MACHINE LEARNING

BREAK THROUGH INTO LIFE PREDICTION OF LITHIUM ION BATTERIES

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Why do we need to predict life

Lithium-ion (Li-ion) batteries have been widely used as energy storage systems, such as electric vehicles (EVs) and hybrid electric vehicles (HEVs).

To inform the user whether a battery should be replaced and avoid unexpected capacity fade.

To decide whether a battery should be recycled as scrap metal or used for less demanding “second-life” applications.

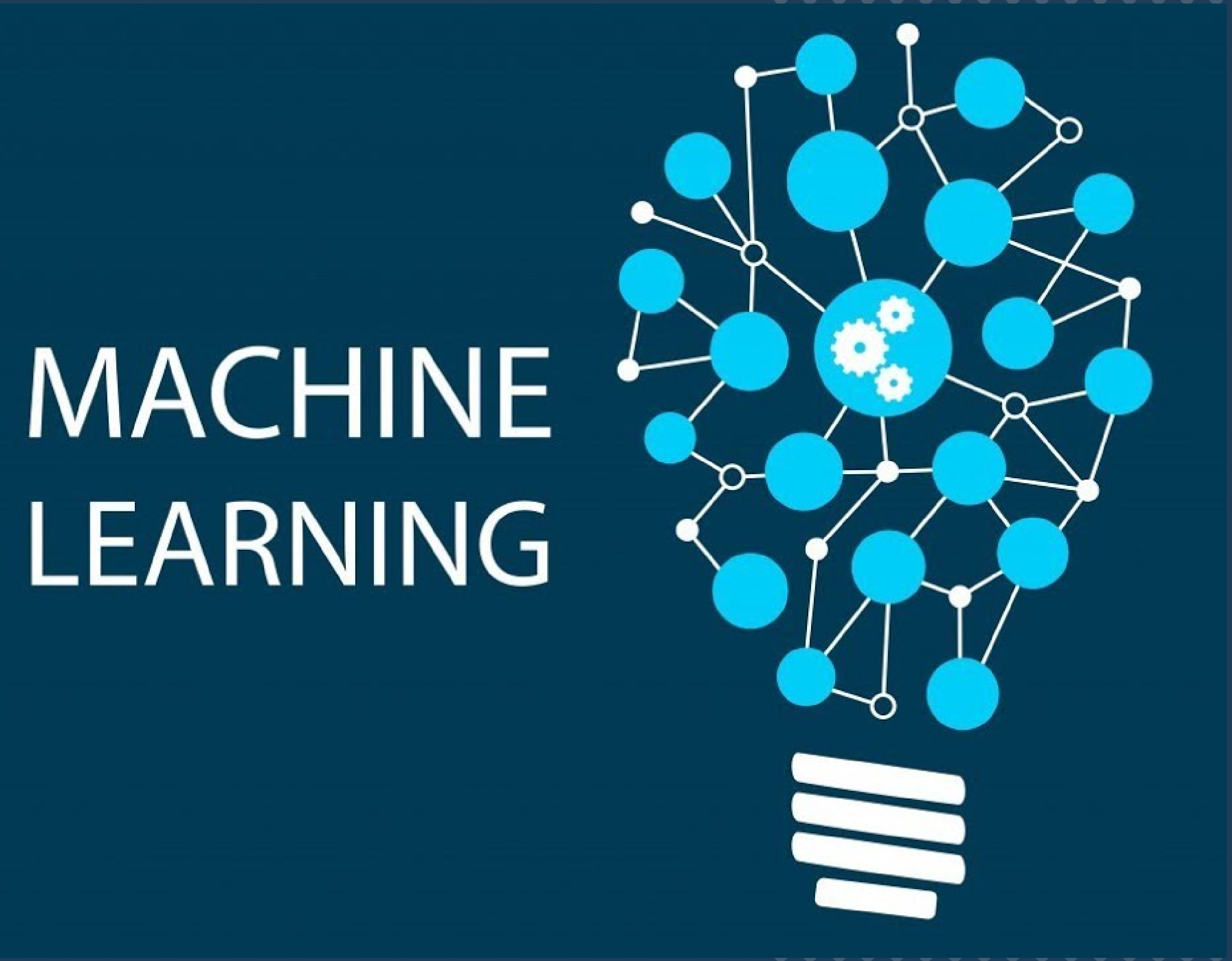
Stumbling block: Accurate prediction of battery state of health (SoH) and remaining useful life (RUL)

Conventional approach

The conventional approach to battery life prediction relies on modelling microscopic degradation mechanisms, such as the growth of the solid-electrolyte interphase, lithium plating and active material loss

Issue in current approach

- Time consuming
- Difficult to do conduct every degradation mechanism
- Hazardous condition as the cell ages



Whats Now

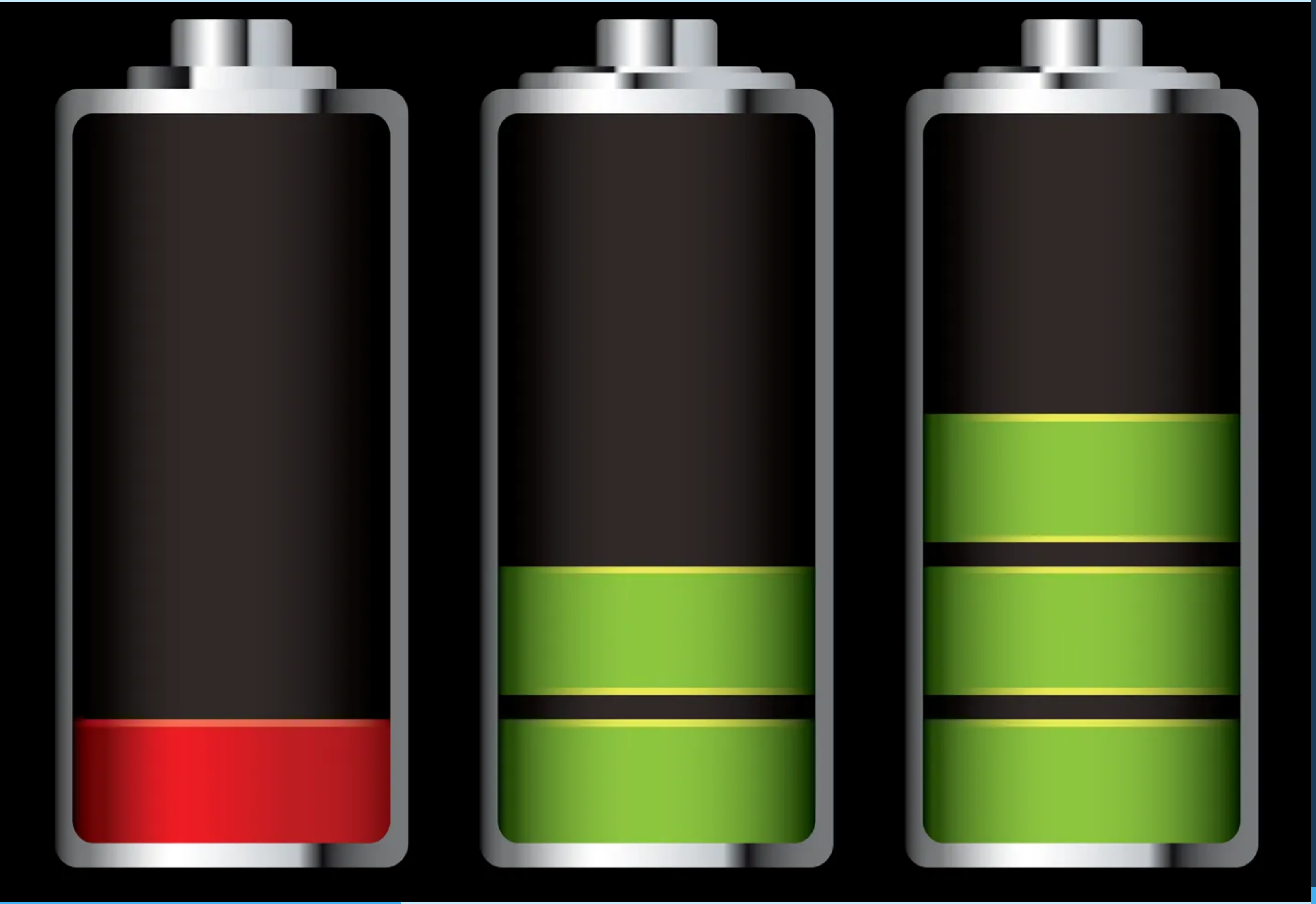
Data driven approach

The idea is to perform real-time, measurements on the battery, and use Machine Learning to relate those measurements to battery health without modelling a physical mechanism

Measurement of capacity curve and impedance can be feed as input to the ML model

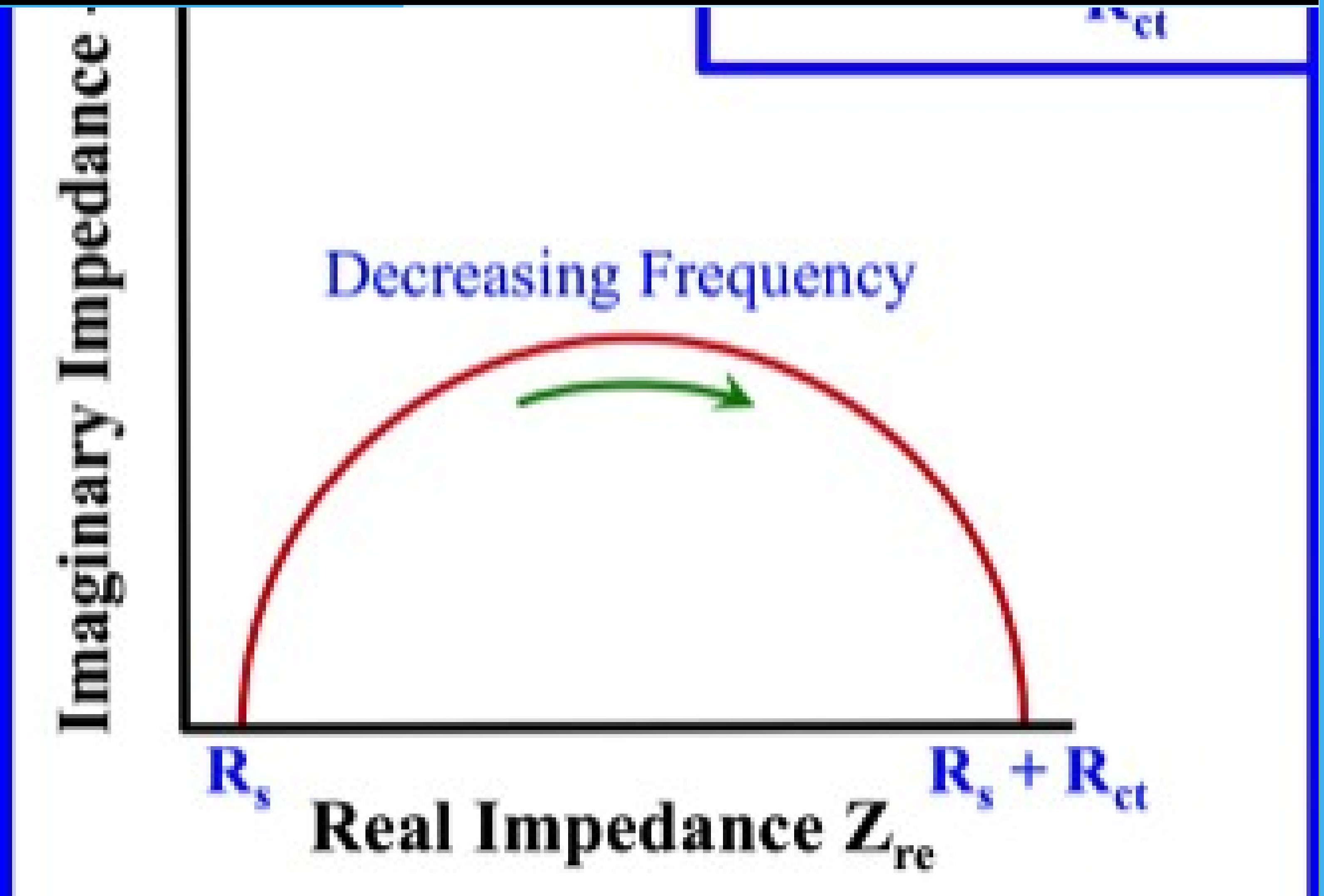
Where do we go next?

HOW DO WE GET DATA FOR OUR MODEL?



Severson dataset

124 commercial (LFP)/graphite cells cycled under fast-charging conditions until End-of-Life. The dataset contains in-cycle measurements of temperature, current, charge and discharge capacity till each cell reaches 80% of the nominal capacity. Cells with widely varying cycle lives ranging from 150 to 2,300 cycles.



Cambridge dataset

12 commercial LiCoO2 /graphite cells cycled in three climate chambers set to 25˚C, 35˚C and 45˚C.

EIS is measured during charging/discharging in the frequency range of 0.02 Hz–20 kHz

Severson dataset

Main highlights

- Original method is built to generate the result after using the first 100 charge/discharge cycles with a mean absolute error of 9.5% and root mean square error of 200 cycles.
- Change in discharge voltage curves between cycle 100 and 10: ΔQ 100-10 (V) are used as features in the ML model

Where we can improve

- Using a large number of initial cycles for their predictions.
- Can make predictions only once, i.e., after 100 cycles
- High error

Method 1

- USES FIRST 100 CYCLES GIVES A TEST MEAN ABSOLUTE ERROR (MAE) OF 6.7%
- CAN MAKE CONTINUOUS PREDICTION TILL ITS END OF LIFE (EOL)

Method 2

- USES FIRST 10 CYCLES FOR CELLS WITH EOL LESS THAN 1000 WITH MAE OF 11% , AND FIRST 40 CYCLES FOR CELLS WITH EOL GREATER THAN 1000 WITH MAE OF 13.8%
- CAN MAKE CONTINUOUS PREDICTION TILL ITS EOL

REASON FOR THE SUCCESS OF METHOD 1

- Analyzing the data, and dividing it into two categories

  1) Short life cell (EOL <1000)   2) Long life cell (EOL>1000)

DIVE INTO THE METHOD 1

- Mean, variance, minimum of change in discharge voltage curves between the 100th and 1st cycle: $\Delta Q_{100-1}(V)$ is used as feature.
- Short life cells (22) are tested with Lasso algorithm giving MAE of 5.2%.
- Long life cells (18) are tested with Random Forest algorithm giving MAE of 8.5%
- This making the aggregate MAE equal to (22*5.2%+18*8.5%)/40= 6.7%

REASON FOR THE SUCCESS OF METHOD 2

- Analyzing the data, and dividing it into two categories

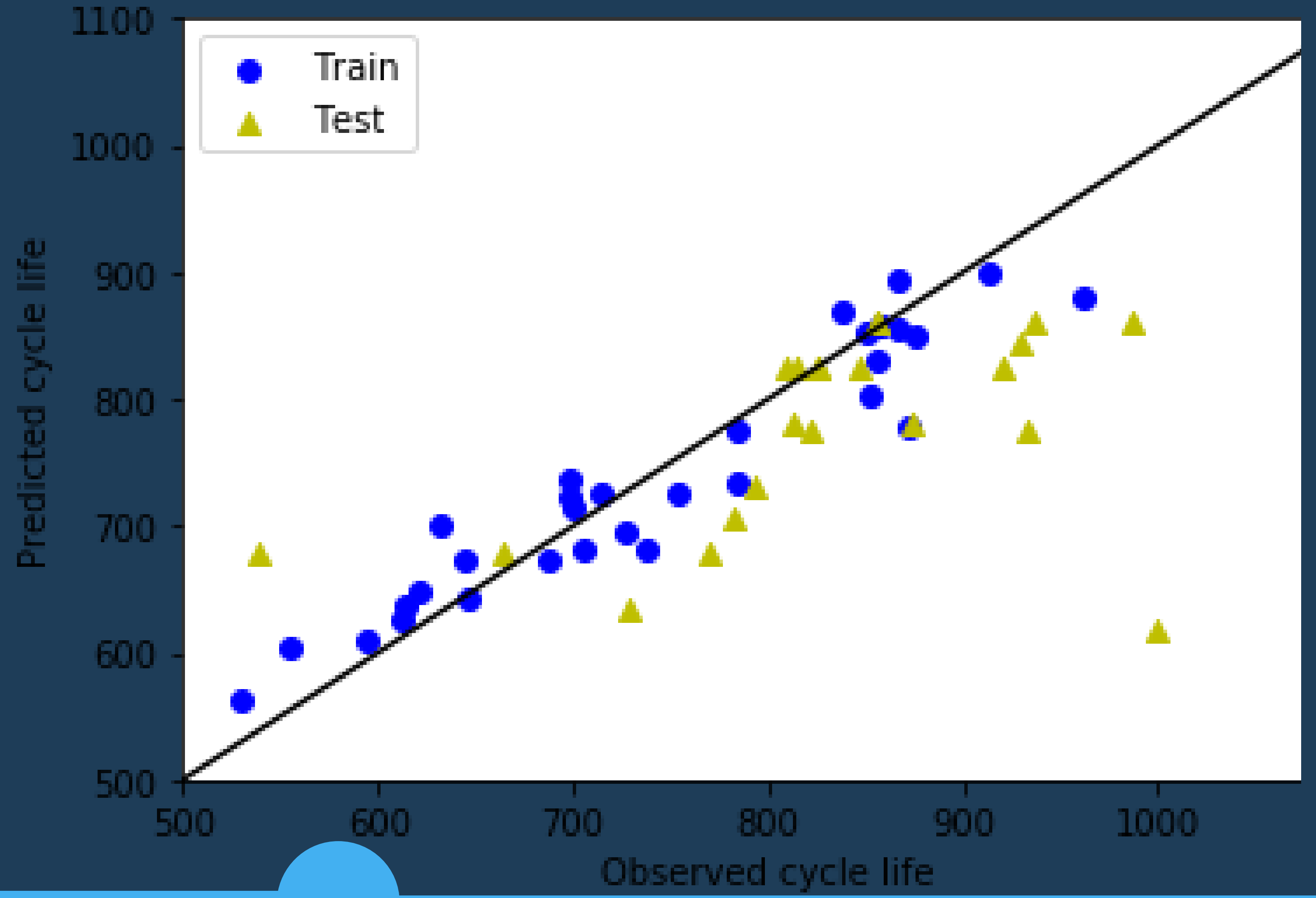
    1) Short life cell (EOL <1000)   2) Long life cell (EOL>1000)

- Scrutinizing the capacity variation with the cell aging

    1) The capacity is increasing for initial cycles till 10th cycle and at 10th cycle its maximum

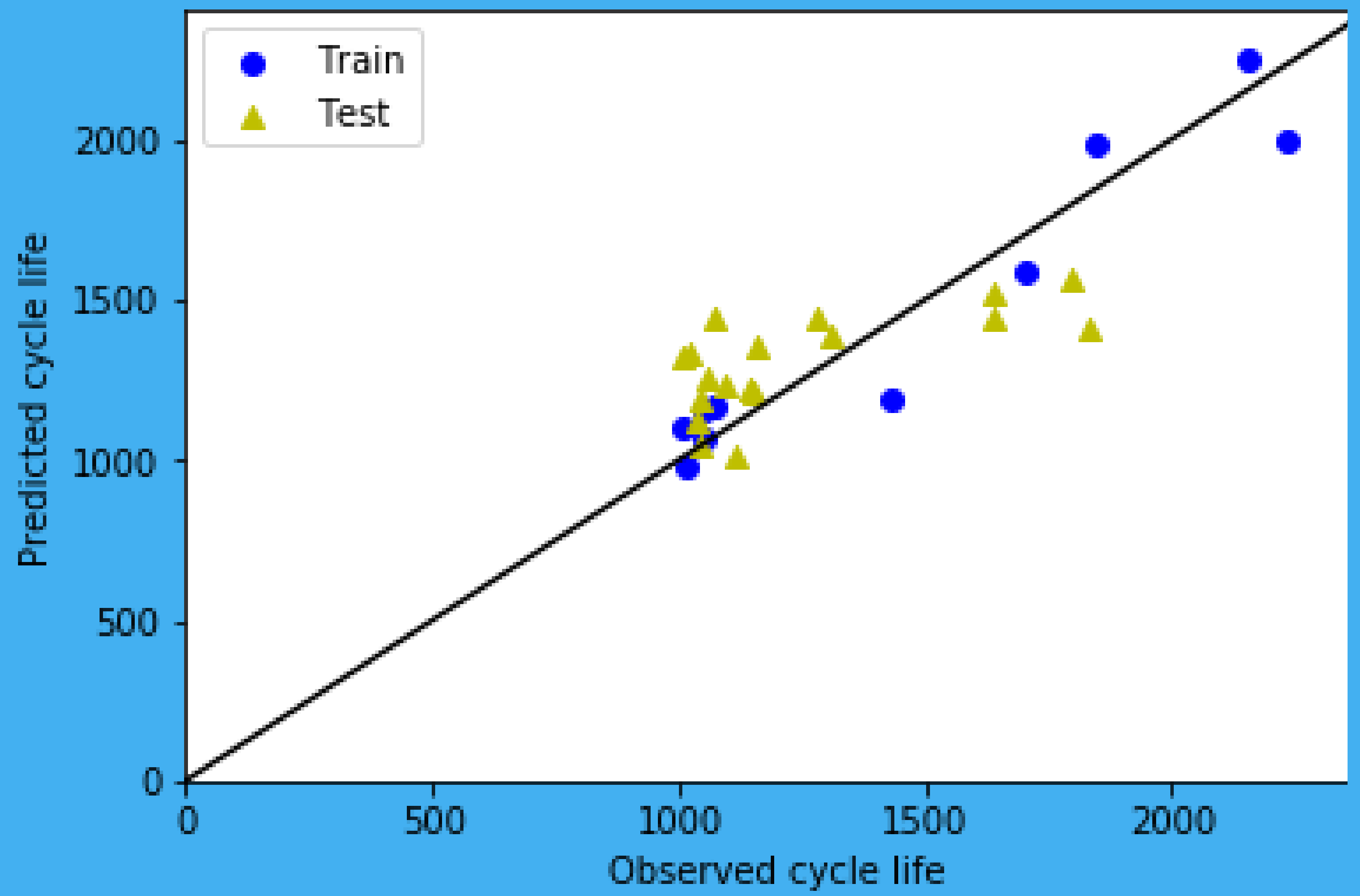
    2) The capacity starts decreasing from 10th cycle, and then it falls till 40th cycle, there is local minima at cycle number 40

Dive into method 2



Short life cells

- Mean, variance, and minimum of ΔQ10−1(V) as features
- Random Forest algorithm works great giving a MAE of 11% with just first 10 cycles
-



Long life cells

- Mean, variance, and minimum of ΔQ40−10(V) as features.
- Lasso algorithm works great with a MAE of 13.8% and RMSE of 211 cycles nearly same as in Severson literature with using just initial 40 cycles.

Cambridge dataset

Main highlights

- Predict RUL using the EIS spectrum, which are key indicators of the SoH of a battery.
- Knowledge of the cycling temperature is not required as long as the future operating temperature of a battery is close to its previous operating temperature.
- Inputs is $[Z_{re}(\omega_1), Z_{re}(\omega_2), \ldots Z_{re}(\omega_{60}), \ldots Z_{im}(\omega_1), Z_{im}(\omega_2), \ldots Z_{im}(\omega_{60})]$ are the real (Z_{re}) and imaginary (Z_{im}) parts of impedance spectra collected at 60 different frequencies.

TRAINING AND TESTING DATASETS

- Datasets contains 12 cells: 25 ◦ C (25C01–25C08), 35 ◦ C (35C01 and 35C02) and 45 ◦ C (45C01 and 45C02)
- Cells used for traning model : 25C01 - 25C04, 35C01, 45C01

CELLS-EOL	RMSE (CYCLES) BY OUR MODEL	RMSE (CYCLES) IN PAPER
45C02-396	28.6	32
35C02-252	28.8	36.5
25C05-150	10.5	15.5
25C06-120	13.7	18
25C08-38	9.7	5

REASON FOR THE SUCCESS

- Developed a new features: [Zre(2) - Zre(1), Zre(3) - Zre(2), ...Zre(60) - Zre(59), ... Zim(2) - Zim(1), ... Zim(60)-Zim(59)]
- Using a better ML algorithm: Relevance Vector Machine

EARLY WORK

- Severson Dataset
  - New algorithm
  - New feature generation
  - Dataset division
- Cambridge Dataset
  - Study of ECM parameters
  - Genration of new features from Impedance.py

TAKE A LEAP BACK IN TIME

NEW ALGORITHMS

Linear regression, Decision Tree, Random Forest, Lasso, Neural Network, Bayesian approach, Support Vector Machine, Relevance Vector Machine were tested to refine the outcome.

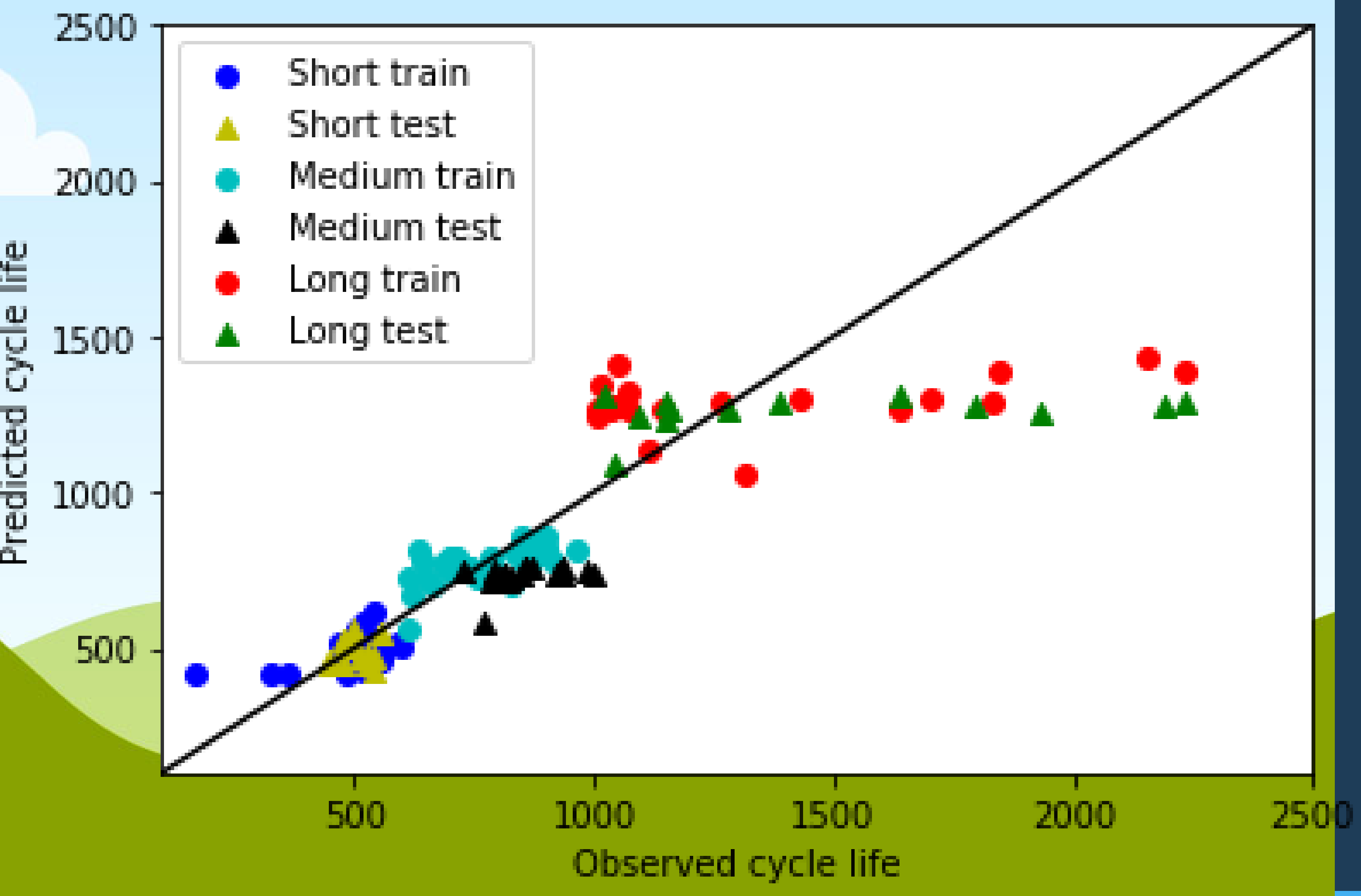
NEW FEATURES

Generated new features : $\Delta Q_{i-j}(V)$ for i,j belongs to $10<j<i<100$, to see their correlation with the RUL of a cell.

DATASET DIVISION

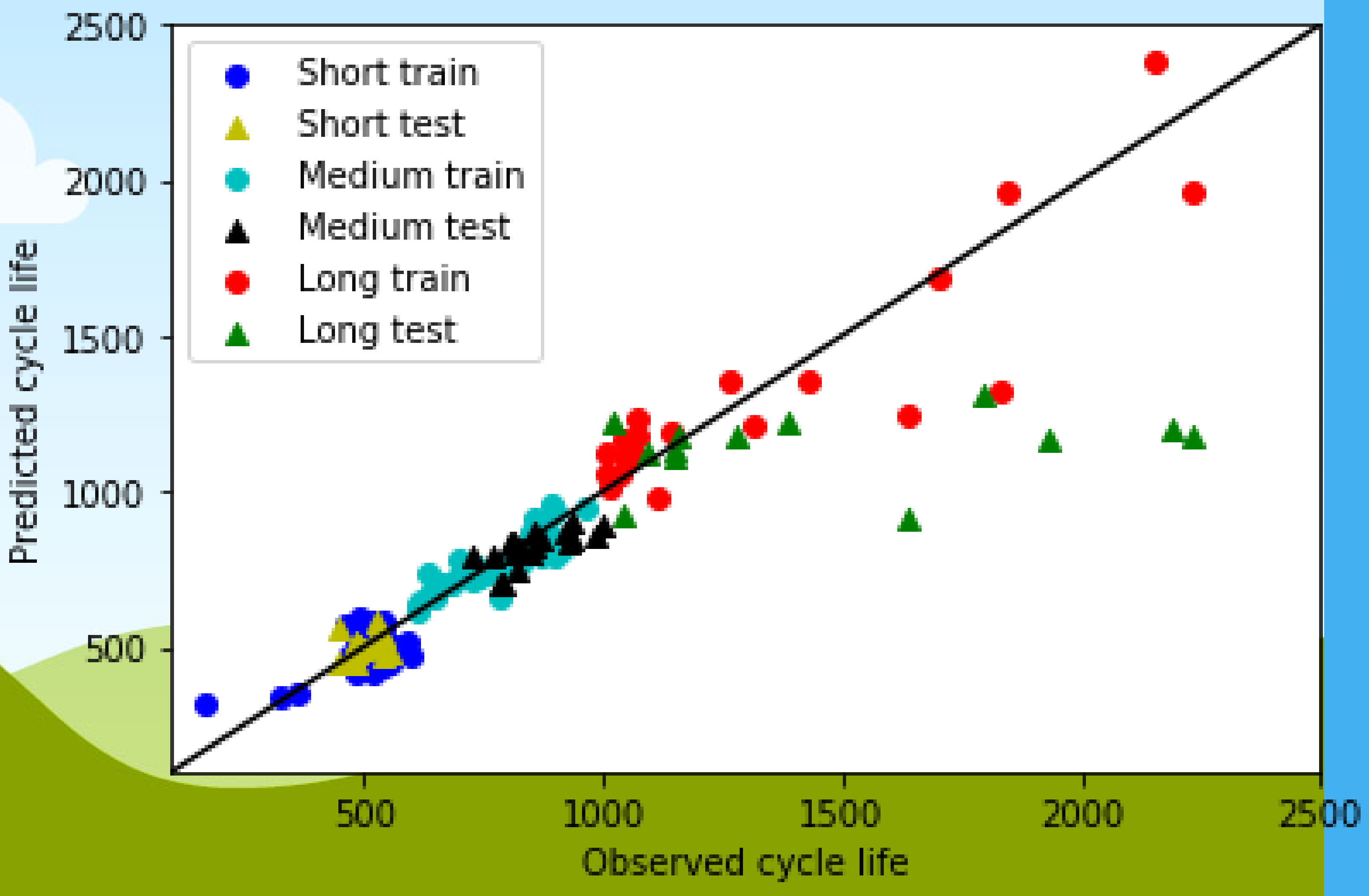
Divided datasets into 3 categories:

1) Short life cells (EOL < 600)
2) Medium life cells
   (600 < EOL < 1000)
3) Long life cells (EOL > 1000)



ΔQ10–1(V) is used as feature

Short life cells are fitting well while medium and long life cells are giving the same RUL for every cell..

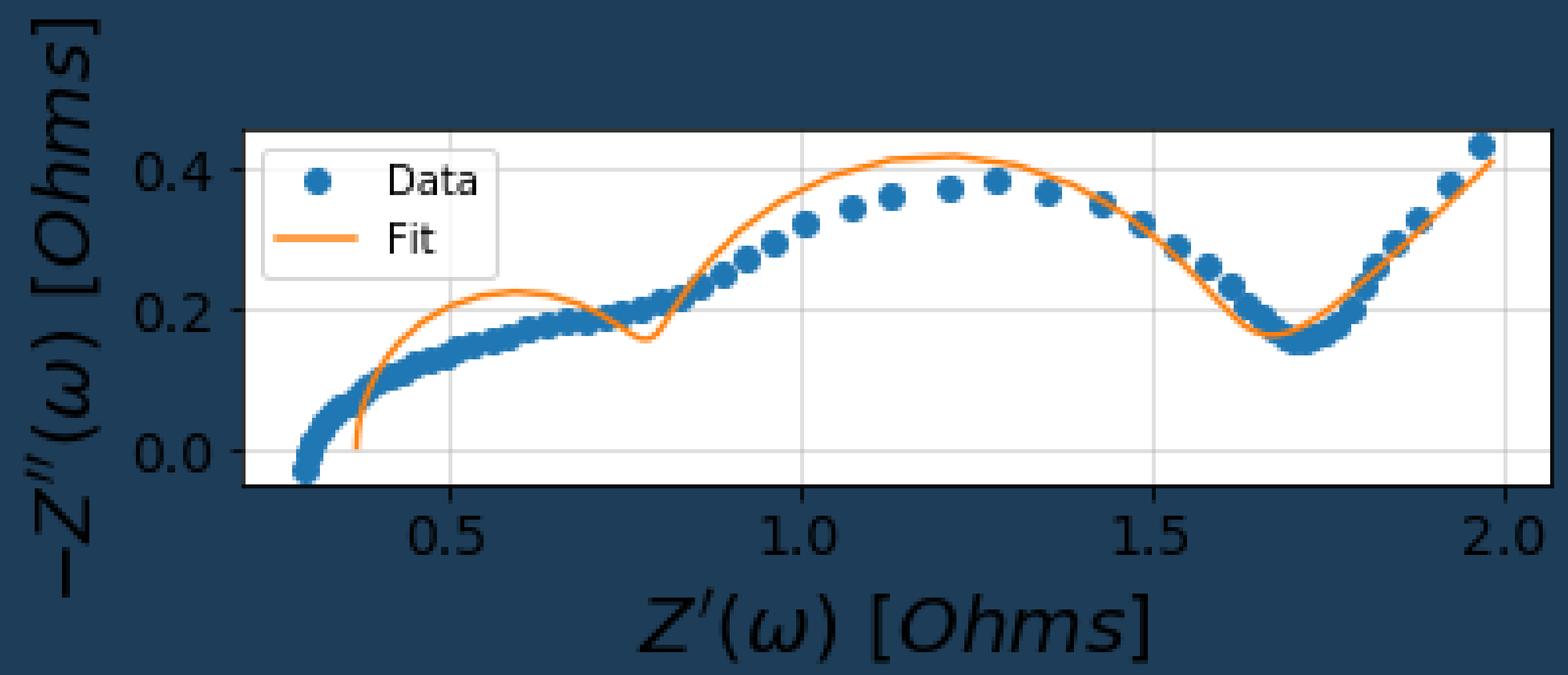


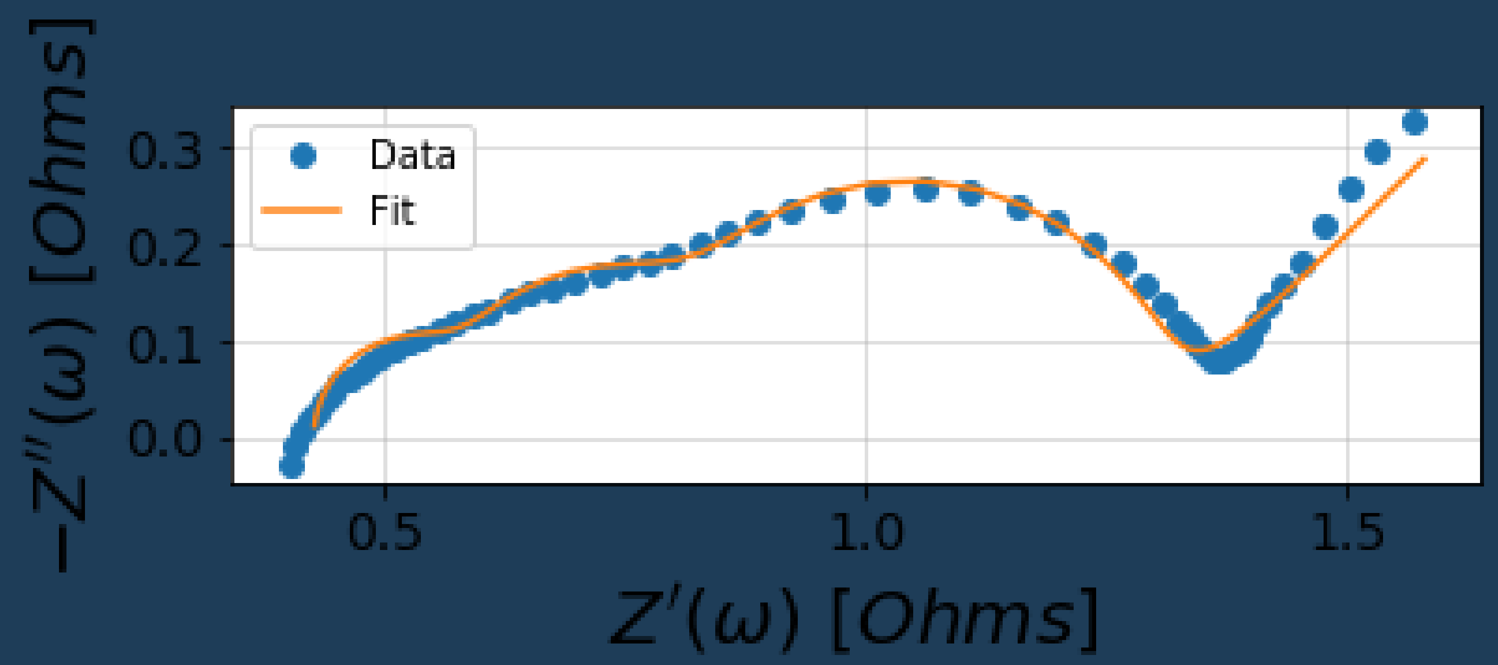
ΔQ100–1(V) is used as feature

Medium life cells result have improved drastically, and the long-life cells are performing the same as Severson paper results.

Timeline

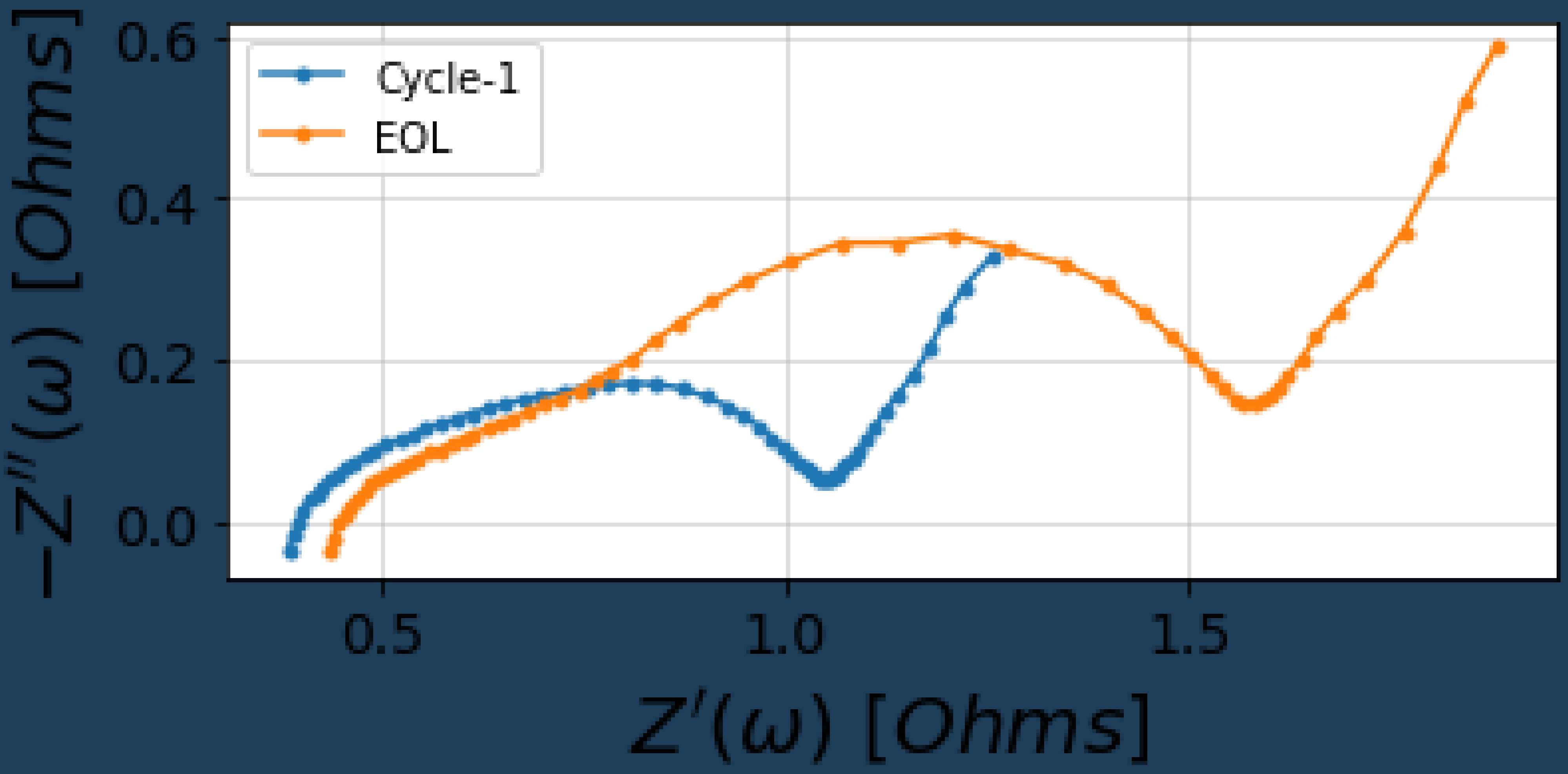
- Study Equivalent Circuit Model (ECM) through Impedance.py
- Generated new EIS data with Impedance.py
- Find out a flaw in Impedance.py
- Future scope of using Impedance.py





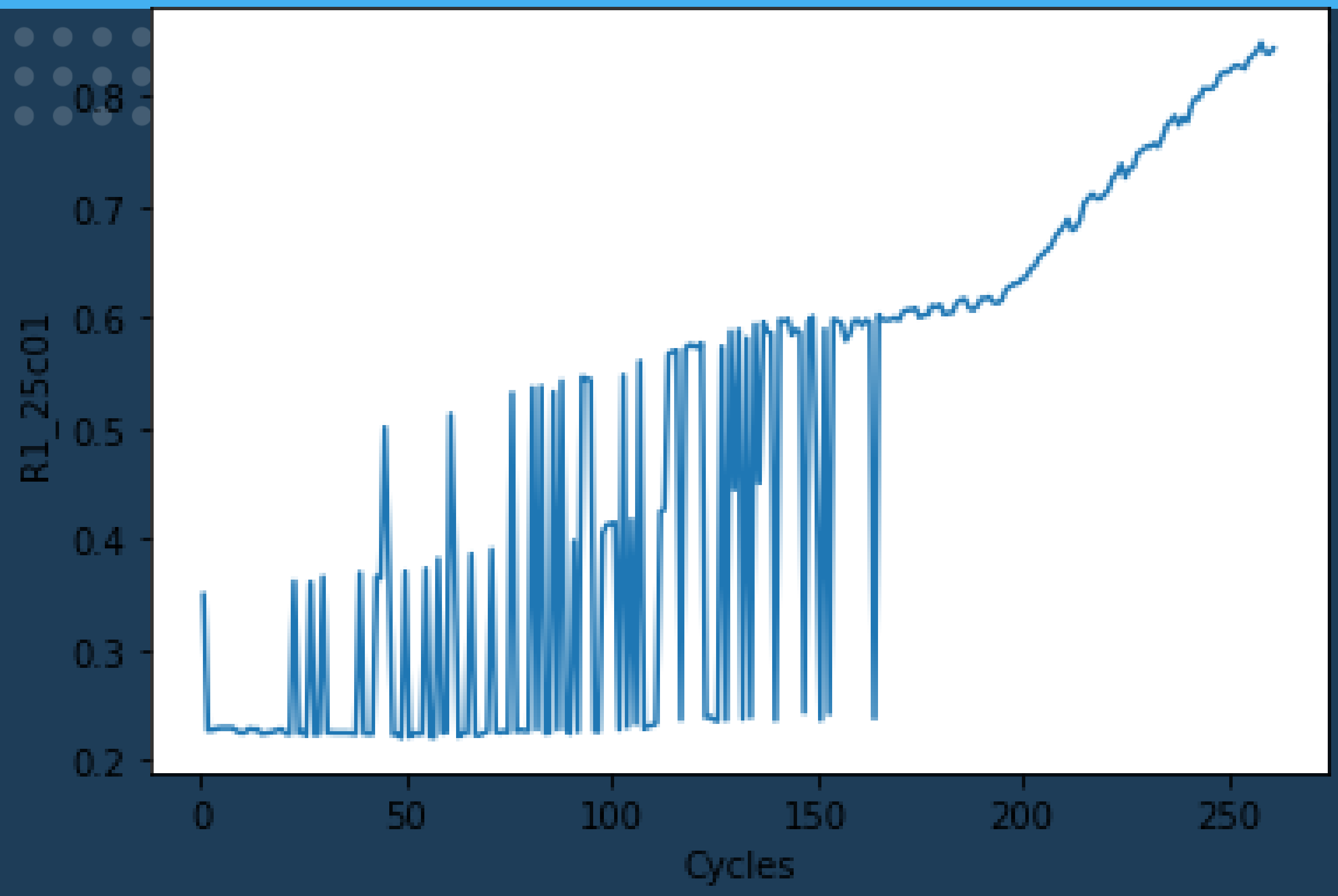
ECM selection

3-RC Warburg ECM is fitting better than 2-RC Warburg

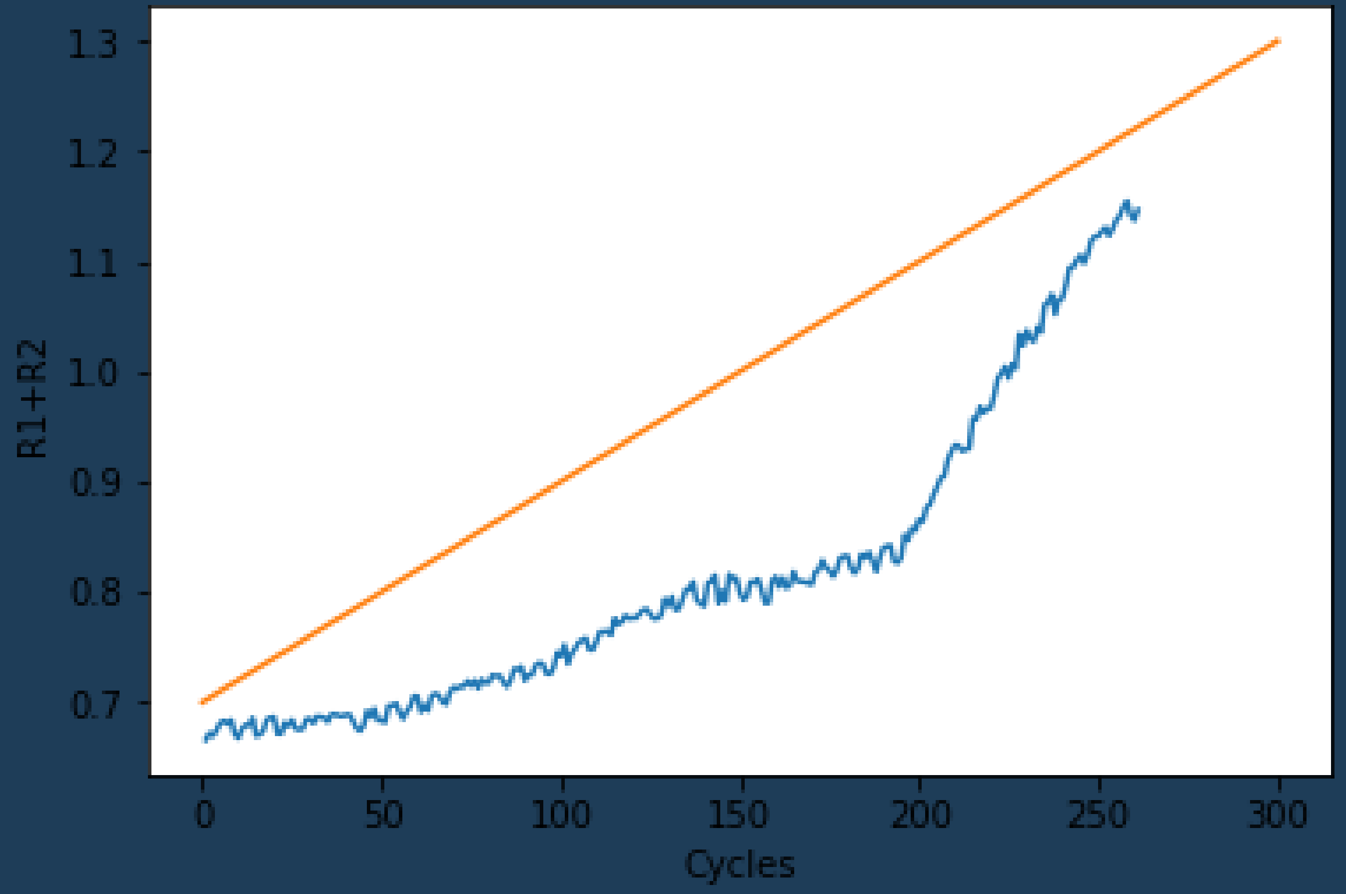


Study of parameters

Here is the Nyquist plot of 3RC-Warburg impedance.The increase of impedance with the cell aging. There are 9 parameters which can be calculated and can be used as features.



This figure represent the variation of one of the 3-RC Warburg ECM parameter calculated with the Impedance.py. It's fluctuating with the cell aging



This figure represent the variation of another 3-RC Warburg ECM parameter which calculated through code. It's varying pretty smoothly as the cell ages.

These four parameters were calculated using code and used as feature in the model giving results nearly same as Cambridge paper. This show potential for their future use as a feature in the model

R0

R1+R2+R3

LOCAL MAXIMA OF SEMI-CIRCLES

SLOPE OF WARBURG IMPEDANCE LINE

Thank you