.

Our related works:

1. B. Gou, **Y. Xu** and X. Feng, "A Hybrid Data-Driven and Model-based Method for Modeling and Parameter Identification of Lithium-Ion Batteries," ***IEEE Trans. Industry Applications, 2023.***
2. G. Dong, **Y. Xu**, and Z. Wei, "A Hierarchical Approach for Finite-time H-∞ State Observer and Probabilistic Lifetime Prediction of Lithium-Ion Batteries," ***IEEE Trans. Energy Conversion, 2022.***
3. W. Liu and **Y. Xu**, "Data-Driven Online Health Estimation of Li-Ion Batteries Using A Novel Energy-Based Health Indicator," ***IEEE Trans. Energy Conversion, 2020.***
4. B. Gou, **Y. Xu**, et al, "State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-ion Battery Using A Hybrid Data-driven Method," ***IEEE Trans. Vehicular Technology, 2020.*** - **Web of Science highly cited paper**
5. B. Gou, **Y. Xu**, et al, "An Ensemble Learning-based Data-Driven Method for Online State-of-Health Estimation of Lithium-ion Batteries," ***IEEE Trans. Transportation Electrification, 2020.***
6. W. Liu, **Y. Xu** et al, "A Hierarchical and Flexible Data-Driven Method for Online State-Of-Health Estimation of Li-ion Battery", ***IEEE Trans. Vehicular Technology, 2020***.
7. W. Q. T. Poh, Y. Xu, and R. T. P. Tan, "Data-driven estimation of li-ion battery health using a truncated time-based indicator and LSTM," ***Proc. IEEE PES General Meeting, Orlando, FL, USA, Jul. 2023.***
8. B. Gou, **Y. Xu**, et al "Remaining Useful Life Prediction for Lithium-ion Battery Using Ensemble Learning Method," ***Proc. IEEE PES General Meeting, Atlanta, US, Aug. 2019.*** – **Best Paper Award**
9. W. Liu and **Y. Xu**, "A Comprehensive Review of Health Indicators of Li-ion Battery for Online State of Health Estimation," ***IEEE EI2 Conference***, **2019**.
10. **Y. Xu**, B. Gou, "Ensemble-Based Reliable Machine Learning and Decision-Making Algorithm for Lithium-Ion Battery Health Monitoring", ***Technology Disclosure, TD 2018-275, 2018.*** – **licensed to the industry.**
11. **Y. Xu**, Y. Yang, W. Liu, "Online SOH Estimation of LIB Under Dynamic Discharging Profiles," ***Technology Disclosure, TD/2021-132, 2021.***
12. **Y. Xu**, W. Liu, C. Ren, "Expanding SOH Estimation Model of LIB to Different Conditions Using Transfer Learning," ***Technology Disclosure, TD/2021-133, 2021.***
13. **Y. Xu**, G. Dong, "A Hierarchical Framework for Battery States Estimation And Lifetime Prediction," ***Technology Disclosure, TD/2021-134, 2021.***

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