

Random forest regression for lithium ion battery capacity estimation *

Yi Li

* Li, Y., Zou, C., Bercibar, M., Nanini-Maury, E., Chan, J.C.W., van den Bossche, P., Van Mierlo, J. and Omar, N., 2018. Random forest regression for online capacity estimation of lithium-ion batteries. *Applied energy*, 232, pp.197-210.



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1. Background and motivation

Why do we need to know battery state of health (SOH)?



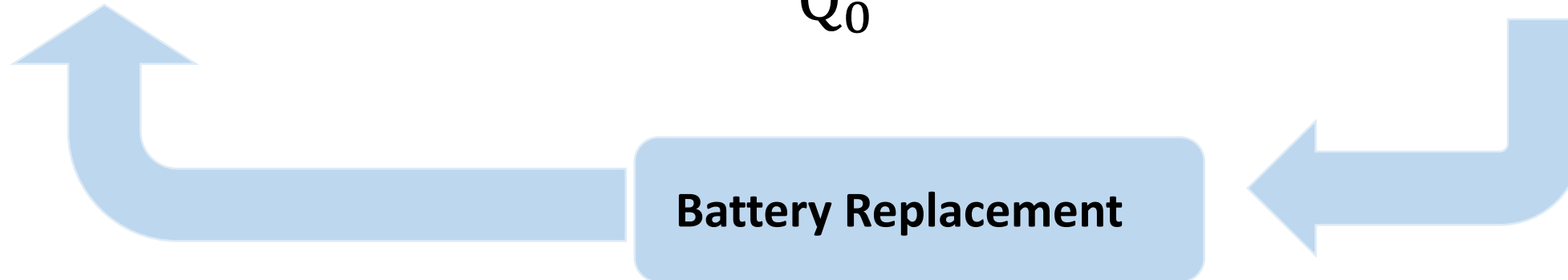
Battery Ageing



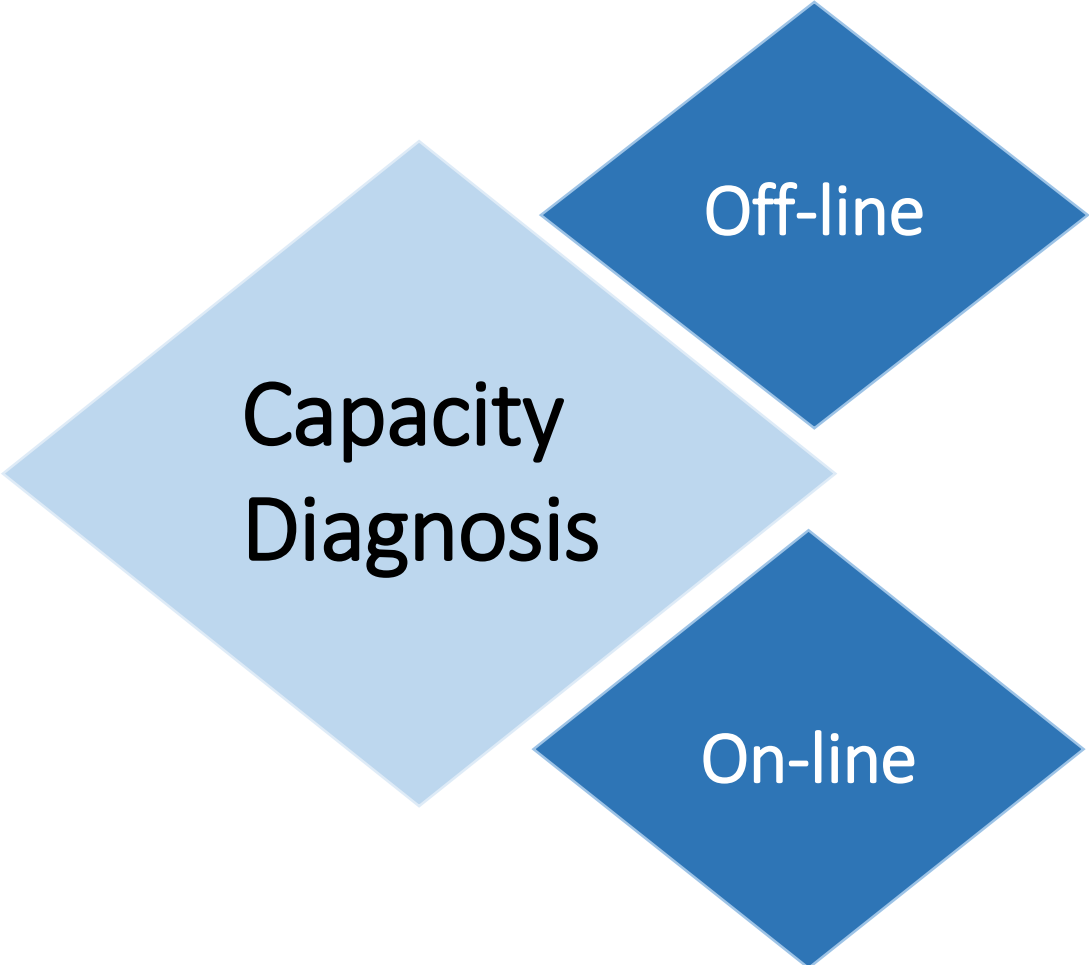
SOH = 100%

$$\text{SOH} = \frac{Q_t}{Q_0} \times 100\%$$

SOH = 80%



1. Background and motivation



Capacity Diagnosis

Off-line

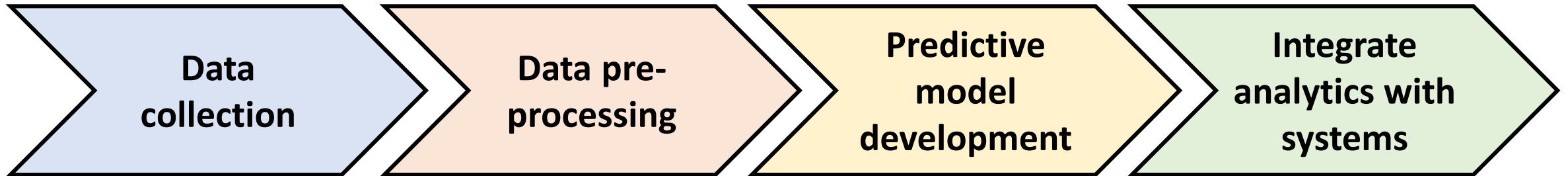
- Capacity test: fully charge and then discharge

On-line

- Model Driven
- Data Driven
 - Empirical/Semi-empirical model
 - Machine learning
 -

Machine Learning for SOH estimation

Step 1



- Historical data base
- Data collection from sensors (e.g. I, V, T)

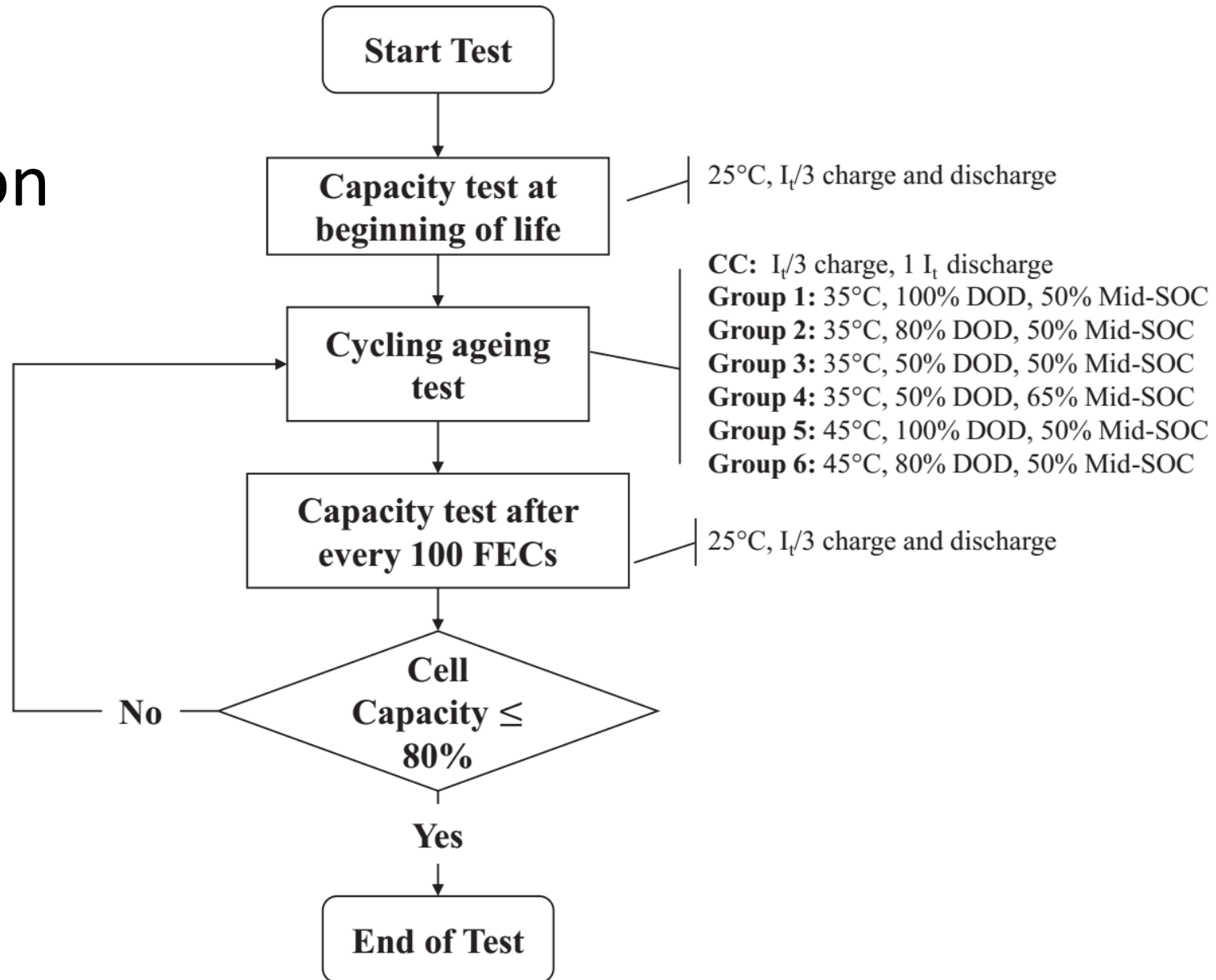
- Reducing noise in data
- Data reduction/transformation
- Feature extraction

- Model creation
- Parameter tuning/optimization
- Model validation

- Embedded in BMS

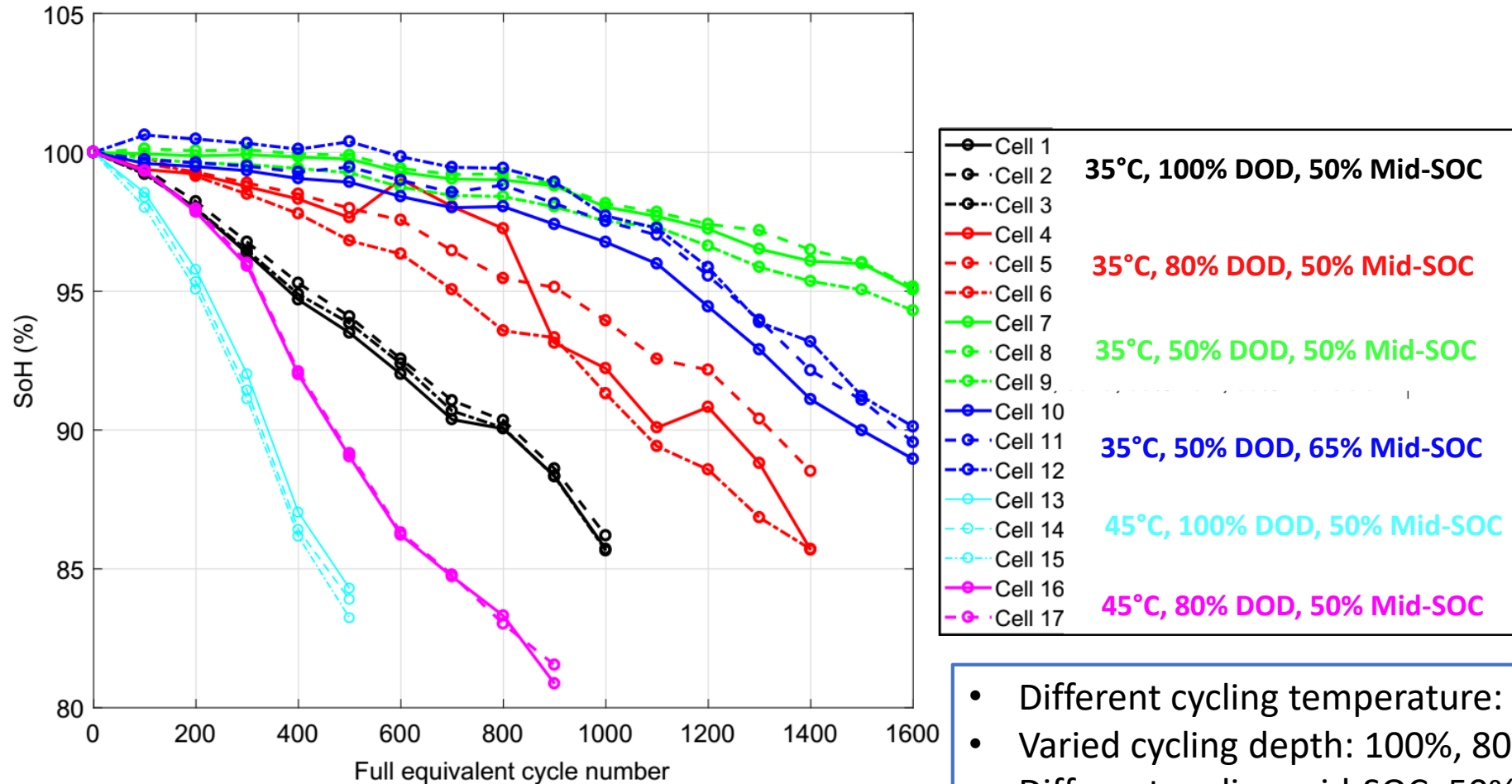
2. Data & Model

Step 1. Data collection



2. Data & Model

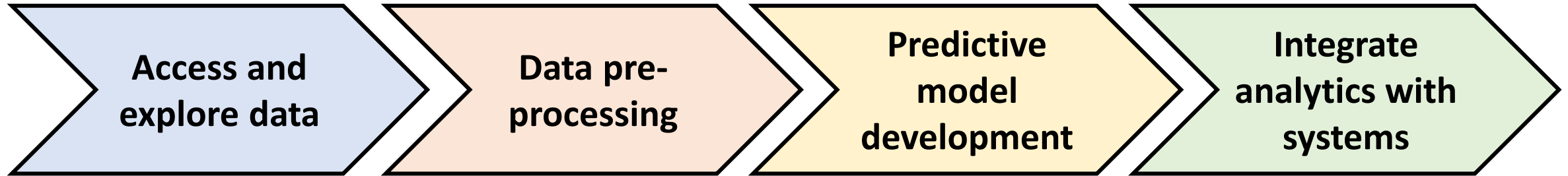
Capacity fade result :



- Different cycling temperature: 35, 45°C
- Varied cycling depth: 100%, 80%, 50%
- Different cycling mid-SOC: 50%, 65%

2. Data & Model

Step 2



- Historical data base
- Data collection from sensors (e.g. I, V, T)

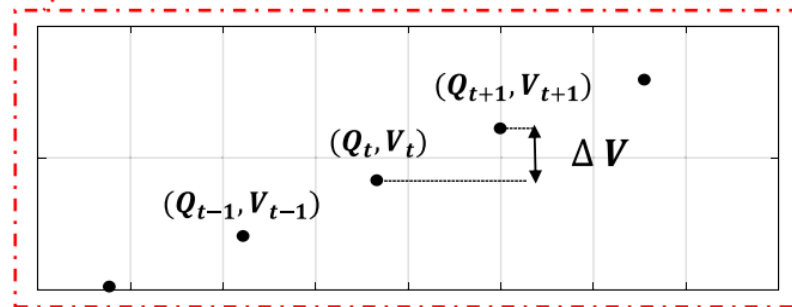
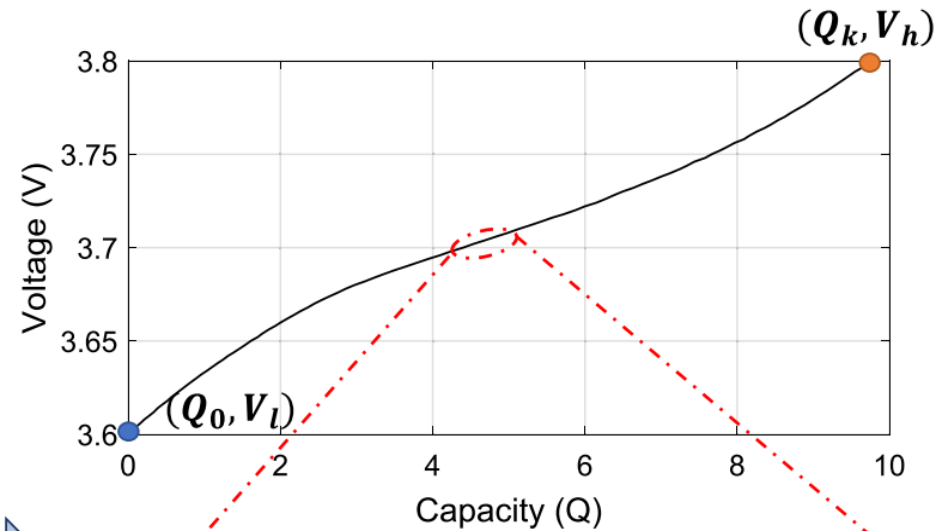
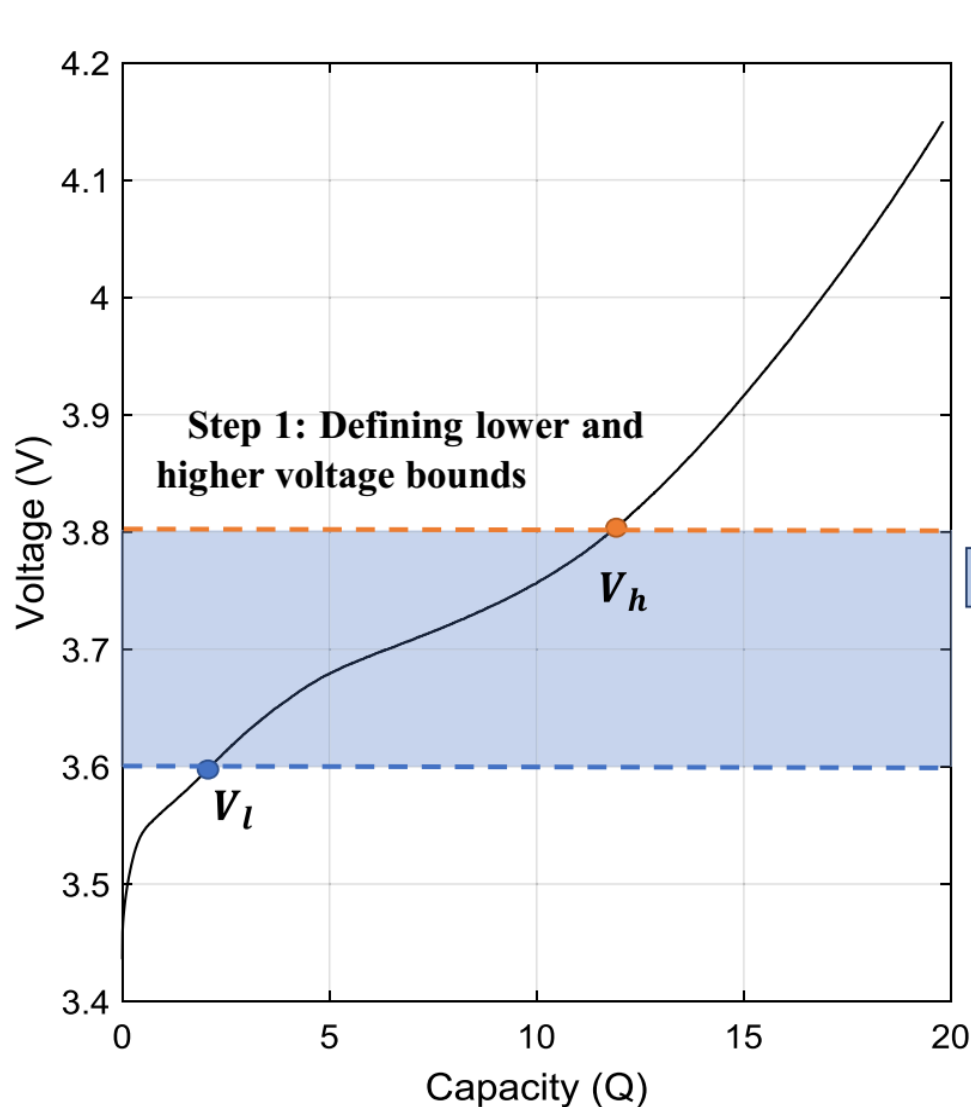
- Reducing noise in data
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2. Data & Model

Step 2. feature selection

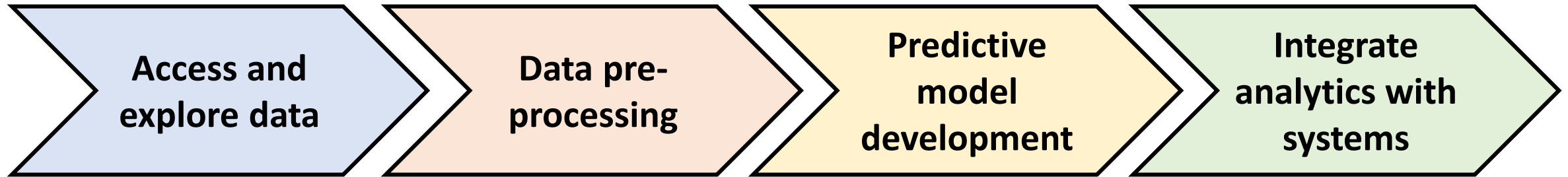


Step 2: Features extraction

$$\{X_i, Y_i\} = \{(x_0, x_1, \dots, x_k), Y_i\} = \{(Q_0, Q_1, \dots, Q_t, \dots, Q_h), Y_i\}$$

2. Data & Model

Step 3



- Historical data base
- Data collection from sensors (e.g. I, V, T)

- Reducing noise in data
- Data reduction/transformation
- Feature extraction

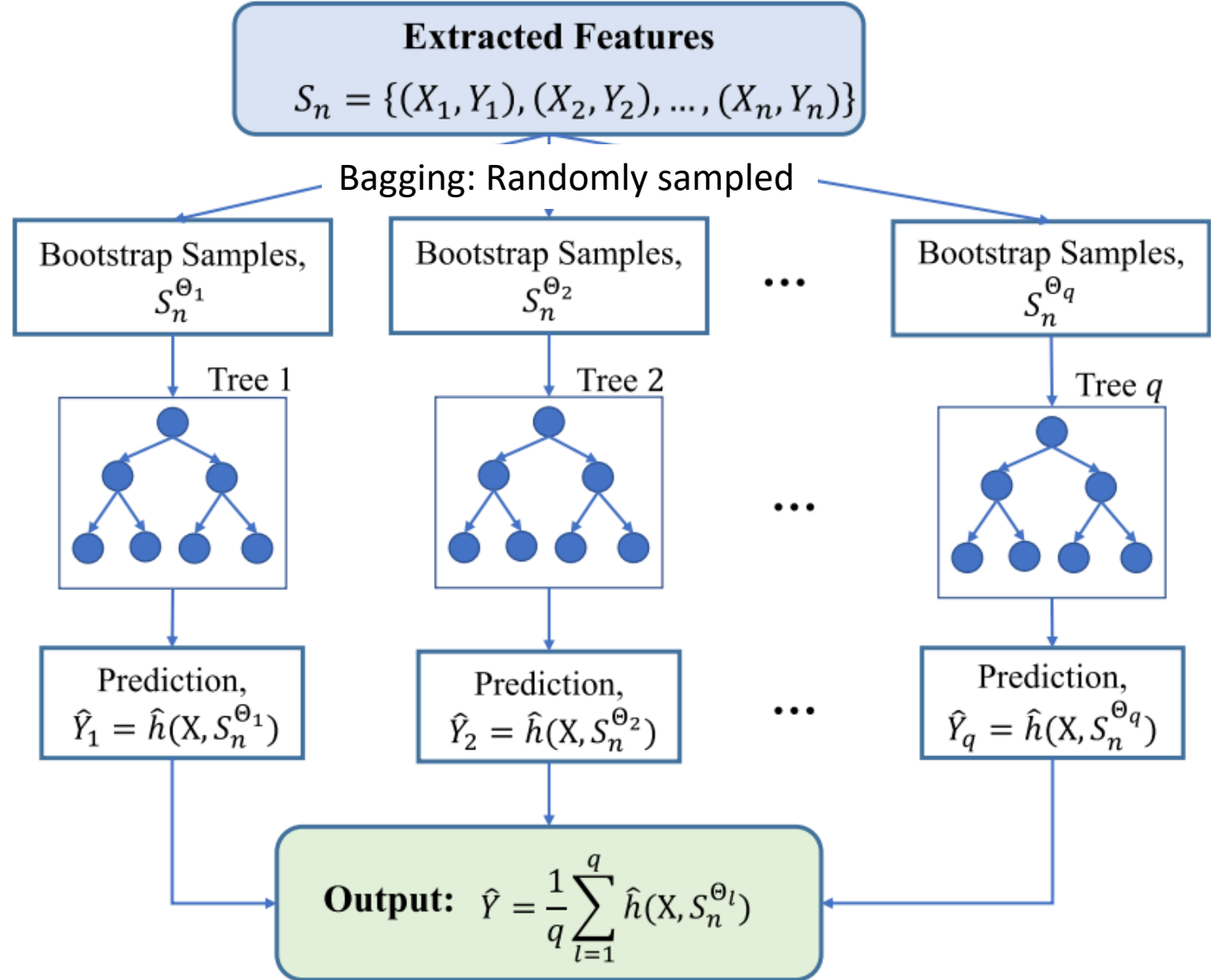
- Model creation
- Parameter tuning/optimization
- Model validation

- Embedded in BMS

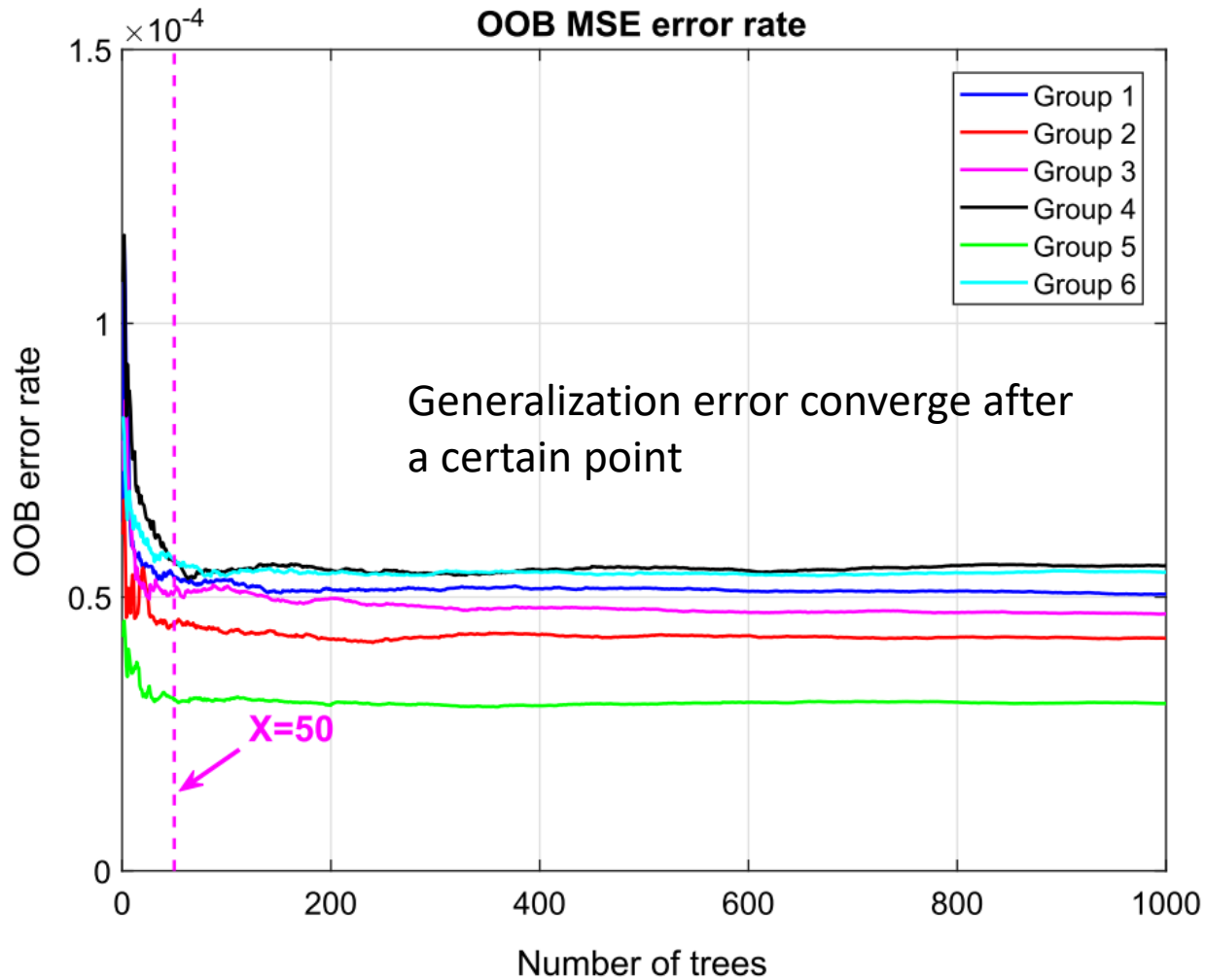
2. Data & Model

Step 3. Algorithm selection

Random Forest Regression:
An ensemble method



2. Data & Model



Offline parameter tuning

n_{tree}: the number of trees
m_{try}: the number of random features for each split in the forest to build (default number)

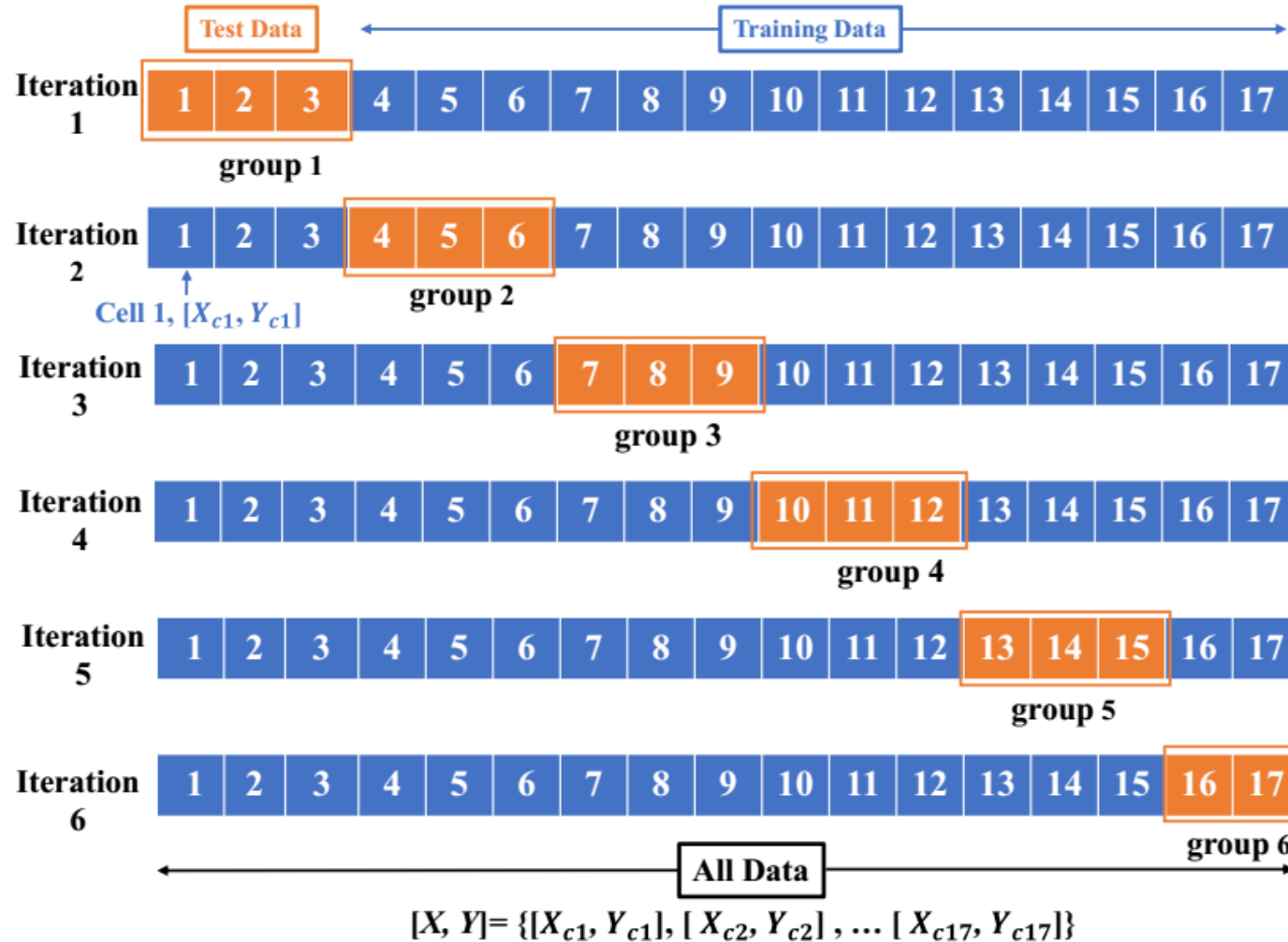
$$Loss = MSE = \sum (y_i - y_i^p)^2$$

y_i : i th target value

y_i^p : i th prediction

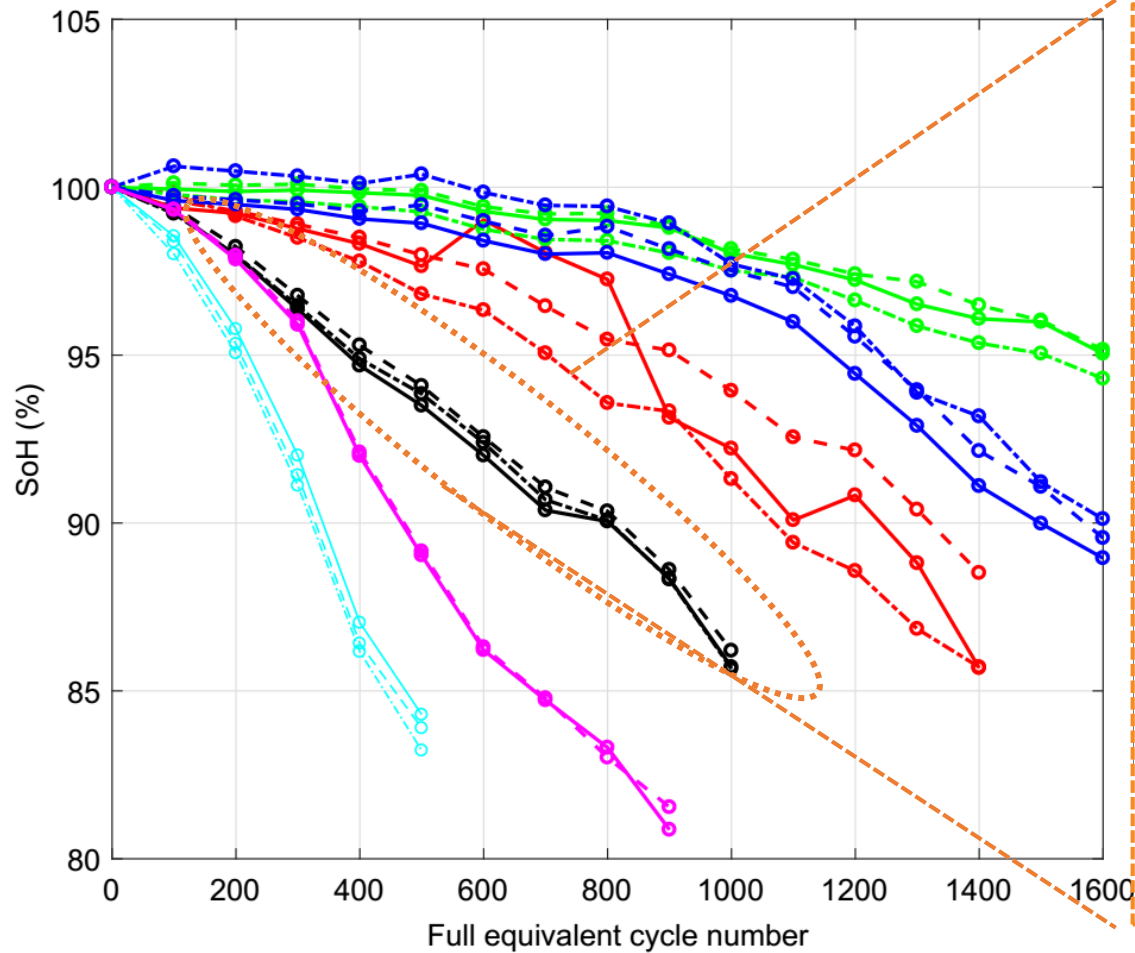
2. Data & Model

Leave n-out cross validation

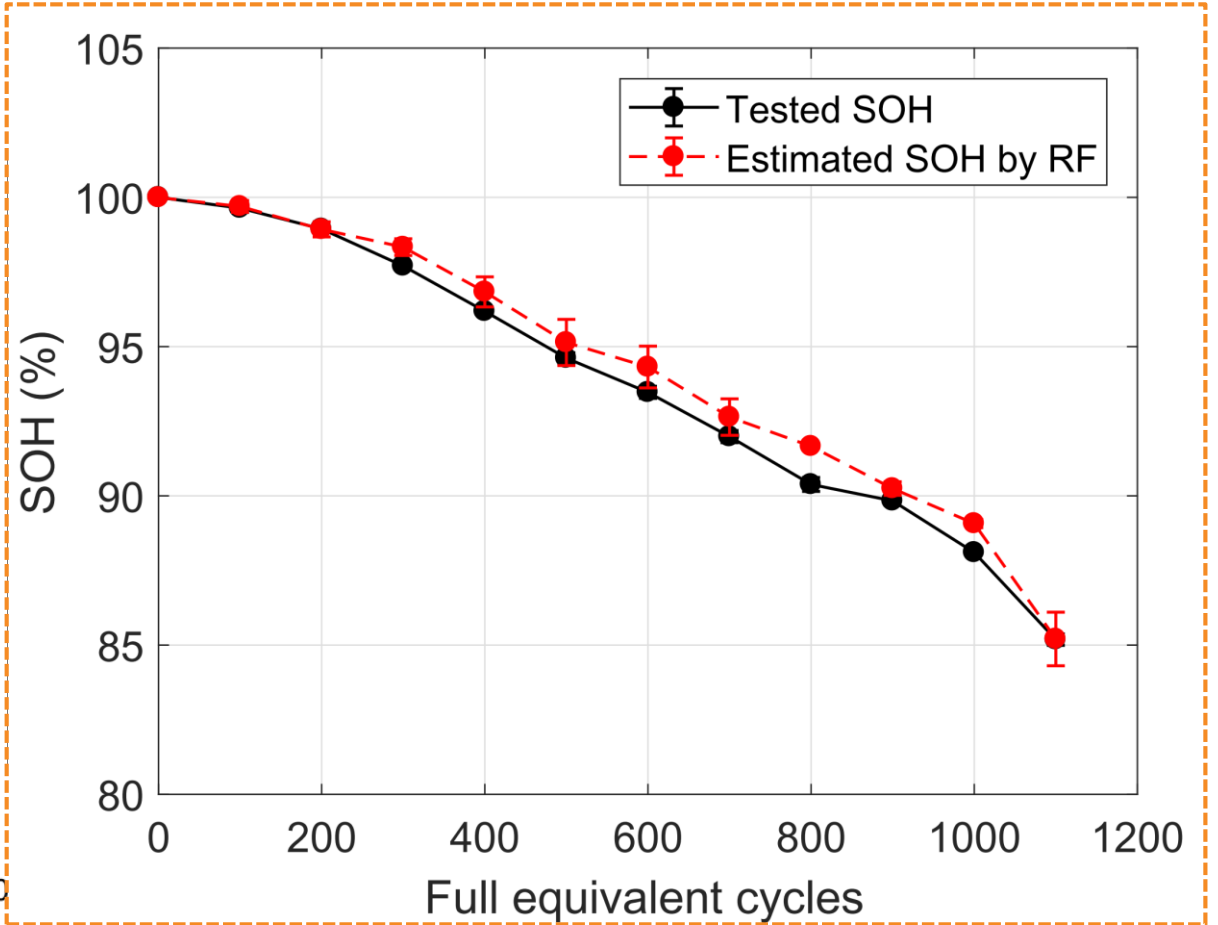


2. Data & Model

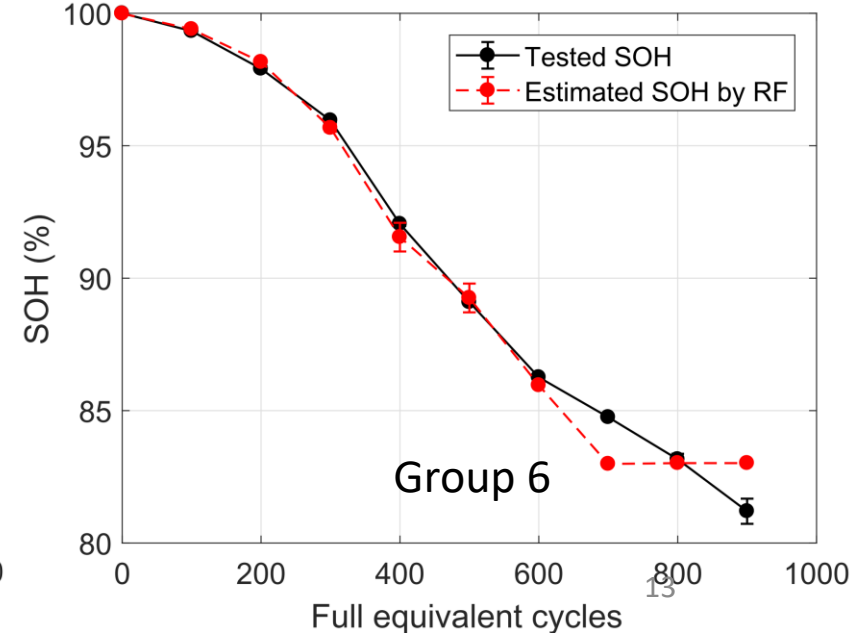
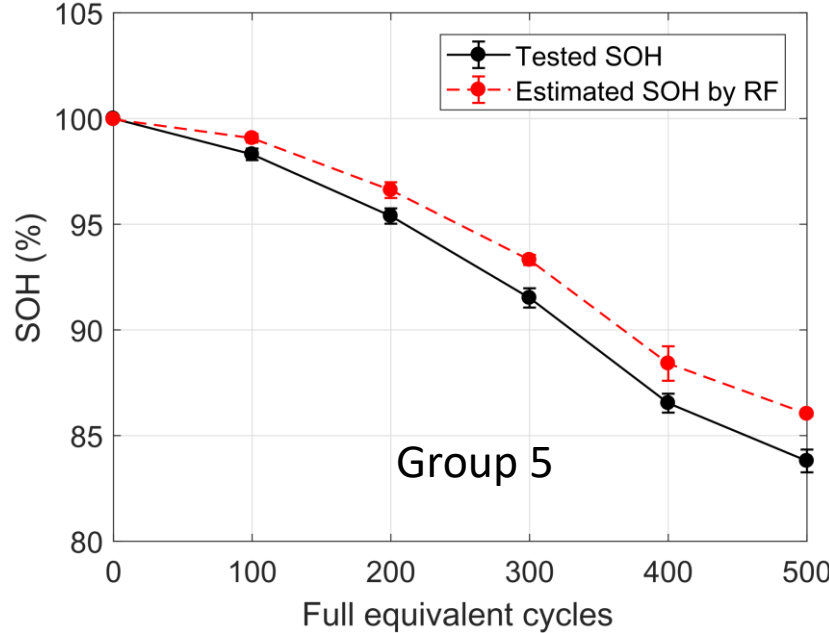
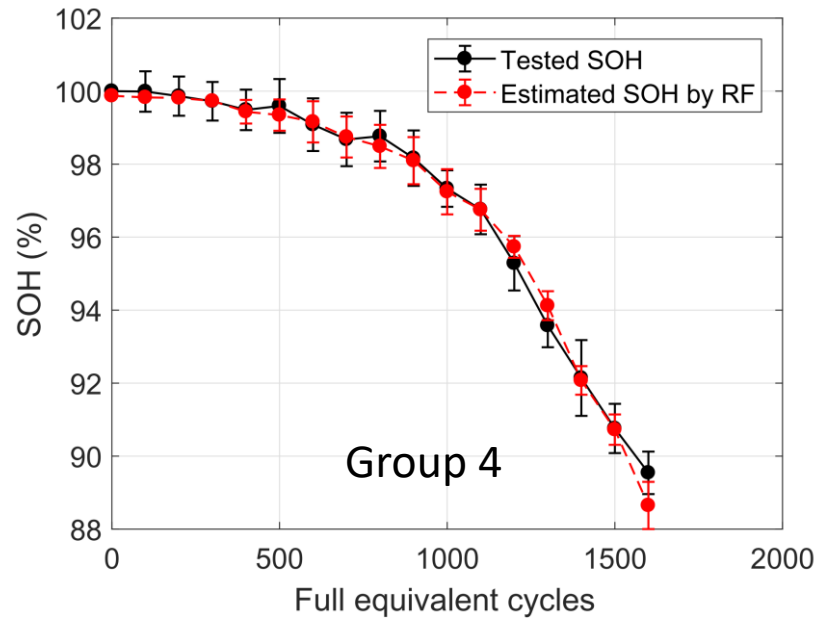
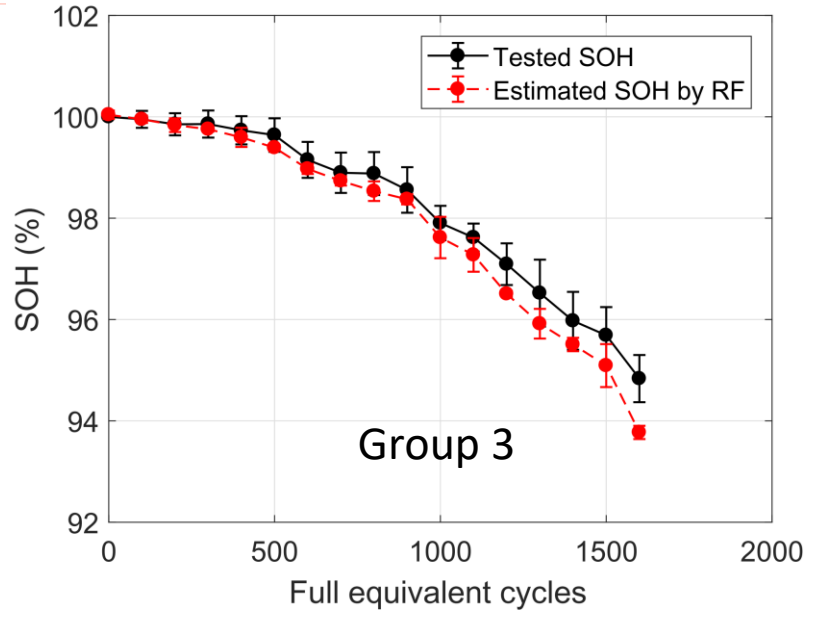
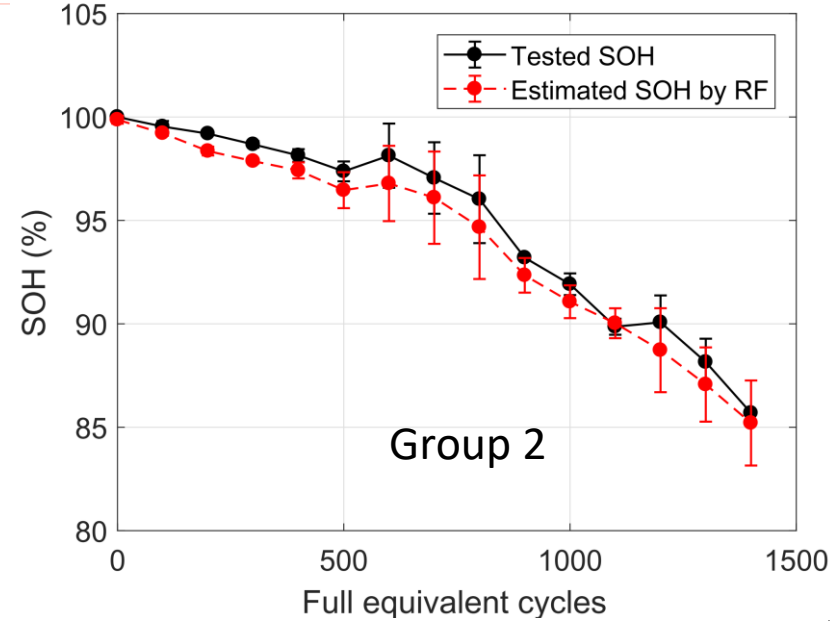
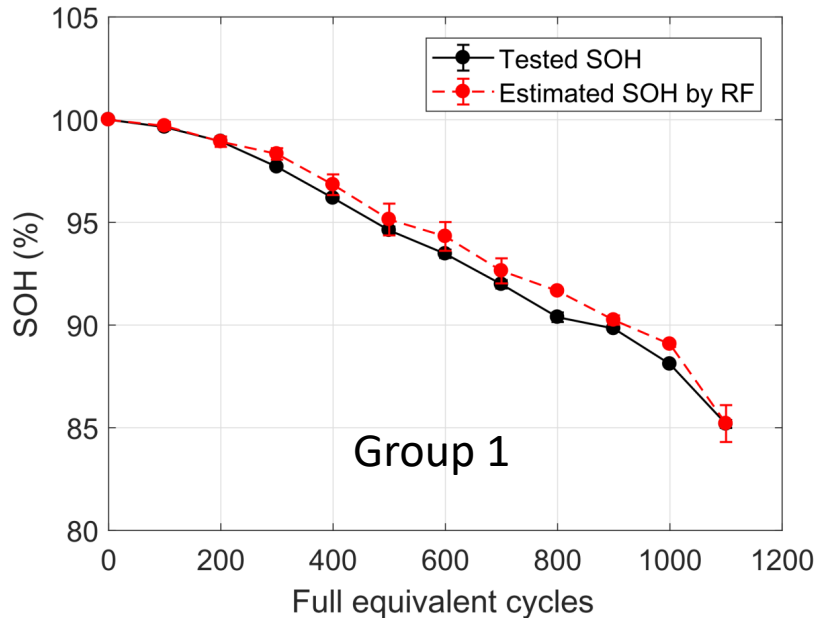
Experimental Results



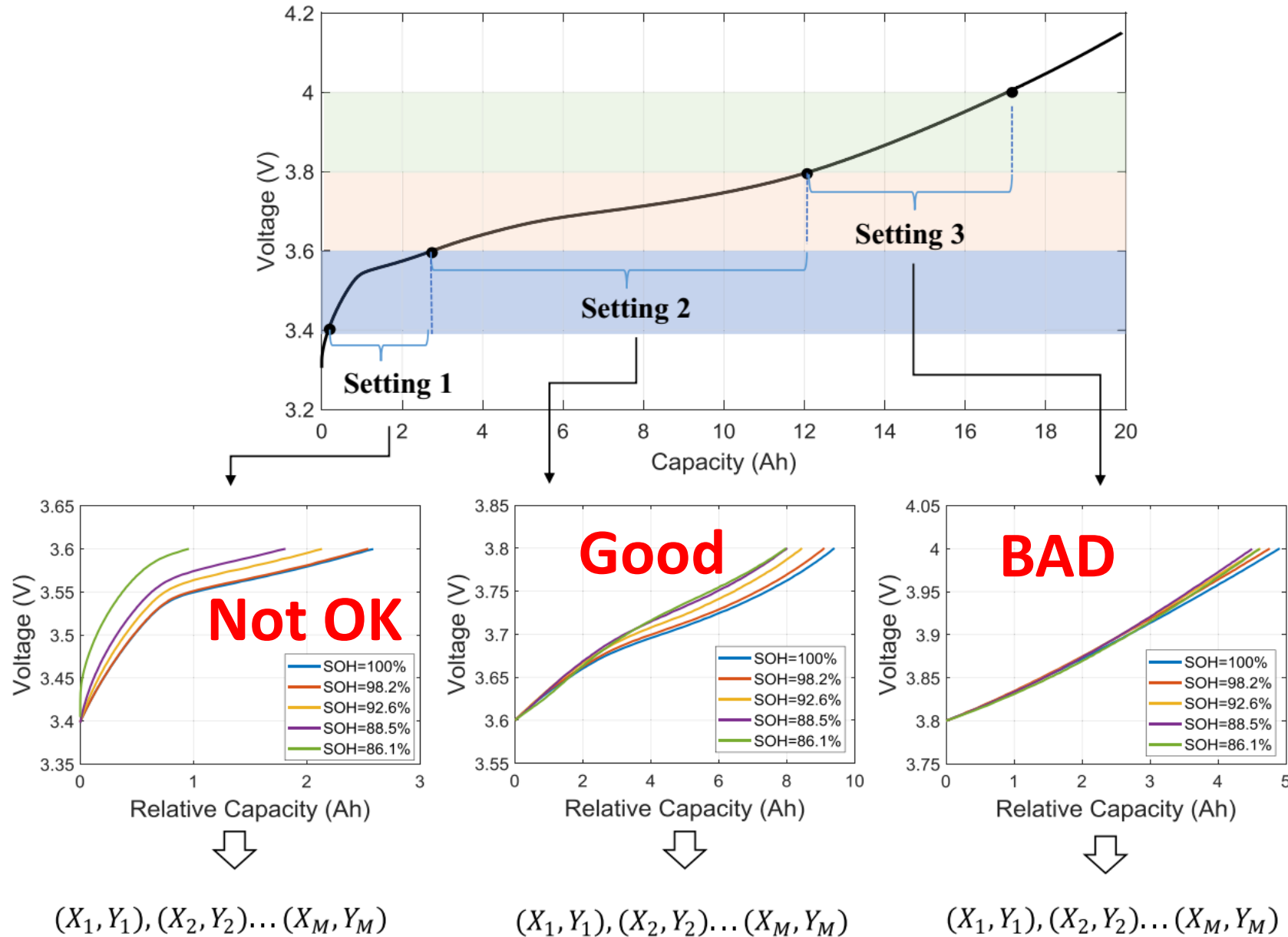
Estimation Results



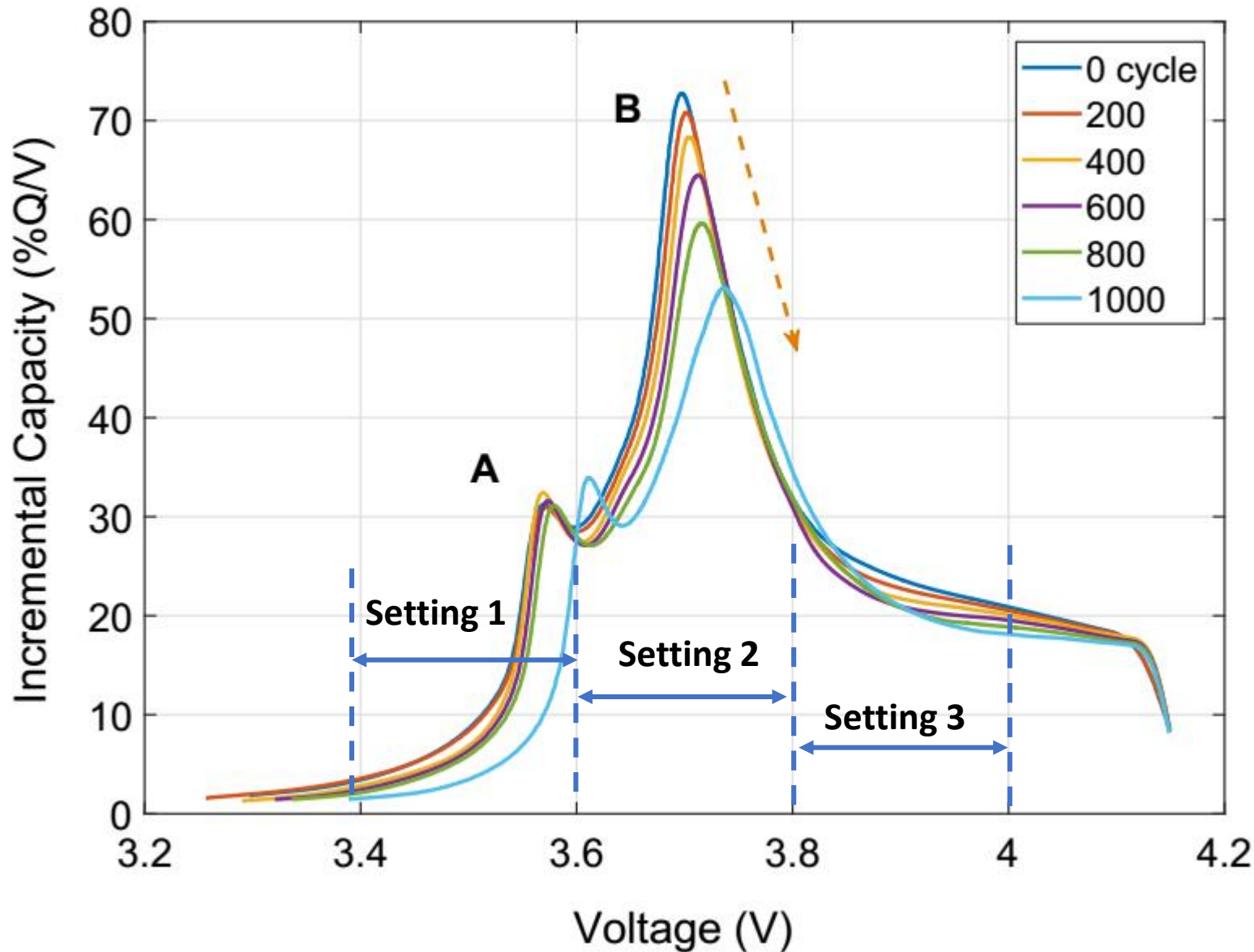
3. Results & Conclusion



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Incremental Capacity analysis

$$IC = \frac{dQ}{dV} \approx \frac{\Delta Q}{\Delta V} = \frac{Q_t - Q_{t-1}}{V_t - V_{t-1}}$$

Conclusion

- A online capacity estimation method with random forest regression was proposed
- Low effort for input feature collection
- IC analysis was used for input feature selection

Limits:

- Only charging voltage-capacity curves at 25°C are used for input feature selection
- Require constant current rate
- Low charging C-rate (C/3)

Outlook

- Dynamic using conditions
- Battery pack
- Health prediction

Thank you!

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 THE FARADAY
INSTITUTION



Tuesday, 3rd

Shahin Nikman - Parallel Session 1b | 3 pm



Wed, 4th - Parallel Session 5a | 4pm

Michael Mercer



Beatrice Wolff



Robert Burrell



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