电池全生命周期健康管理

Comprehensive Design

Mar 15， 2024

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Outline

- **Background, Significance and Objectives**
- **Progress report**
- **Plan**

电动汽车

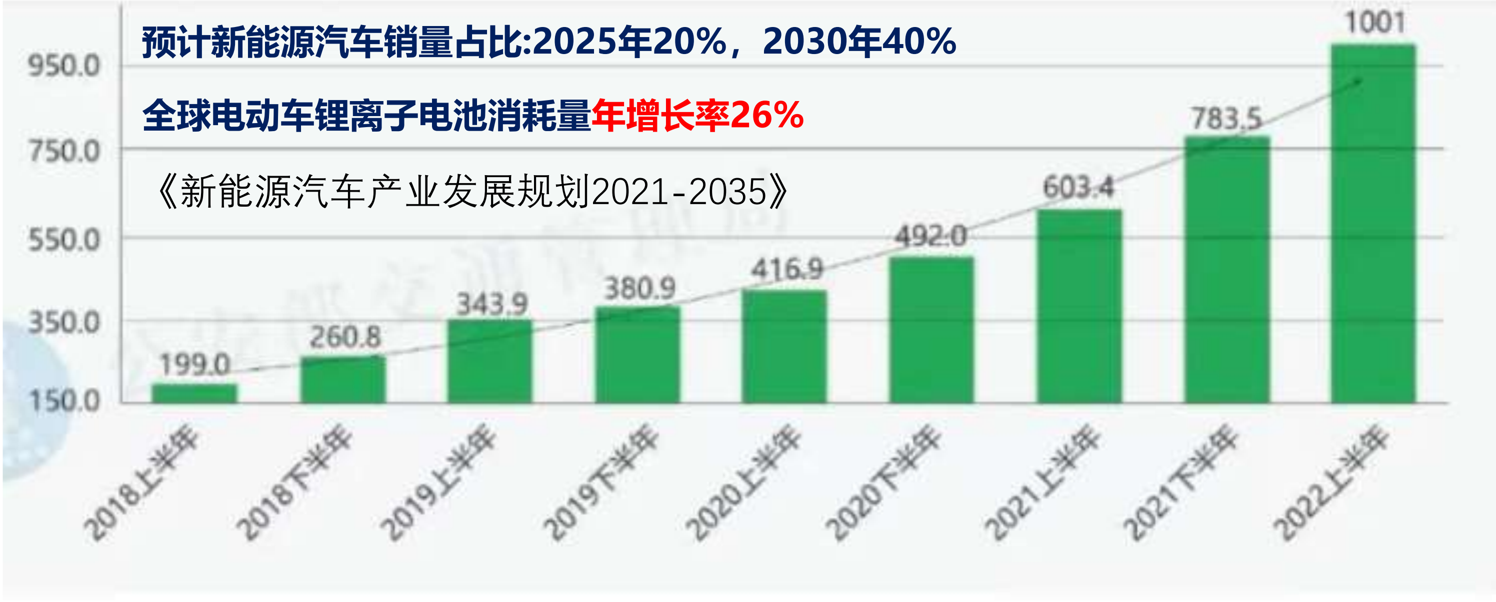
- 锂电池最大市场，目前30多个国家或地区已经宣布退出燃油车时间表
- 2021年全球新能源汽车销量650万辆（占9%），同期增长108%
- 2022上半年中国销售250万辆，同比大增121%，欧洲114万辆，北美50万

- 奥地利 2035
- 比利时, 2026
- 美国加州, 2035
- 加拿大, 2040
- 智利, 2035*
- 中国, 2035
- 哥斯达黎加, 2050
- 丹麦, 2030
- 埃及, 2040
- 法国, 2040
- 德国, 2030
- 香港, 2035*
- 冰岛, 2030
- 印度, 2030
- 印度尼西亚, 2050*
- 以色列, 2030
- 日本, 2035
- Lausanne, 2030*
- 美国麻州, 2035
- 荷兰, 2030
- 美国纽约州, 2035*
- 挪威, 2050
- 新加坡, 2040
- 斯洛文尼亚, 2030
- 西班牙, 2040
- 斯里兰卡 2040
- 瑞典, 2030
- 台湾, 2040
- 泰国, 2025*
- 英国, 2030

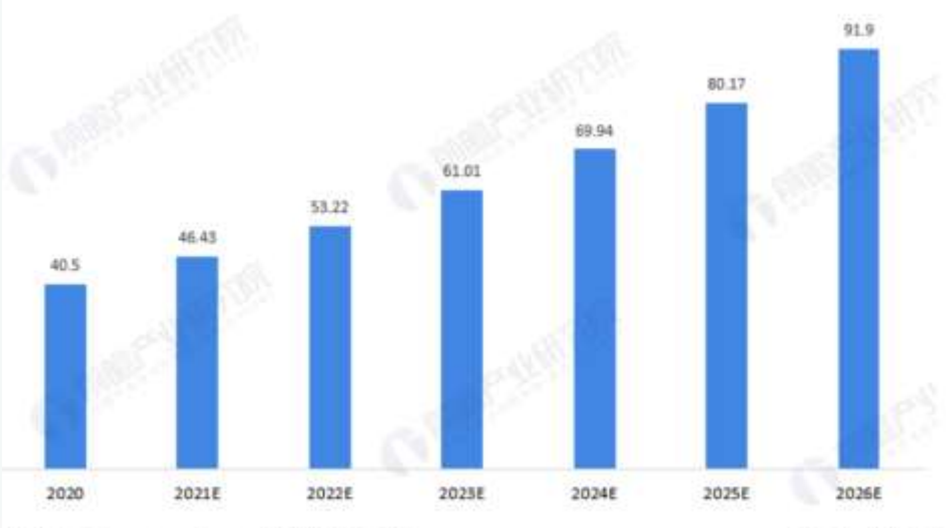
预计新能源汽车销量占比:2025年20%，2030年40%

全球电动车锂离子电池消耗量年增长率26%

《新能源汽车产业发展规划2021-2035》



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)



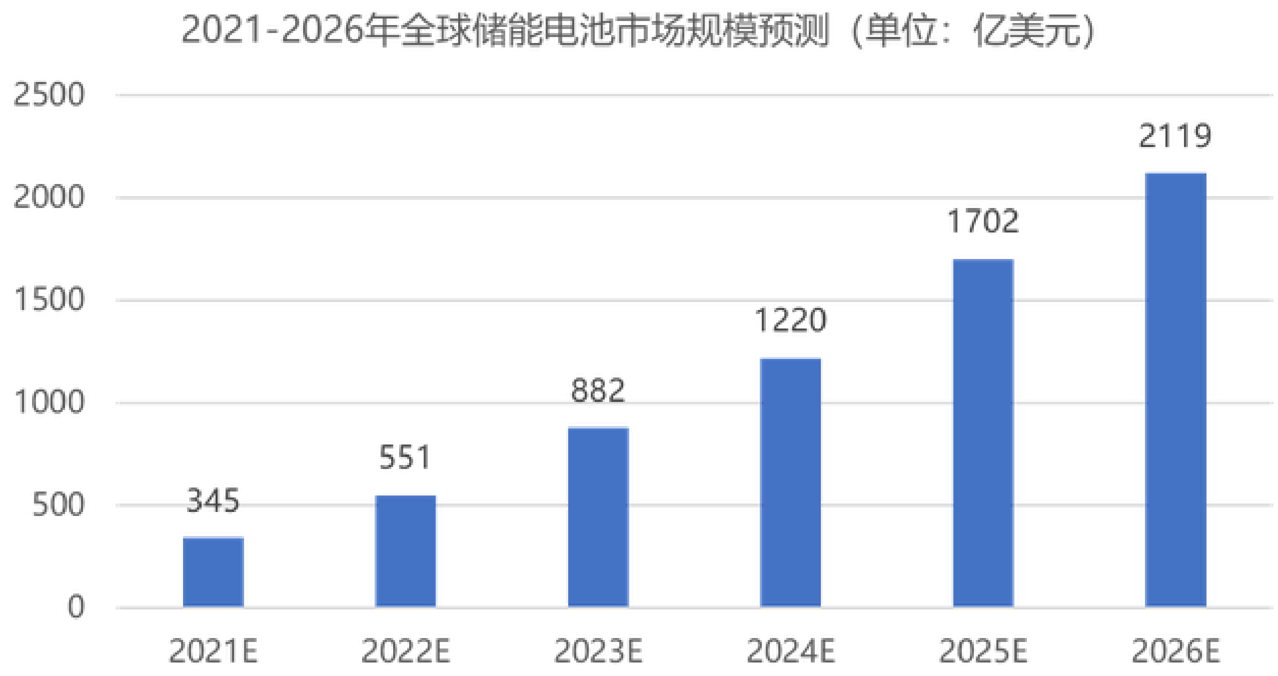
资料来源：Research and Markets 前瞻产业研究院整理

@前瞻经济学人APP

储能

- 电池的下一个超万亿美金市场
- 2021年中国发布《关于加快推动新型储能发展的指导意见》
- 2025年，装机规模达到30GW，2030年全面市场化发展

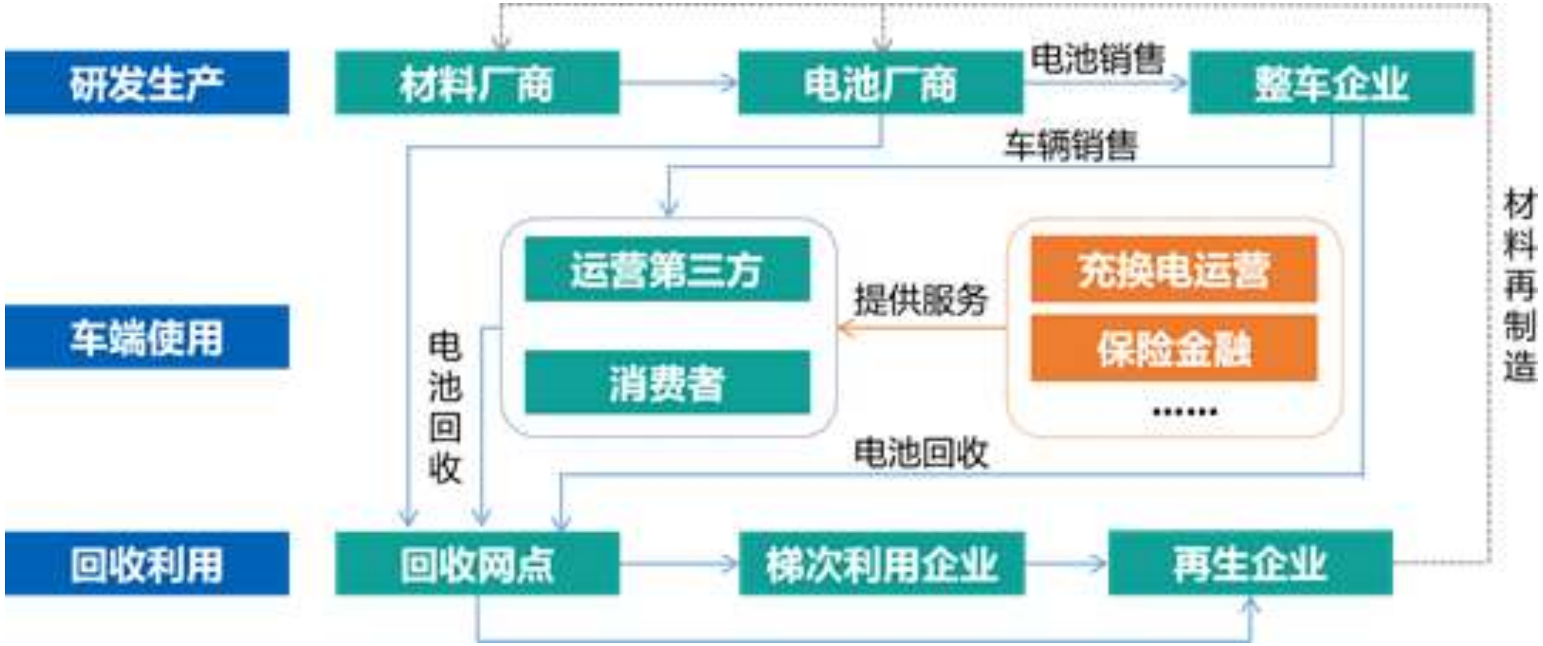
图片来源：《2022储能产业应用研究报告》



Background, Significance and Objectives

Advantage：

1. Improve battery performance and safety
2. Provides support for the secondary utilization of batteries to ensure the reliability of the secondary utilization



Material Science Part

李宗润

- Process Report
- Future Plan

Progress report

Electrochemical Workstation

PC

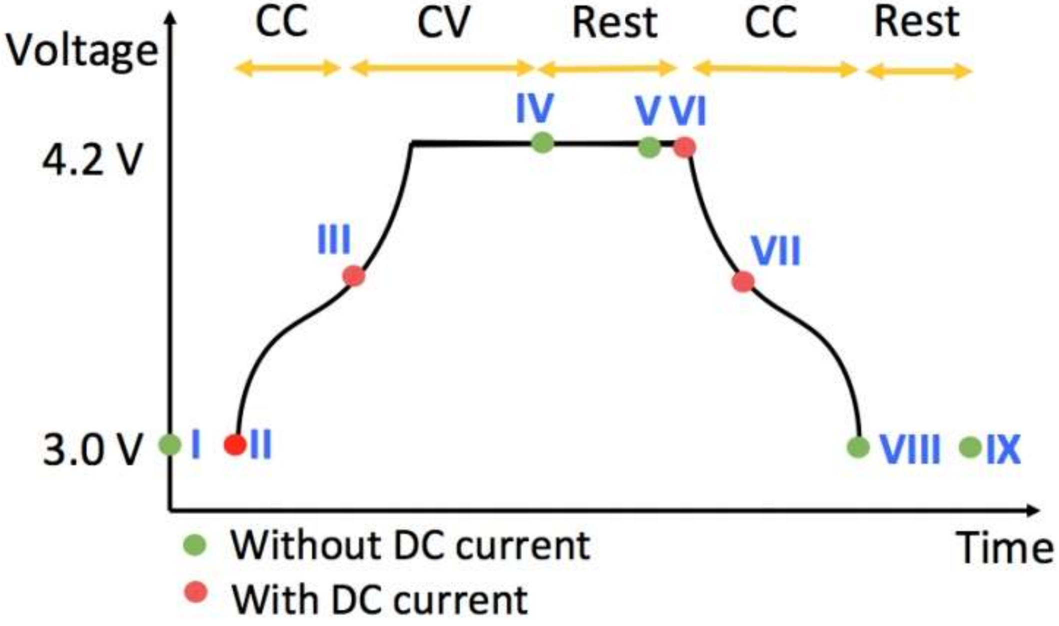
Cycle test equipment

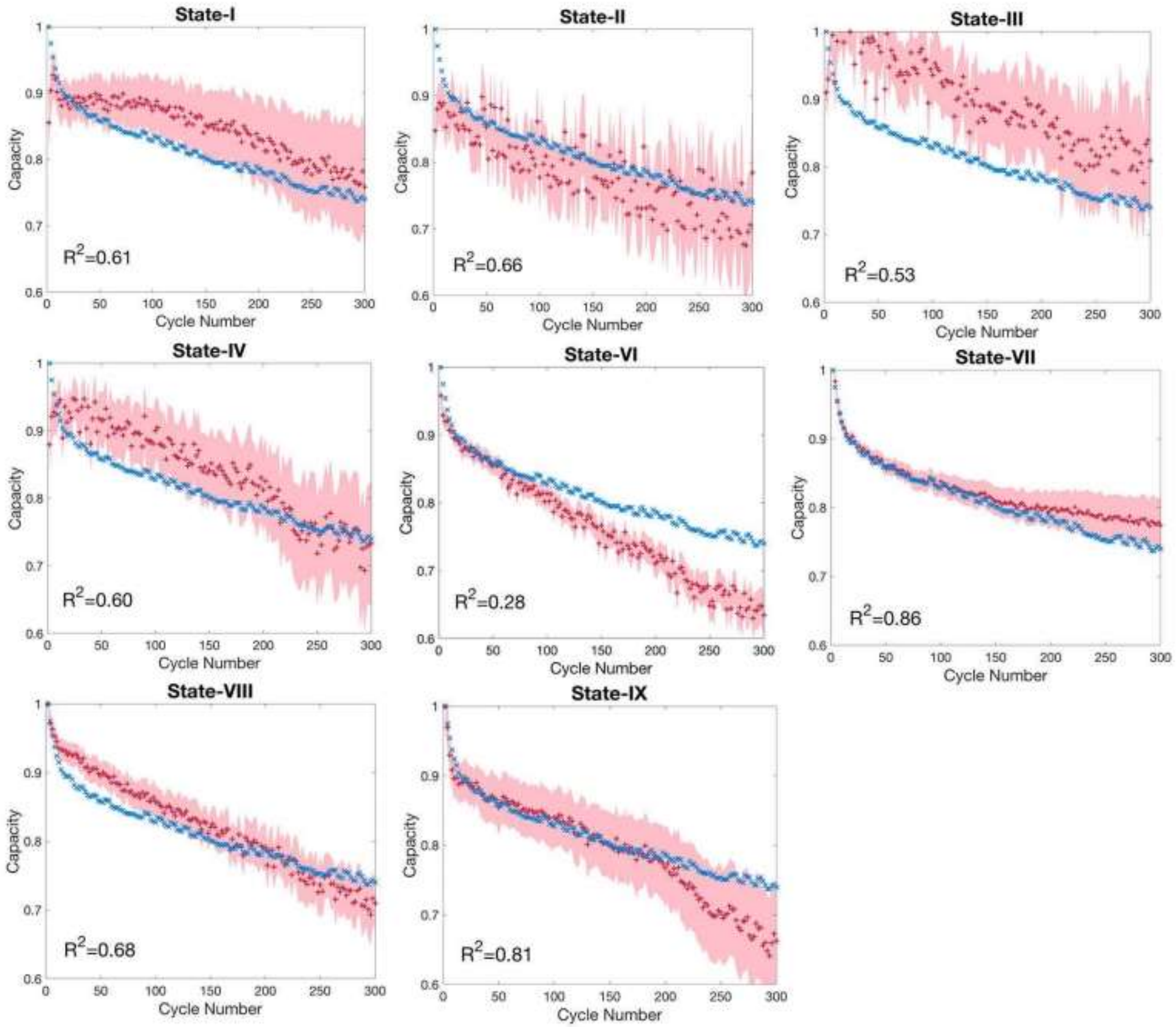
Progress:

- Test platform:
  - Electrochemical Workstation
  - EIS
- Battery:
  - SANYO&PANA (4.3V) ()
  - 18650 (4.3V)
  - Button battery: LIR2032 (3.6V)

Progress report

Problem：



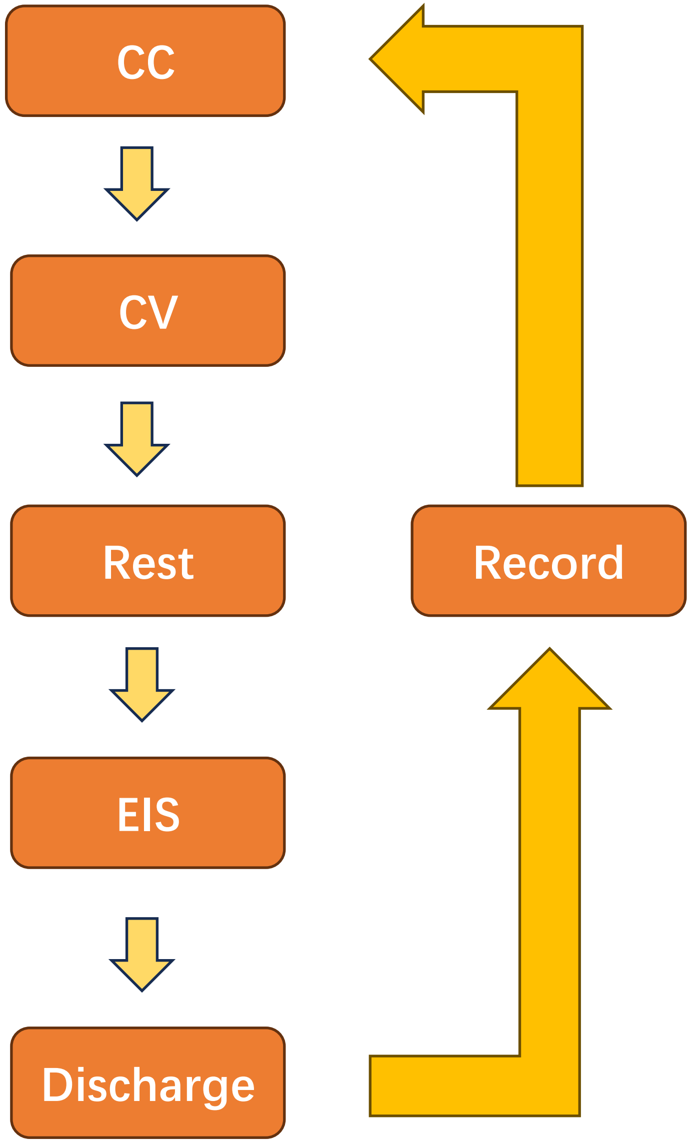


Plan

Button cell test:

Model： LIR2032

Test cycle:



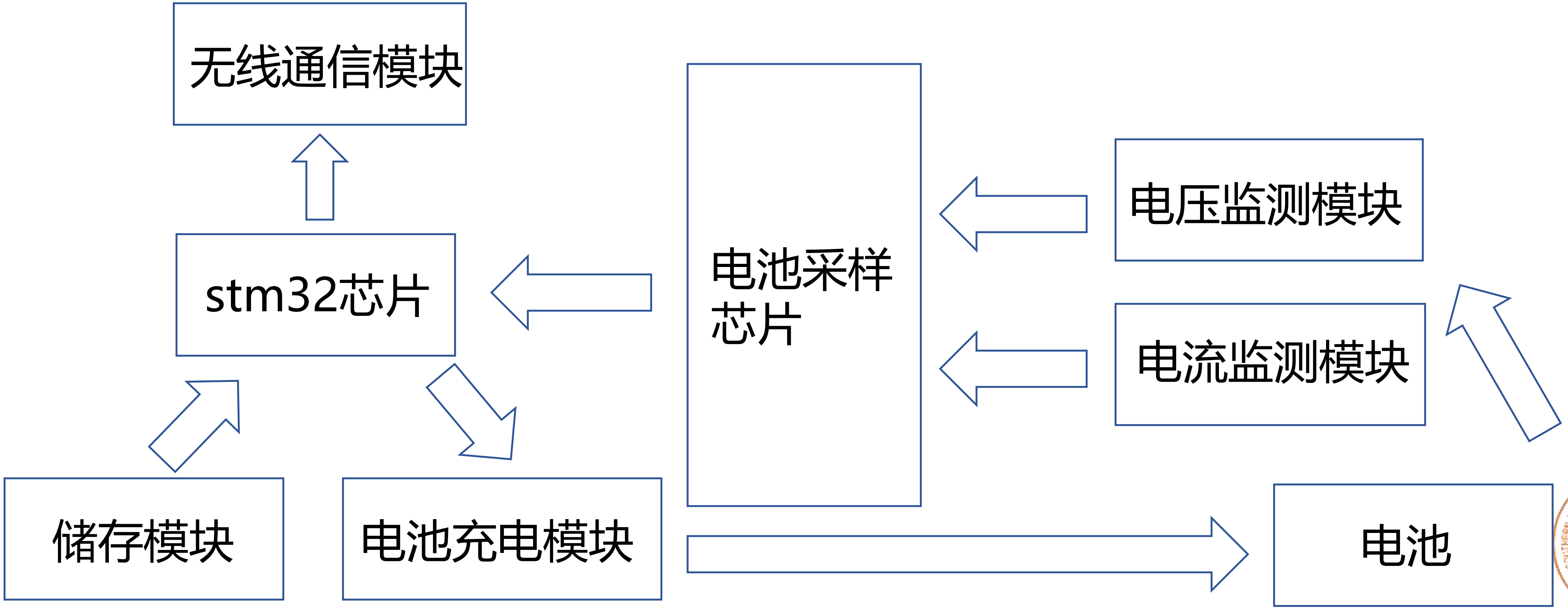
Microelectronics Part

徐涵

- Process Report
- Future Plan

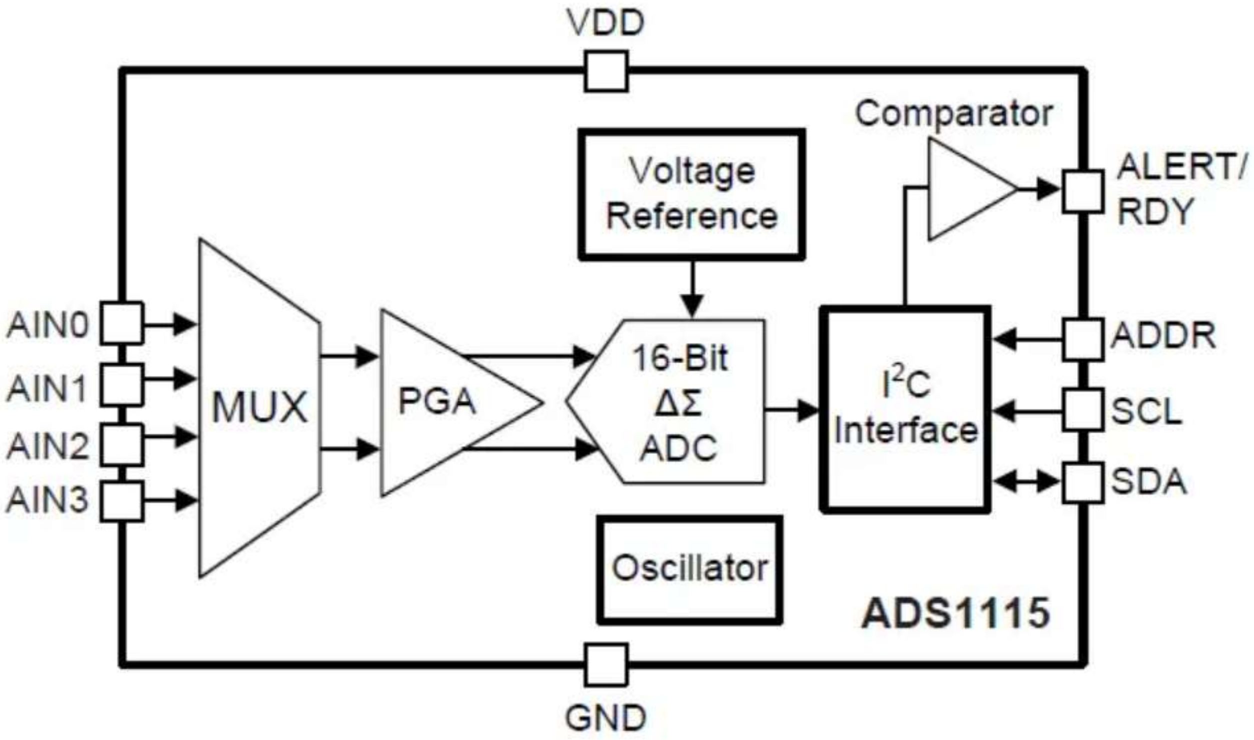
目标：测得电池的完整充放电曲线

工作：搭建控制电池充放电并对电压电流采样的硬件电路



电压监测电路

ADS1115是德州仪器推出的具有IIC接口的16位ADC转换器，超小型X2QFN或VSSOP 封装，低功耗（20uA），宽电压输入2.0V-5.5V

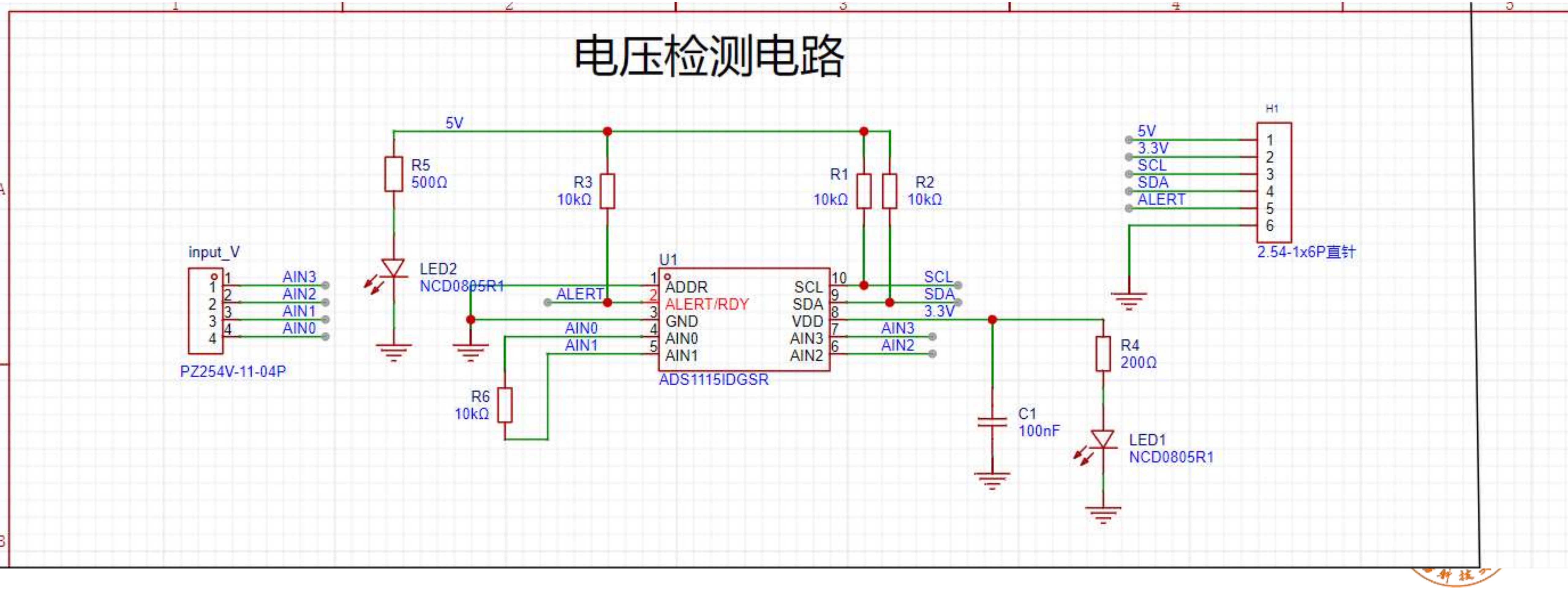


1.量程合适：0-6.144V

2.引脚少，方便封装：ssop10

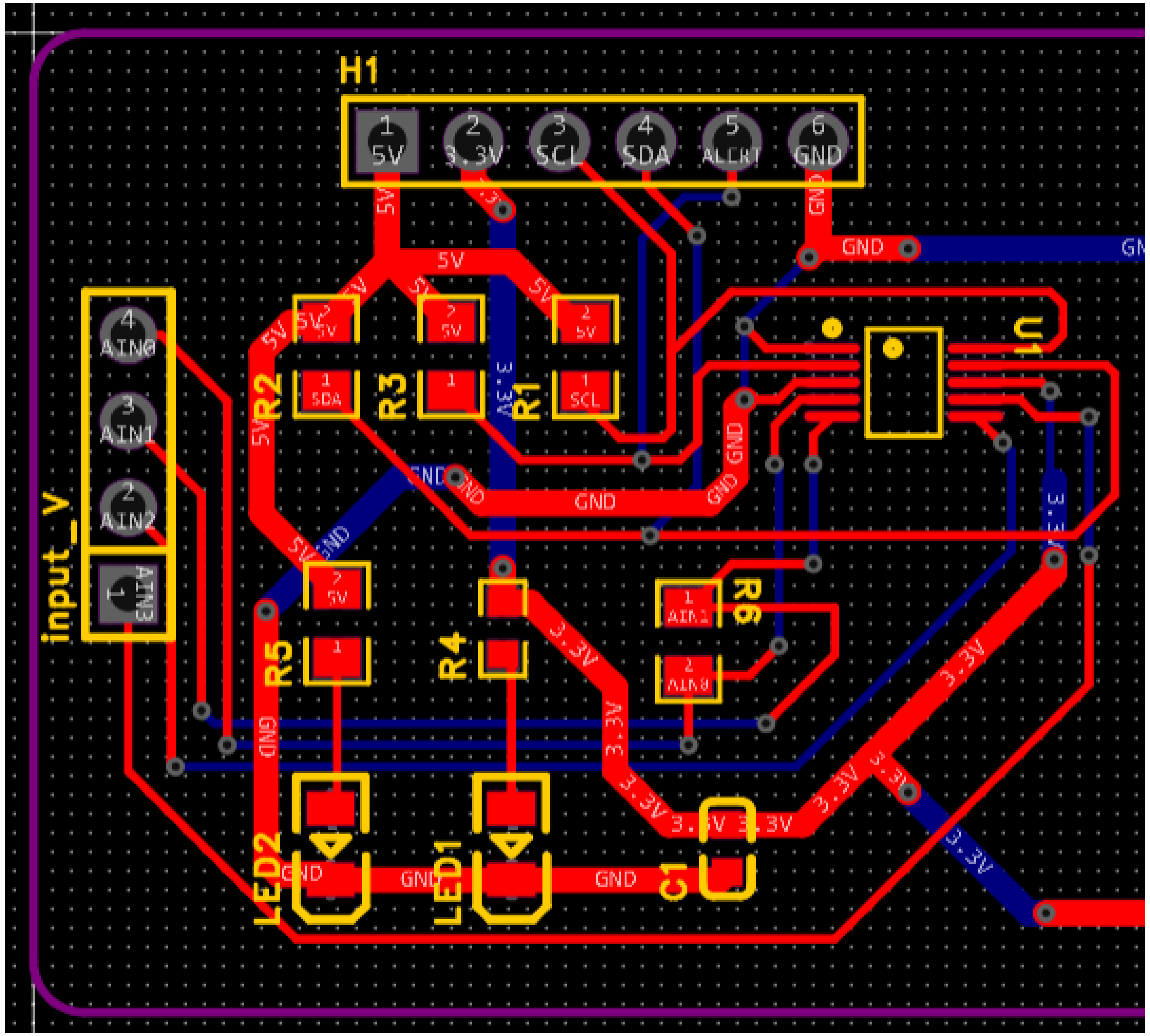
Progress report

电压监测电路



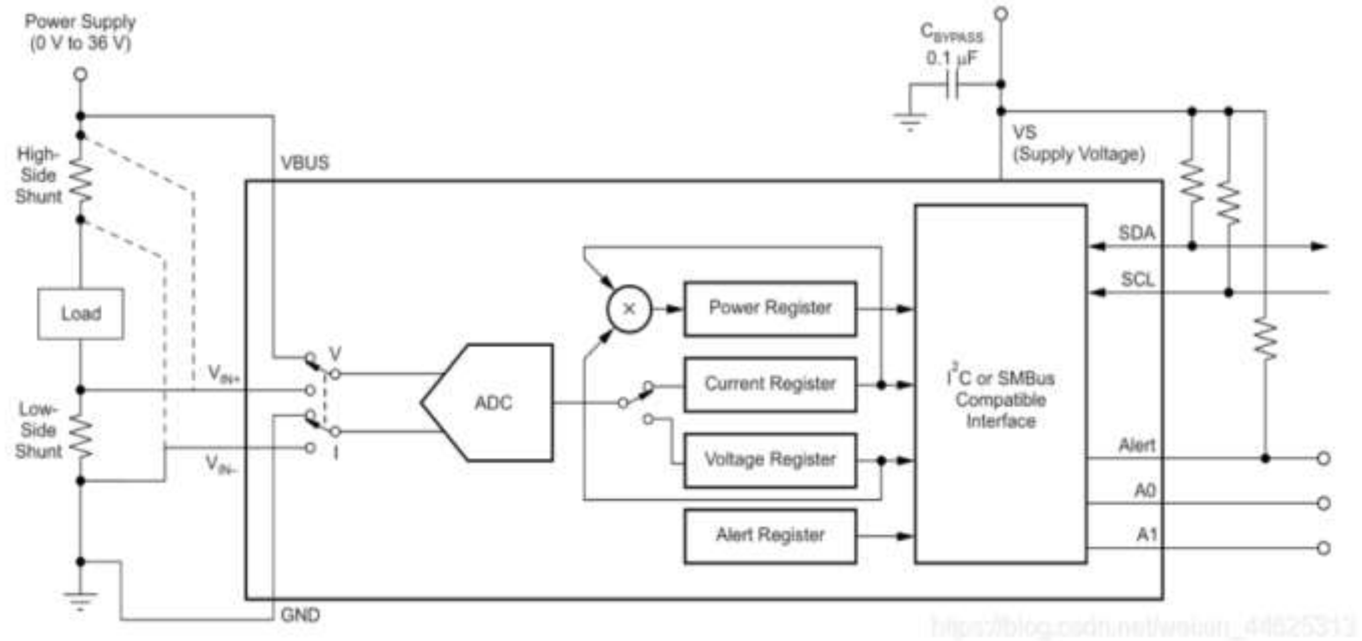
Progress report

电压监测电路



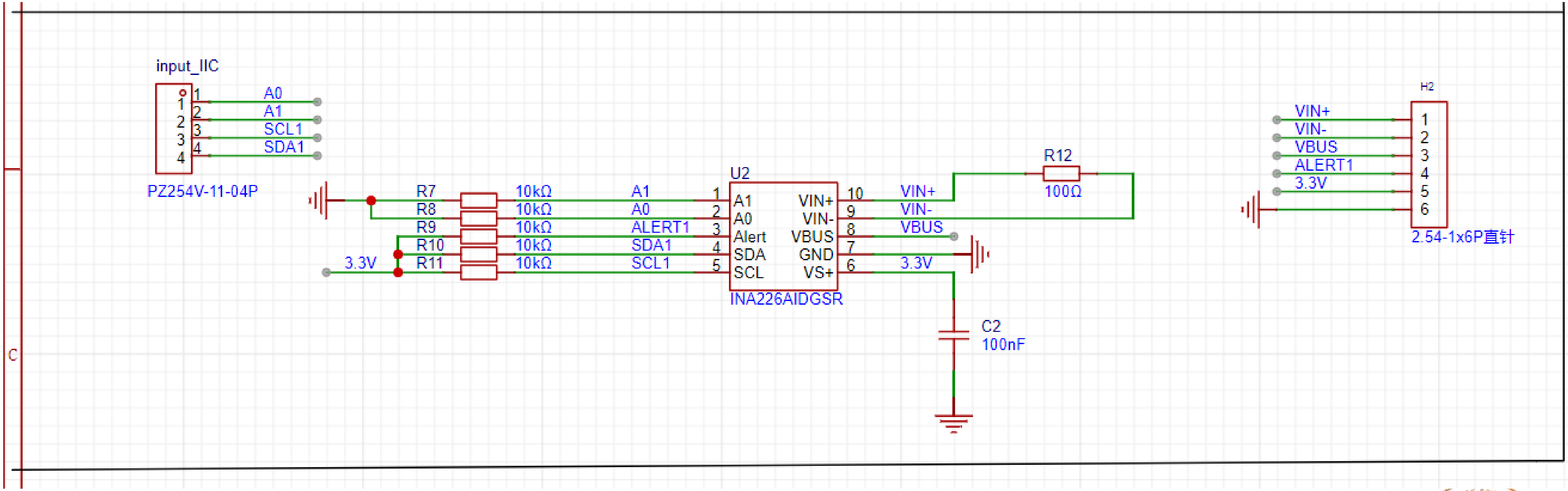
电流监测电路

INA226 是一款分流/功率监视器，具有I2C™或 SMBUS 兼容接口。该器件监视分流压降和总线电源。可编程校准值、转换时间和取平均值功能与内部乘法器相结合，可实现电流值（单位为安培）和功率的直接读取。

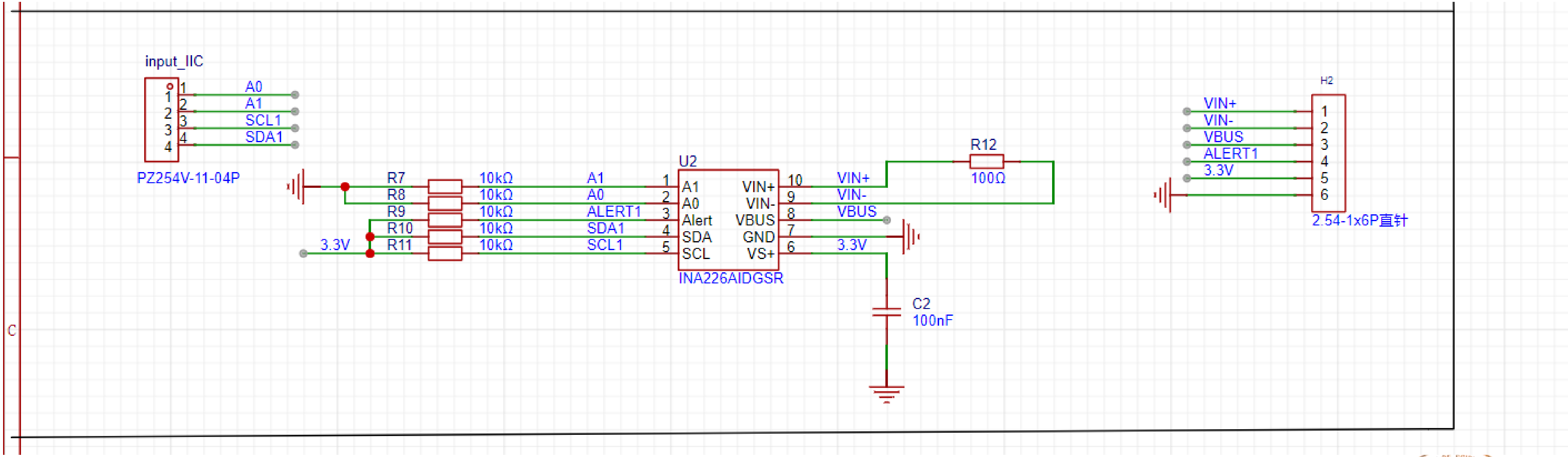


Progress report

电流监测电路

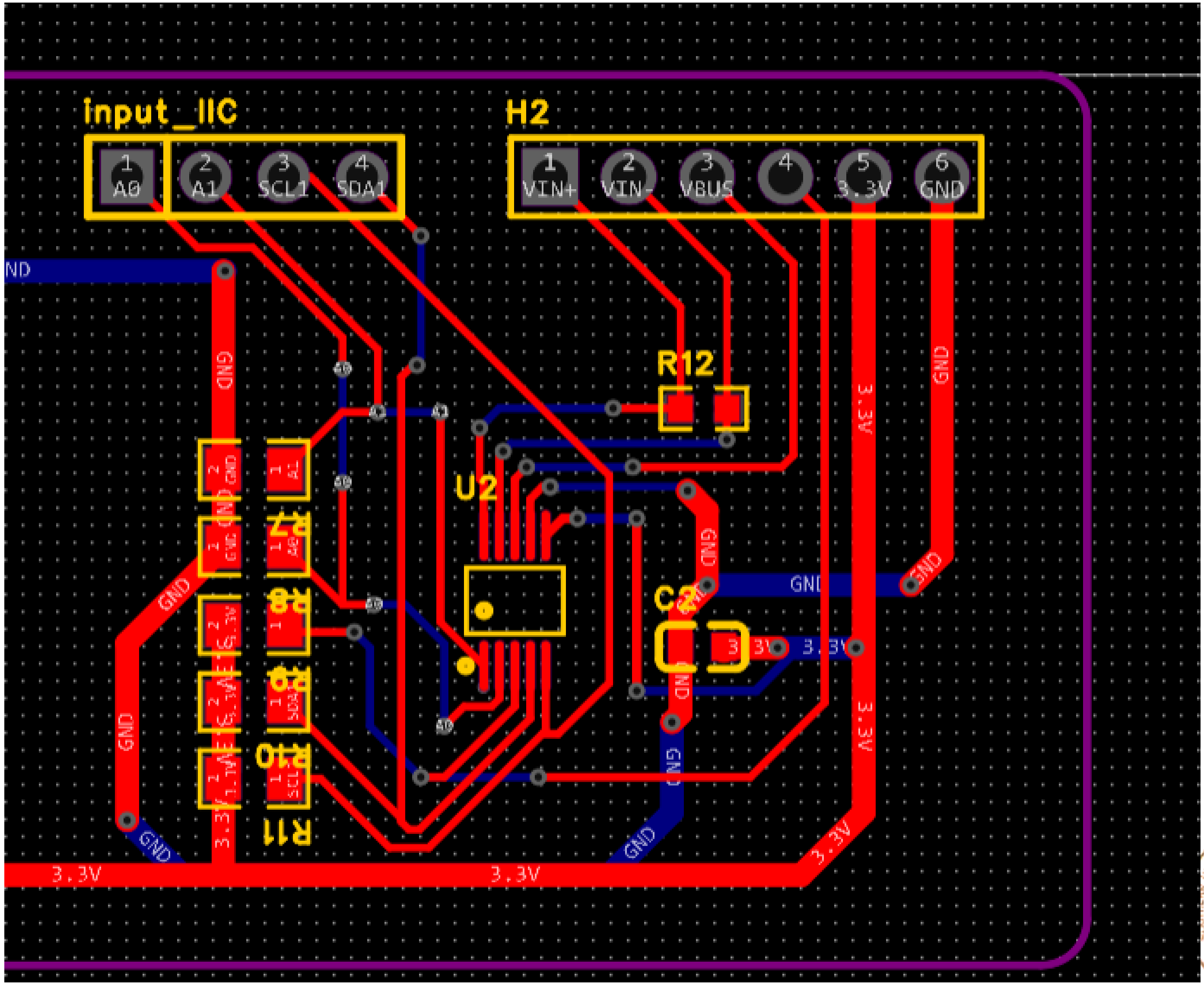


电流监测电路


input_IIC
A0
A1
SCL1
SDA1
PZ254V-11-04P
R7
R8
R9
R10
R11
10kΩ
A1
A0
ALERT1
SDA1
SCL1
3.3V
U2
A1
A0
Alert
SDA
SCL
VIN+
VIN-
VBUS
GND
VS+
INA226AIDGSR
VIN+
VIN-
VBUS
3.3V
R12
100Ω
C2
100nF
H2
VIN+
VIN-
VBUS
ALERT1
3.3V
2.54-1x6P直针

Progress report

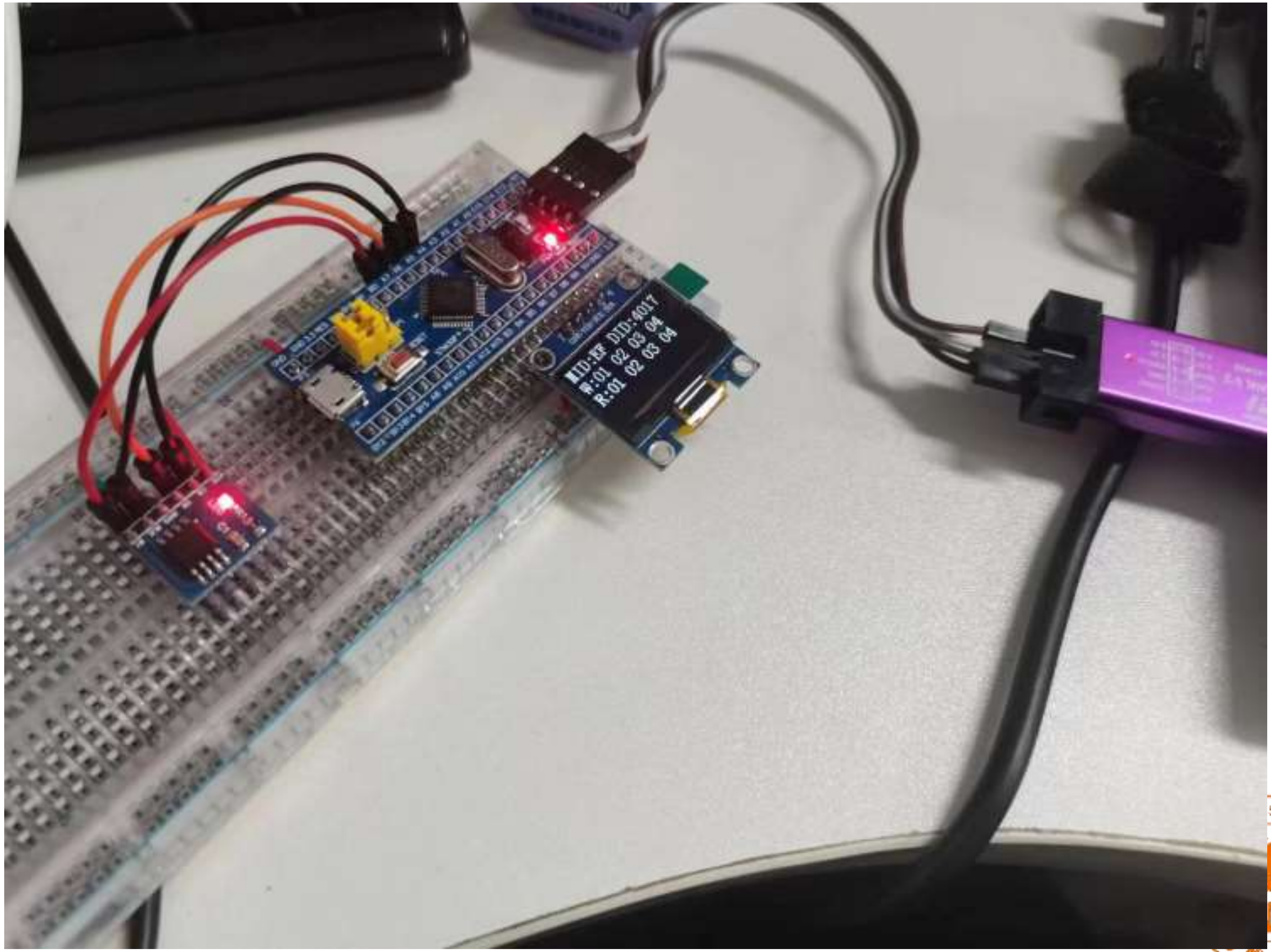
电流监测电路



Progress report

储存模块电路

W25Q64储存芯片



Plan

Personal Thesis Topic	Specific Matters	Owner	Time Frame
电池健康状态监测硬件系统;	完整电池充放电曲线获取	徐涵	3.1-3.15：电压电流监测模块搭建与测试 3.15-3.30：电池充电模块搭建与测试 4.1-4.15：电池完整充放电曲线获得与无线通信模块搭建 4.15-4.30：完整模块运行与测试

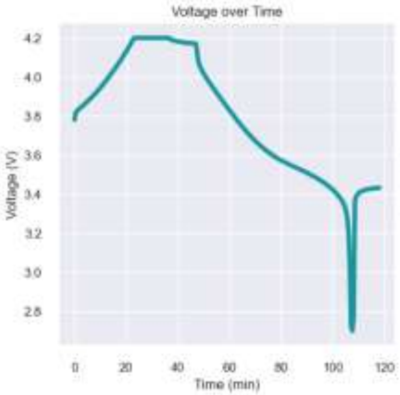
Computer Science Part

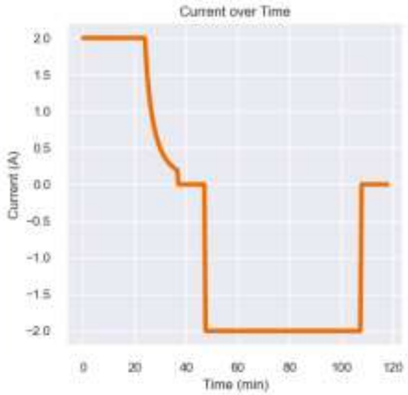
王浩羽

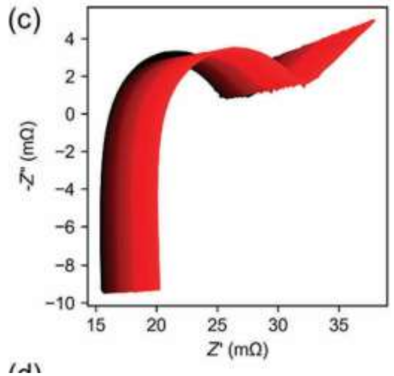
- Goals and Objectives
- Proposed Methods
- Data Exploration
- Data Processing
- Experimental Results
- Future Works

Goals and Objectives

Based on charging curves and EIS curves

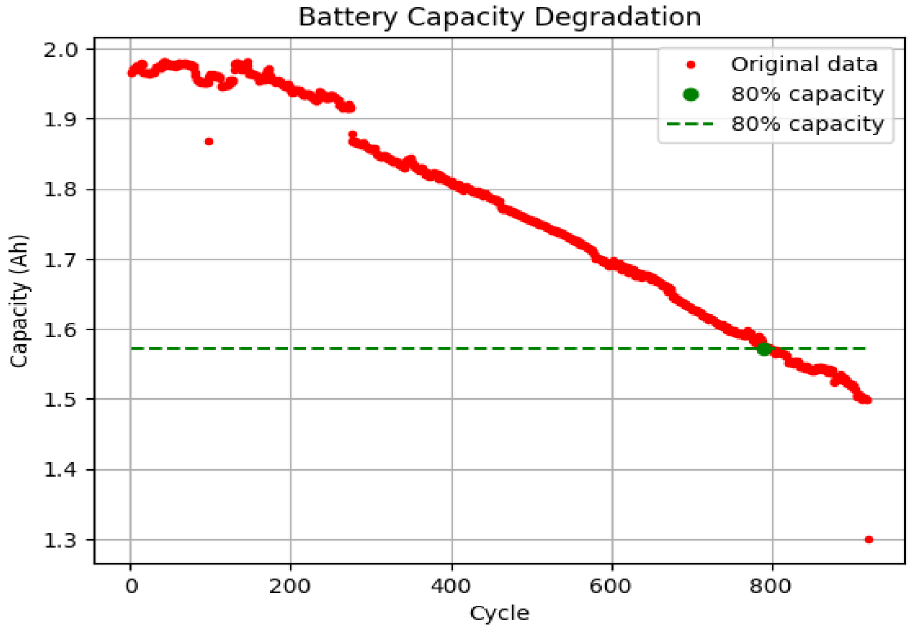






Predict battery Remaining Useful Life (RUL)

Capacity decreases to 80% of original capacity



Proposed Methods

Step1

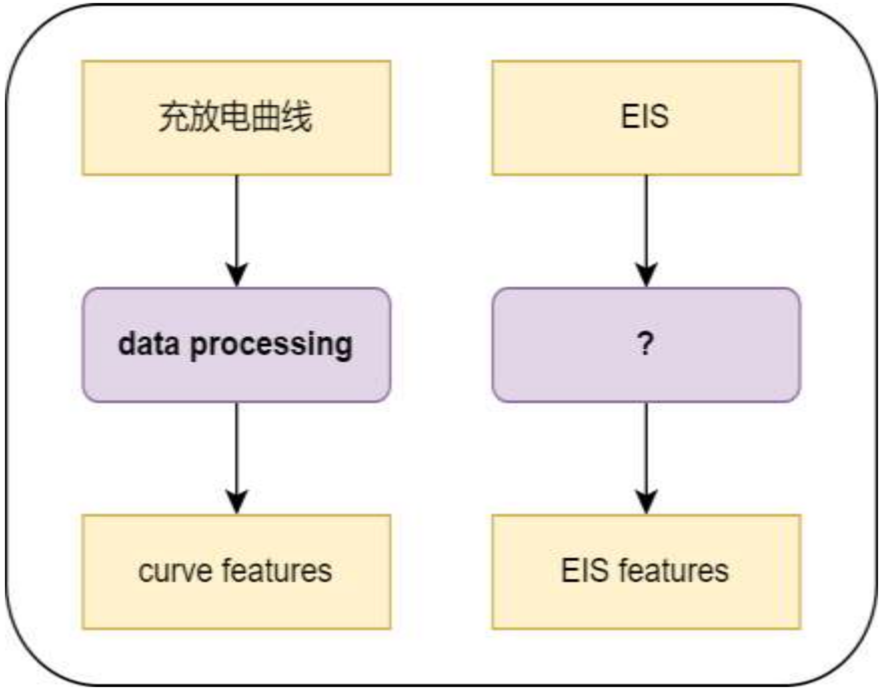
Data Processing

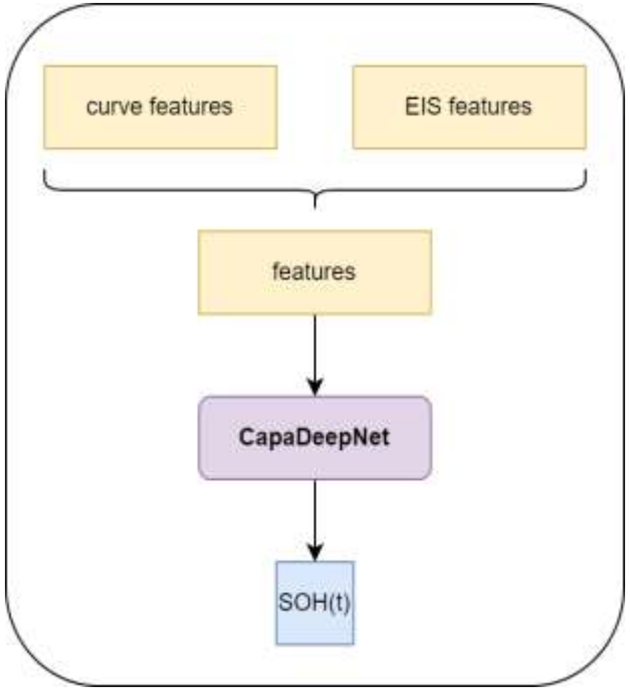
Step2

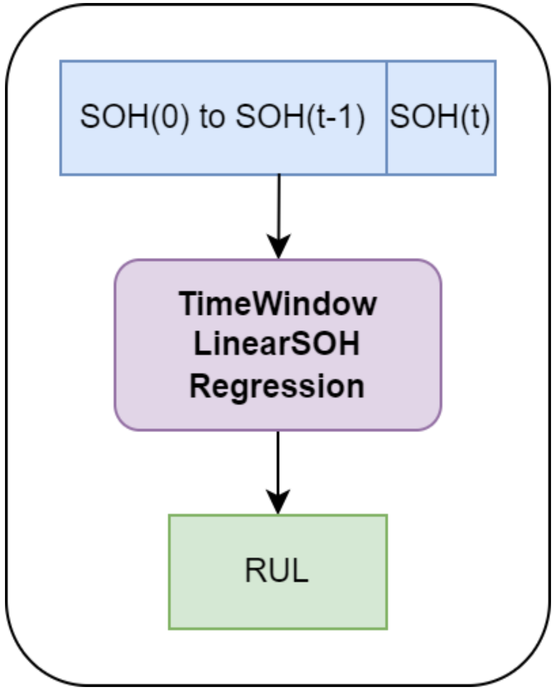
Predict SOH(t)

Step3

Estimate RUL







Data Exploration

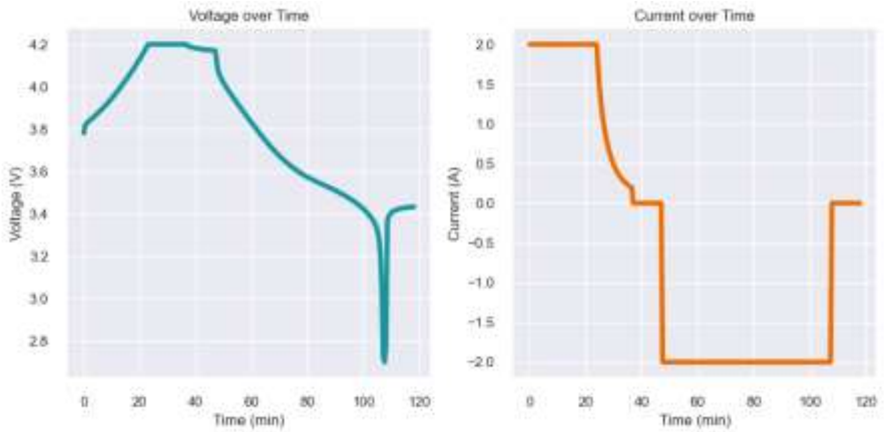
Datasets:

- 6 battery already have
- 2 battery in future

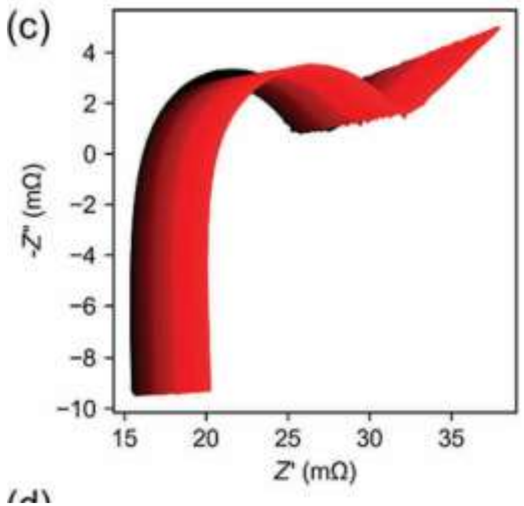
battery	charging protocol	CC current	CV voltage	cycle
0	CC-CV	2.0A	4.2V	584
1	CC-CV	2.0A	4.2V	642
2	CC-CV	2.0A	4.2V	584
3	CC-CV	3.0A	4.2V	679
4	CC-CV	3.0A	4.2V	920
5	CC-CV	3.0A	4.2V	689

Data Exploration

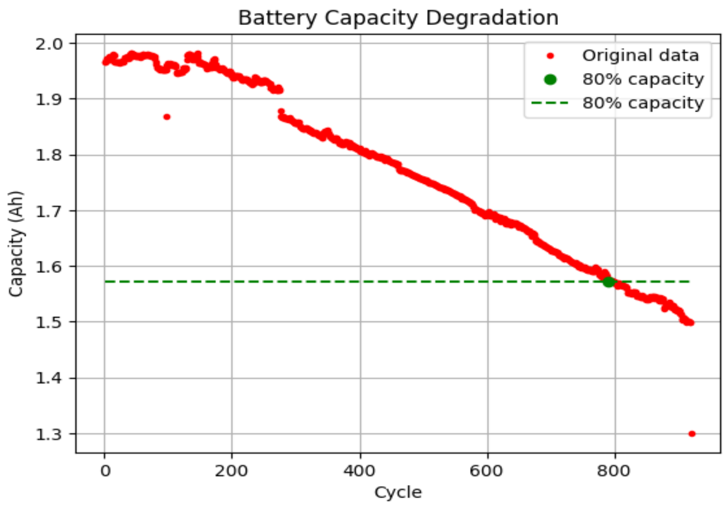
Data in datasets:



Battery charging curves
(1 curve per cycle)



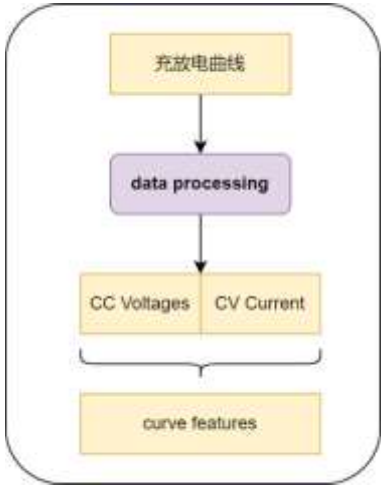
Battery EIS curves
(1 curve per 10 cycle)

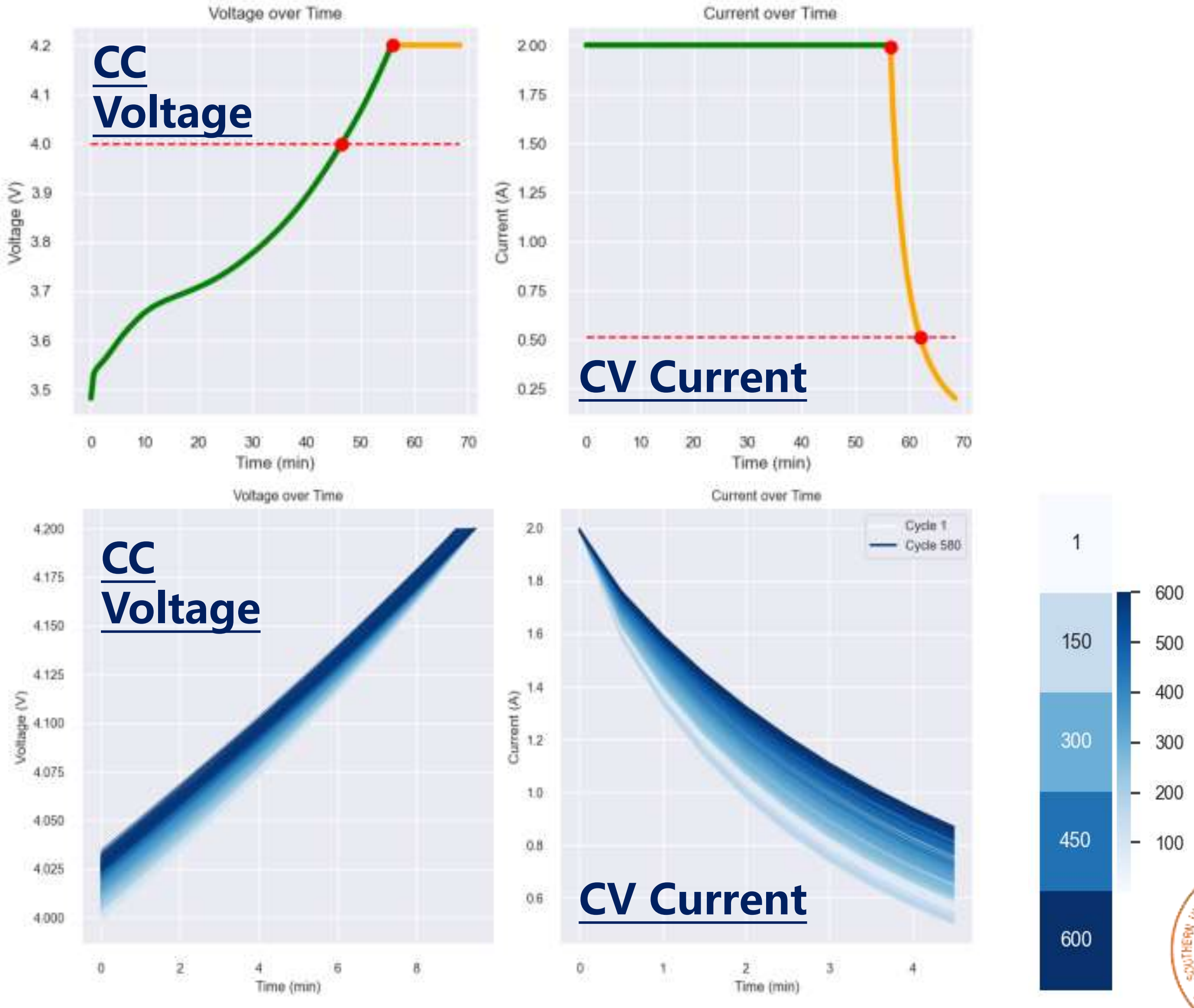


Discharging capacity

Data Processing

Step1: Data Processing





Sample points number

CC -> U: 4.0V ~ 4.2V; I=2.0A
CV -> I: 2.0A ~ 0.5A; U=4.2V

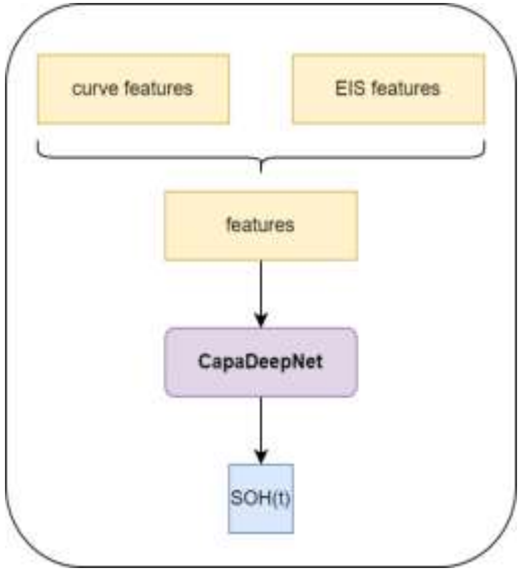
Sample points number

CC Voltage: 20
CV Current: 10

Experimental Results

Step2: CapaDeepNet

Integrative Deep Neural Net of Charging Profiles and Electrochemical Impedance Spectroscopy for Precise Battery Capacity Prediction



DeepNet Structure:

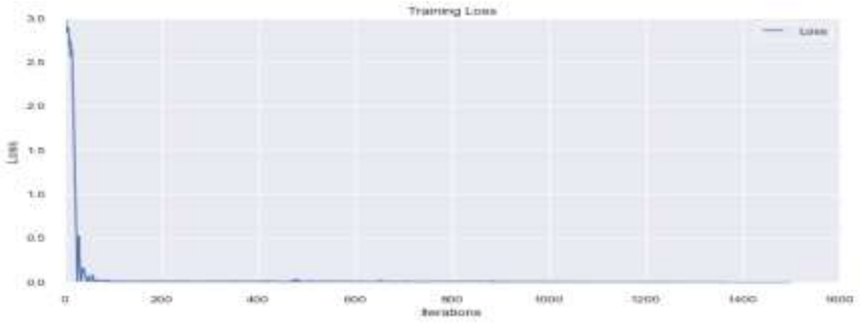
	layer	in-dim	out-dim
1	FC	30	32
2	FC	32	64
3	FC	64	72
4	FC	72	128
5	FC	128	64
6	FC	64	64
7	FC	64	32
8	FC	32	16
9	FC	16	8
10	FC	8	1

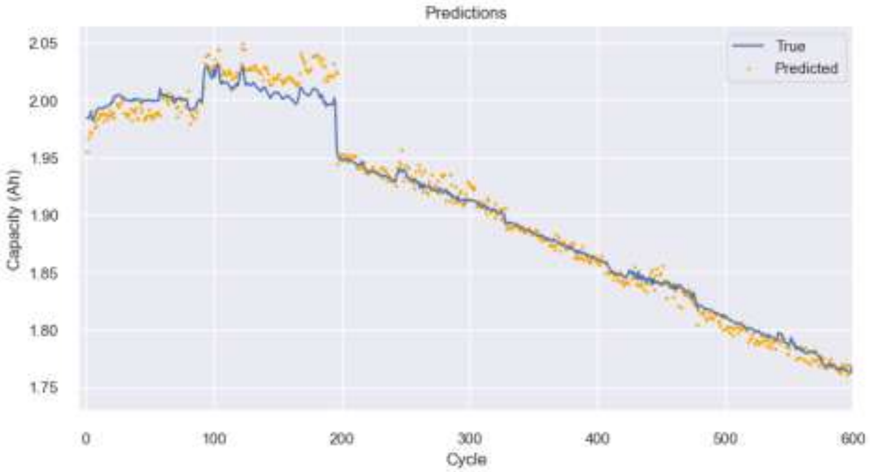
Hyper Params:

- Epoch：50
- Batch Size：16

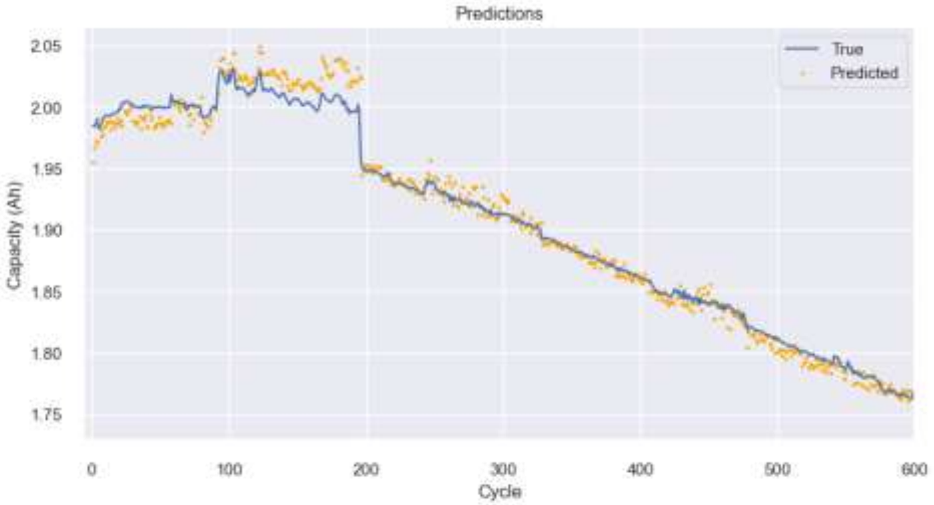
Experimental Results

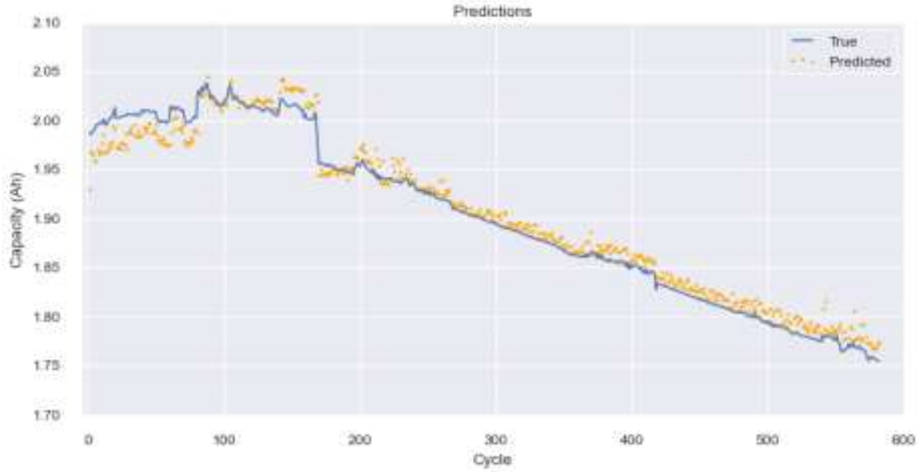
Step2: CapaDeepNet Results





Battery 0: Training Data (training and validation)

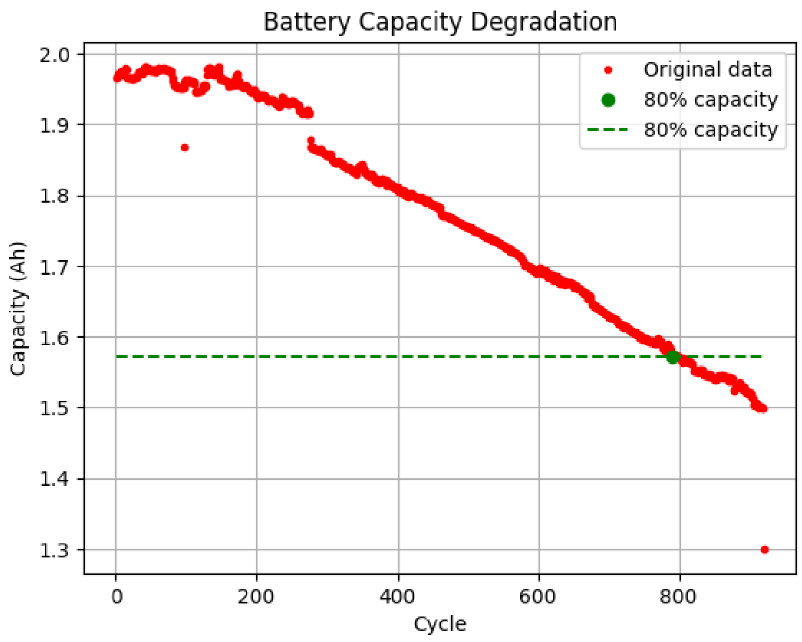




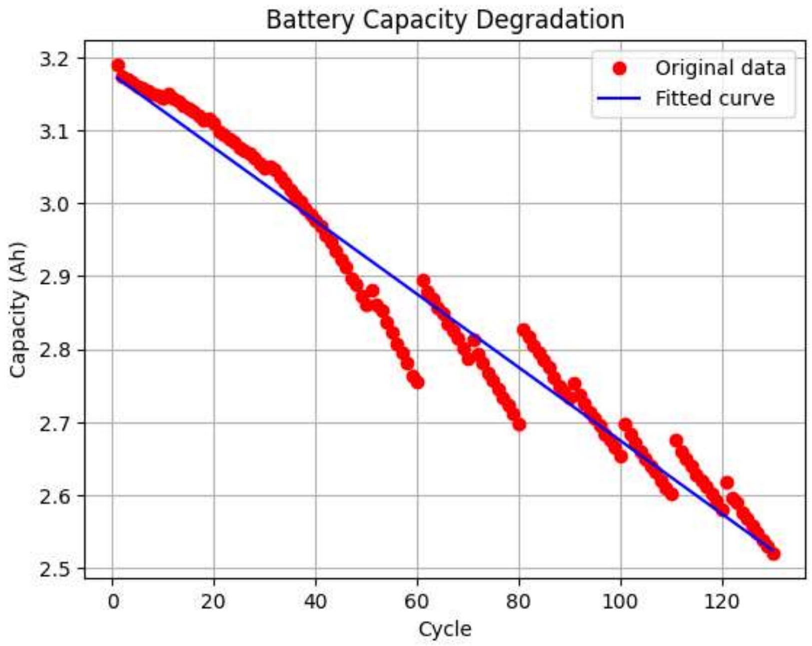
Battery 1 and 2: Evaluation

Experimental Results

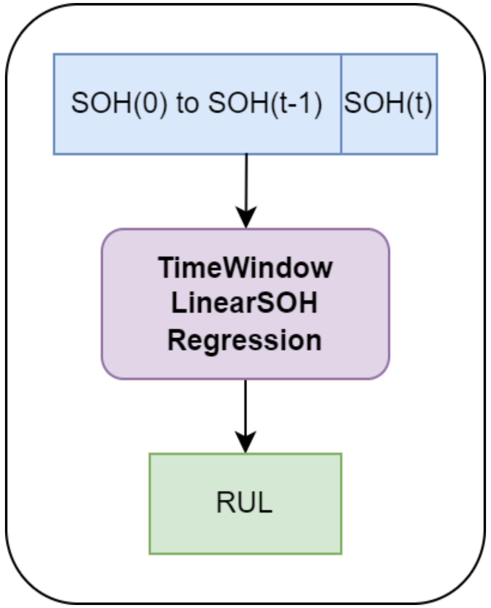
Step3: TimeWindow LinearSOH Regression



Target: 80% capacity



Difficulty: Capacity Regeneration



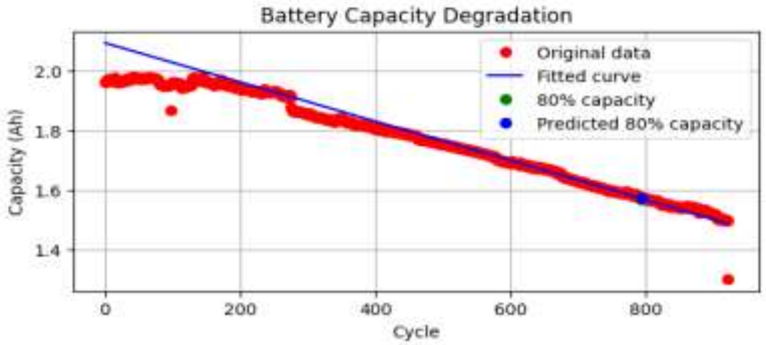
Experimental Results

Step3: TimeWindow LinearSOH Regression

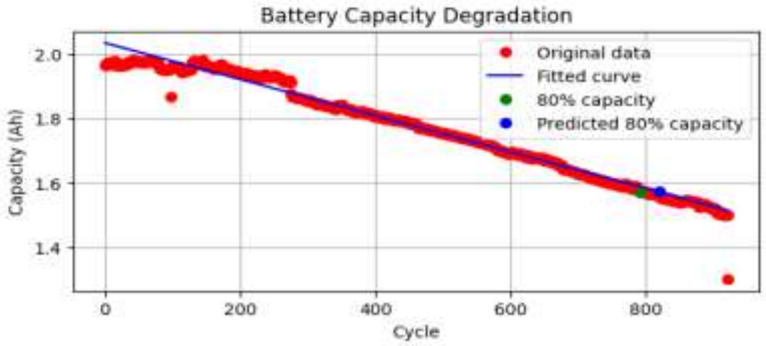
Training data:
capacity of a time window

Time Window Size: 100

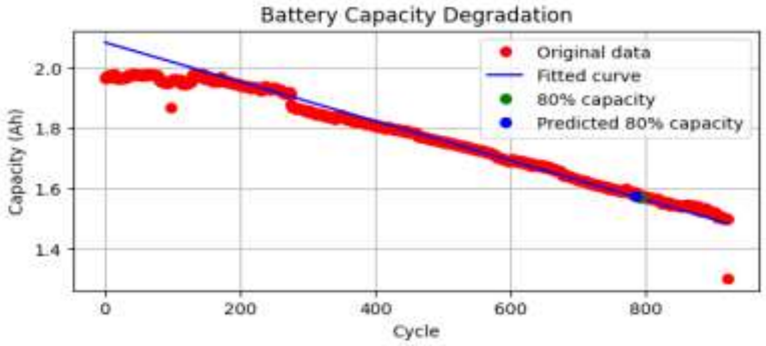
Step: 50



500-600



550-650



600-700

Future Works

To enhance the accuracy and applicability of our model

- Expanding Battery Testing Scope: Testing and Analysis across Various Battery Types
- Refined Feature Extraction from Electrochemical Impedance Spectroscopy (EIS) curves

Plan	Time Frame
Evaluate proposed methods on 6 datasets we already had	3.18 – 3.31
Refine EIS features extracting	4.1 – 4.14
Evaluate with refined methods	4.15-4.28
Prepare materials	4.29 -

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
3．Wang, S., Jin, S., Deng, D., & Fernandez, C. (2021). A Critical Review of Online Battery Remaining Useful Lifetime Prediction Methods. Frontiers in Mechanical Engineering, 7. https://doi.org/10.3389/fmech.2021.719718
4．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. https://doi.org/10.1109/access.2020.2968939
5．Xu, Q., Wu, M., Khoo, E., Chen, Z., & Li, X. (2023). A Hybrid Ensemble Deep Learning Approach for Early Prediction of Battery Remaining Useful Life. IEEE/CAA Journal of Automatica Sinica, 10(1), 177–187. https://doi.org/10.1109/jas.2023.123024
6．Lu, J., Xiong, R., Tian, J., Wang, C., & Sun, F. (2023). Deep learning to estimate lithium-ion battery state of health without additional degradation experiments. Nature Communications, 14(1). https://doi.org/10.1038/s41467-023-38458-w
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