电池生命周期管理系统（计科方向）

Advanced Deep Learning Framework for Enhanced Estimation of Lithium-Ion Batteries' Remaining Useful Lifetime Integrating Electrochemical Impedance Spectroscopy Data Analysis

Comprehensive Design

Nov 25，2023

计算机科学与技术 - 王浩羽

指导老师：宋轩

Outline

- Background and Significance
- Relative Work
- Data Exploration
- Objectives
- Milestones
- Reference
- Q&A

Background and Significance

图表5：2020-2026年全球锂电池行业市场规模情况预测(单位：十亿美元)

Background and Significance

Aging phenomenon:
The performance of Li-ion batteries will **decrease** with time (calendar aging) and use (cycle aging)

Influence:
- increase operating costs
- reduce the service life of the equipment
- affect the safe operation of the equipment

Research:
- Depending on a mass of **historical data**
- Lifetime is different according to different use scenarios and production process

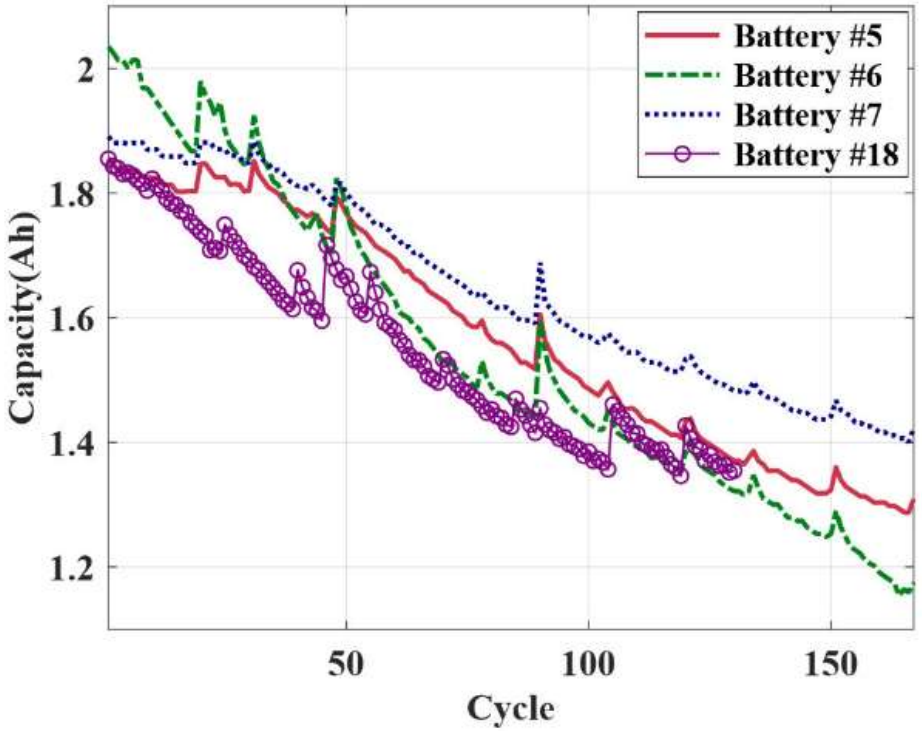


Image source: Park, K., Choi, Y., Choi, W. J., Ryu, H.-Y., & Kim, H. (2020). LSTM-Based Battery Remaining Useful Life Prediction With Multi-Channel Charging Profiles. IEEE Access, 8, 20786–20798.

Background and Significance

Assess

The current health of electric vehicles

History Data

Estimate

working environment

Usage habits

The remaining Useful Lifetime (RUL)

Relative Work - Concepts

Concepts:

- **SOH**: State of Health

$$SOH = \frac{C_{max}(current)}{C_{max}(initial)} \times 100\%$$

C_{max} : The maximum capacity of battery

- **RUL** (Remaining Useful Lifetime), unit: cycle or time;

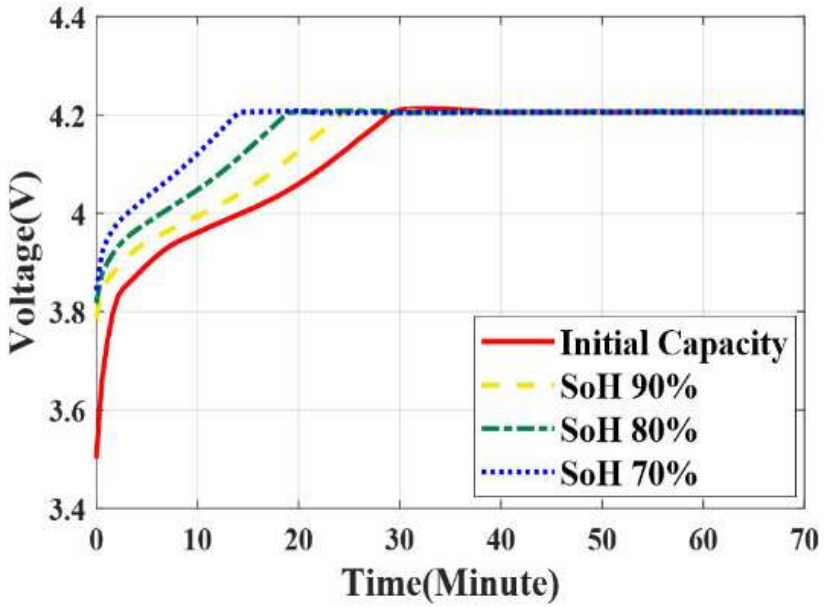
  RUL is defined as the time at which equipment performance first or first arrival time drops to the failure threshold.

  Generally, end of battery service life is **80%** of the initial value;

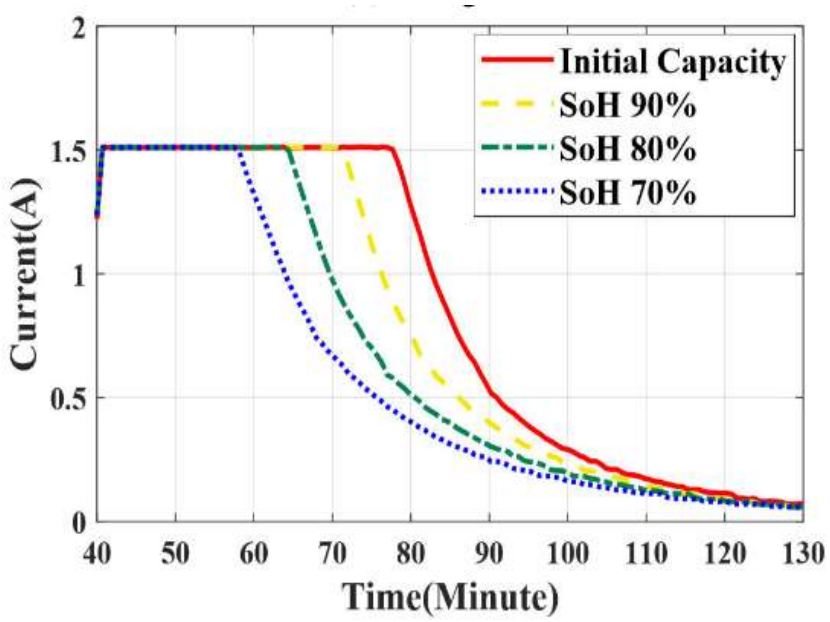
Relative Work - Concepts

Features:

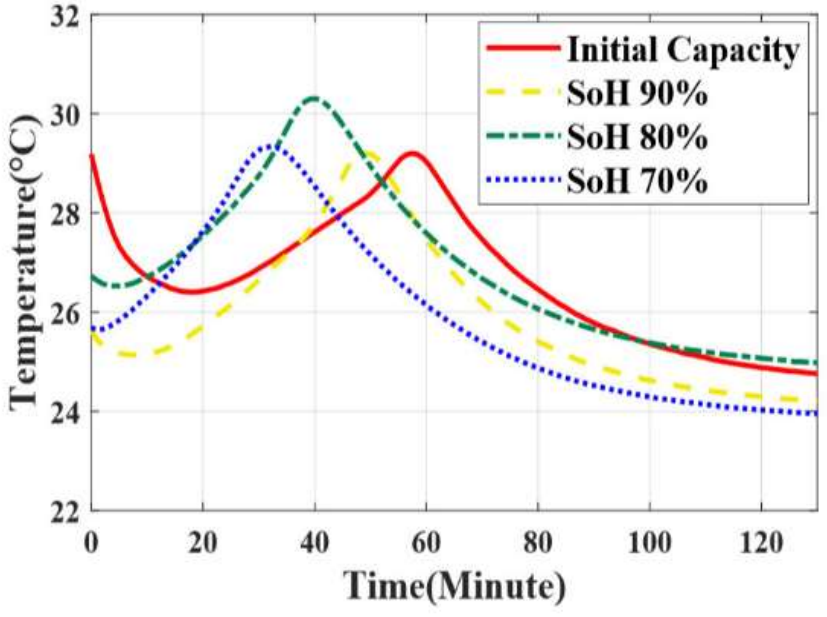
- Charge Cycle 充放电周期
- Charging Curve / Discharging Curve of Voltage, Current and Temperature



(a) Voltage



(b) Current



(c) Temperature

Image source: Park, K., Choi, Y., Choi, W. J., Ryu, H.-Y., & Kim, H. (2020). LSTM-Based Battery Remaining Useful Life Prediction With Multi-Channel Charging Profiles. IEEE Access, 8, 20786–20798.

Relative Work

- RUL prediction with charging curve of time series
  - Model-based techniques
  - Data-driven-based techniques
  - Hybrid-based techniques
- SOH prediction with charging curve of specific charge cycle
- RUL / SOH prediction with EIS

Relative Work - RUL prediction

- Model-based techniques
  - Physics-based model
  - Equivalent circuit model
  - Empirical model

→ Mathematics
Experimental results
Empirical data

→ complexity and computational cost

- Data-driven-based techniques
  - **Machine Learning**
  - Adaptive filtering 自适应过滤
  - Random process 随机过程

→ Simple and Effective

- Hybrid-based techniques

Relative Work – Machine Learning

Machine Learning Model
for RUL prediction and SOH prediction

	RUL	SOH
input	A series of charging curve	A single charging curve
output	A series of RUL Or a single RUL	A single SOH
model	RNN, LSTM, CNN, DNN, ···	ANN, DNN, ···
complexity and cost	Higher and more	Lower and less

Relative Work – EIS

EIS (Electrochemical Impedance Spectroscopy) 电化学阻抗谱

Features:

- R_{ohm} : Ohm Resistance 欧姆阻抗
- R_{SEI} : Solid Electrolyte Interface Resistance 固体电解质界面阻抗
- R_{ct} : Charge Transfer Resistance 电荷传递阻抗

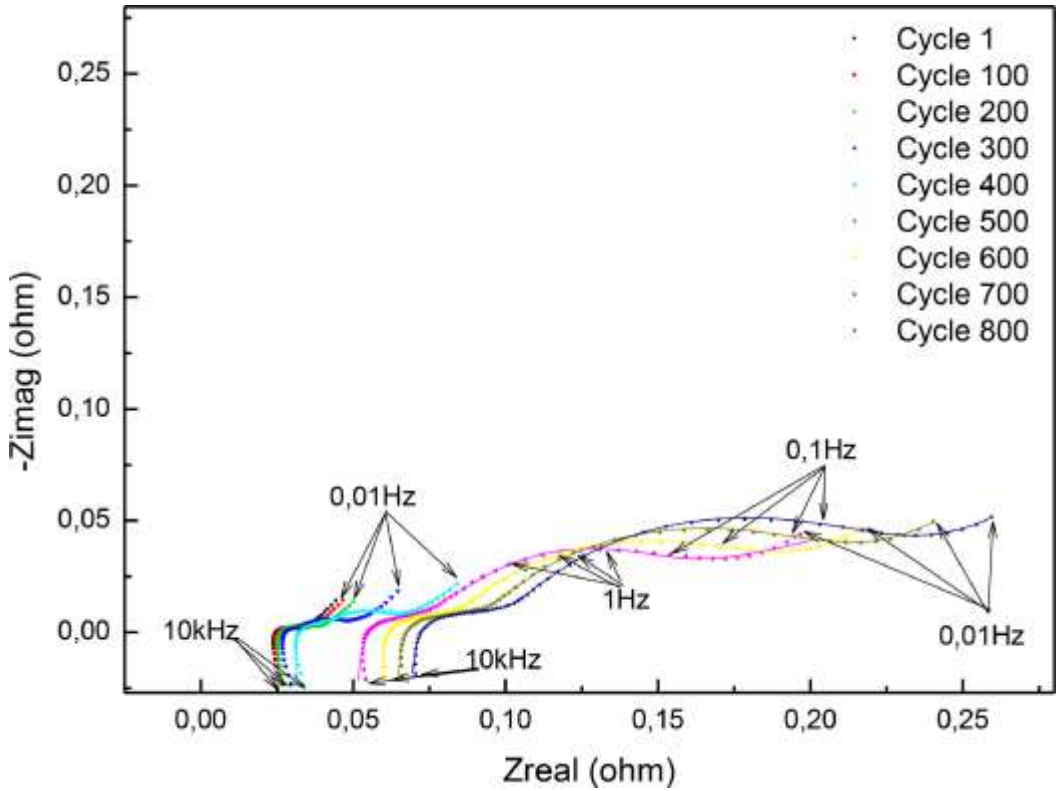


Image source: Ph.D..Jiahao Xu

Relative Work – EIS

EIS

- real-time, non-invasive
- information-rich: materials properties, interfacial phenomena and electrochemical reactions.
- hitherto underused in battery diagnosis

Data Exploration

Capacity data:

- 25℃ => 8 batteries; 35℃ and 45℃ => 2 batteries
- 200 – 350 cycles
- For each cycle, Voltage, Current and Capacity with time are provided

EIS data:

- 200 – 350 cycles
- For each cycle, frequency, Re(Z), Im(Z) with time are provided

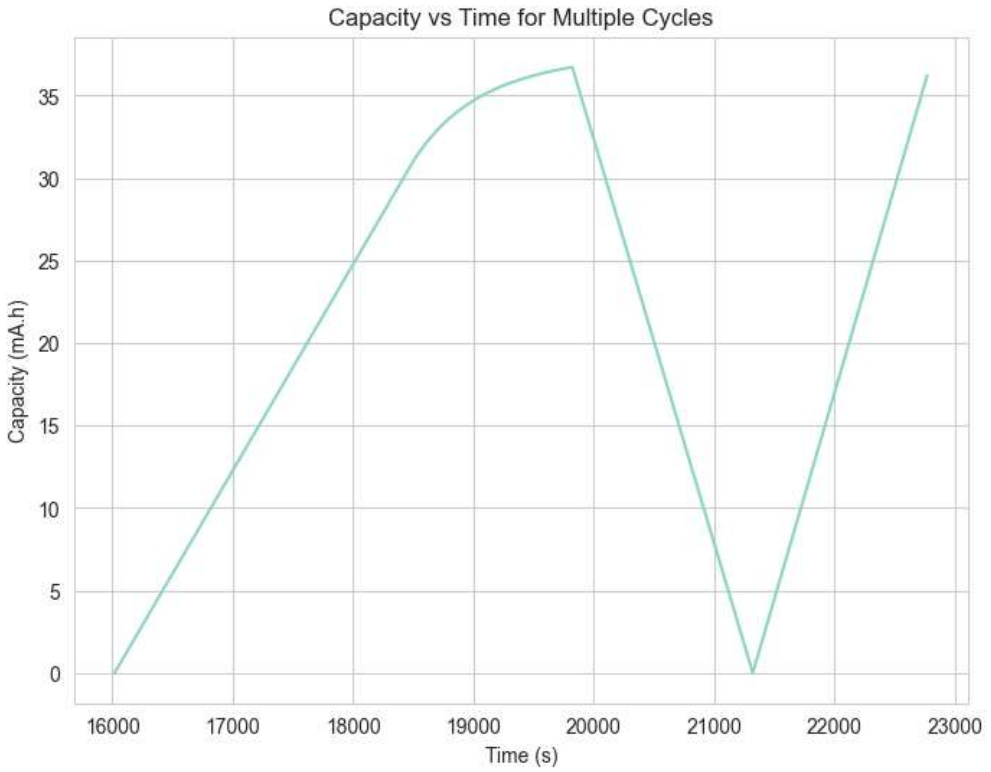
Dataset resource: https:// doi.org/10.5281/zenodo.3633835.

Ref. Zhang, Y., Tang, Q., Zhang, Y., Wang, J., Stimming, U., & Lee, A. A. (2020). Identifying degradation patterns of lithium ion batteries from impedance spectroscopy using machine learning. Nature Communications, 11(1). https://doi.org/10.1038/s41467-020-15235-7

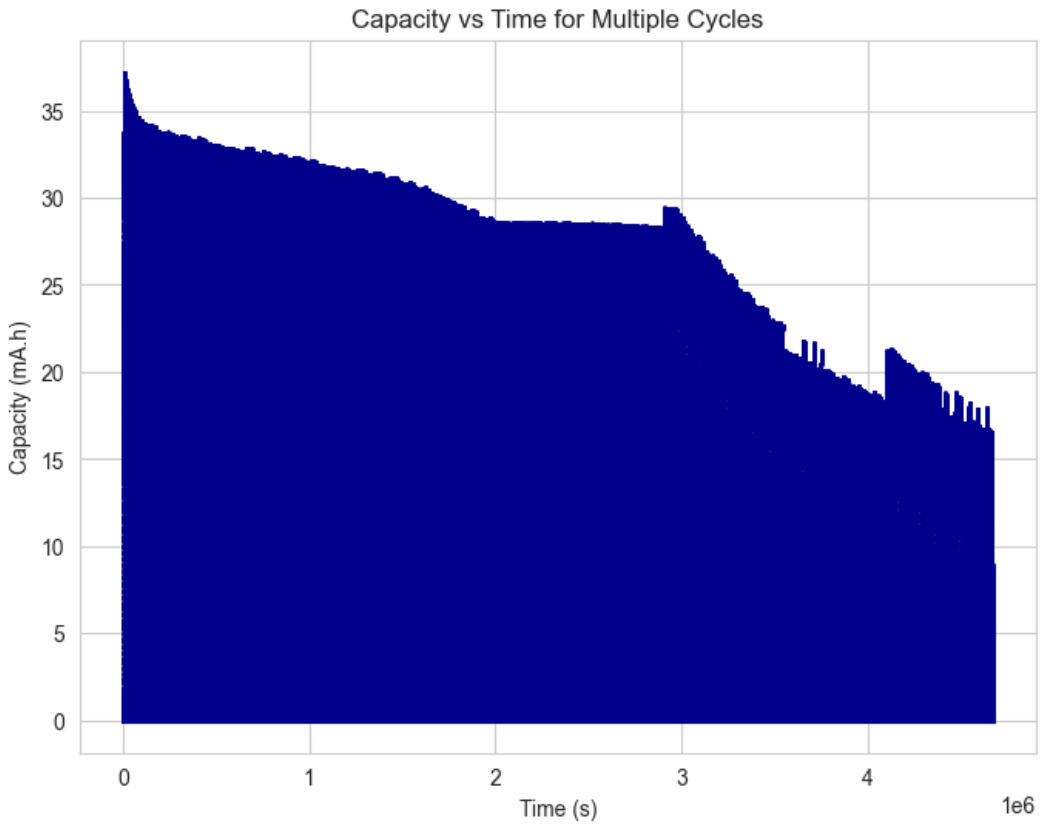
Data Exploration

Capacity data

Cycle 1



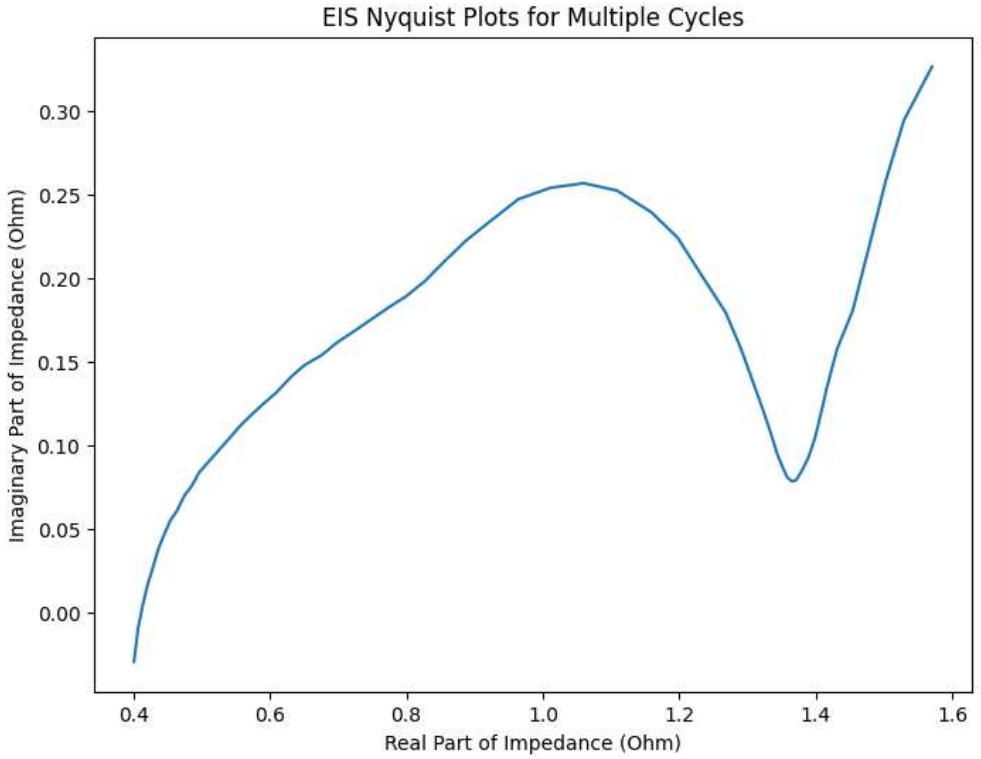
Cycle 1-350



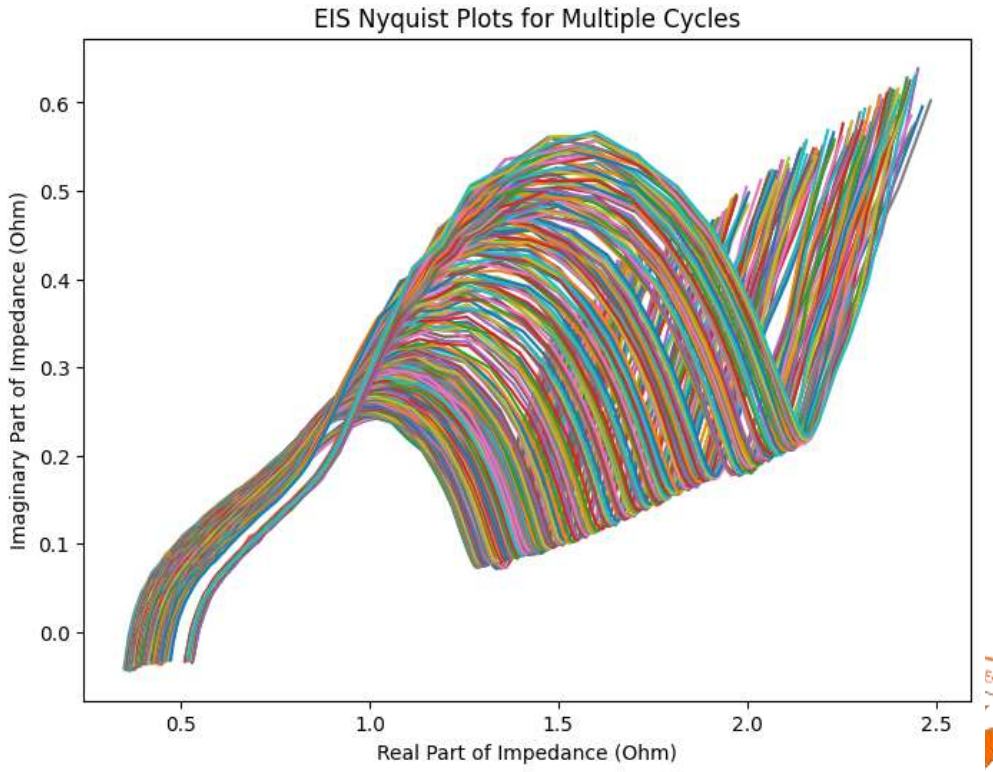
Data Exploration

EIS data

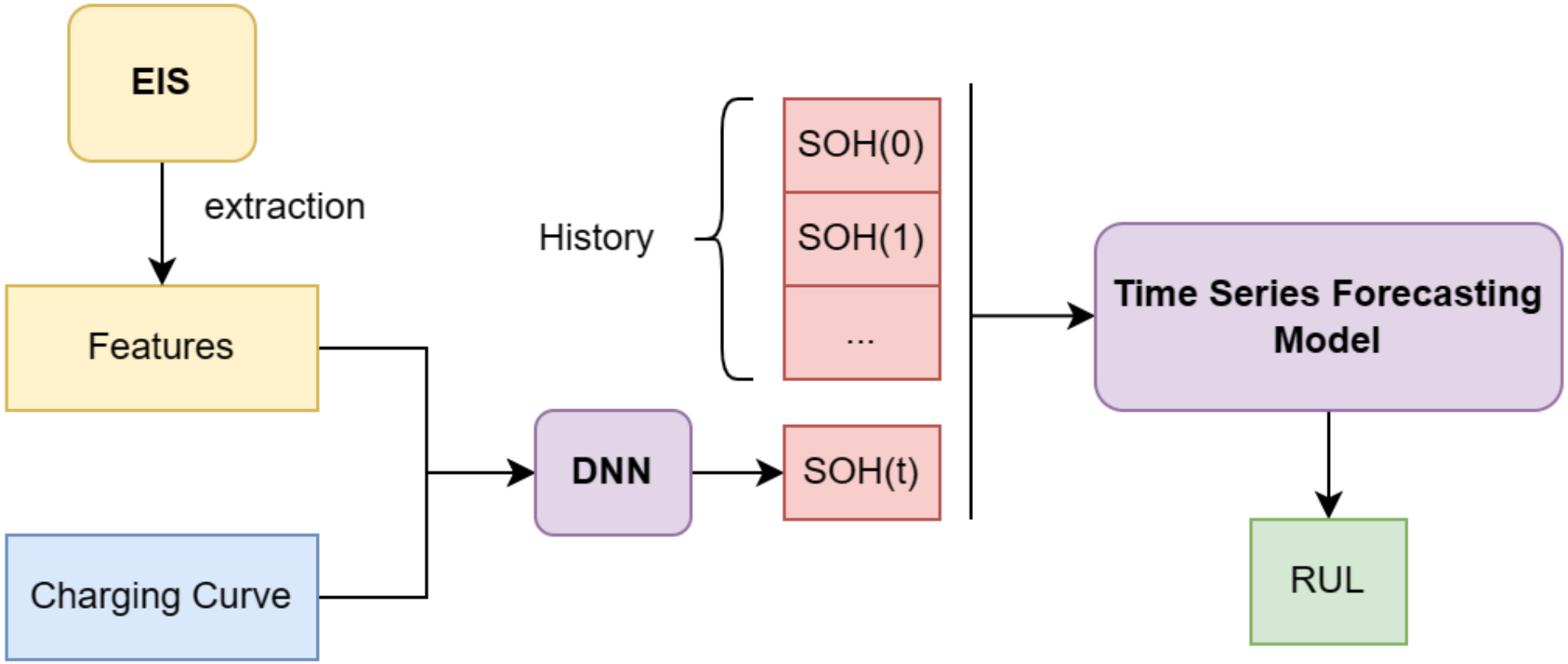
Cycle 1



Cycle 1-350



Objectives


EIS
extraction
Features
Charging Curve
DNN
History
SOH(0)
SOH(1)
...
SOH(t)
Time Series Forecasting Model
RUL

Expected key results（milestones）

Milestones

1. The correlation between EIS features and SOH
2. Model 1: DNN model for SOH prediction
3. Model 2: Time Series Forecasting Model for Regression of SOH(t)

Reference

1．Wang, S., Jin, S., Bai, D., Fan, Y., Shi, H., & Fernandez, C. (2021). A critical review of improved deep learning methods for the remaining useful life prediction of lithium-ion batteries. Energy Reports, 7, 5562–5574. https://doi.org/10.1016/j.egyr.2021.08.182

2．Ansari, S., Ayob, A., Hossain Lipu, M. S., Hussain, A., & Saad, M. H. M. (2022). Remaining useful life prediction for lithium-ion battery storage system: A comprehensive review of methods, key factors, issues and future outlook. Energy Reports, 8, 12153–12185. https://doi.org/10.1016/j.egyr.2022.09.043

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7．Zhang, Y., Tang, Q., Zhang, Y., Wang, J., Stimming, U., & Lee, A. A. (2020). Identifying degradation patterns of lithium ion batteries from impedance spectroscopy using machine learning. Nature Communications, 11(1). https://doi.org/10.1038/s41467-020-15235-7

Q&A

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