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Battery Degradation Modeling for Mining BEVs

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Background – What is Battery Degradation

Battery Degradation:
the decline in performance and capacity of the battery over time

Degradation from Calendar Aging:
due to battery's exposure to environmental conditions, independent of its usage

Degradation from Cycling Aging:
due to repeated charge and discharge cycles, directly related to how the battery is used

Parameters for Battery Degradation

Calendar Aging

- storage temperature
- initial state of charge (SoC)
- initial state of health (SoH)

Cycling Aging

During both charging and discharging process:

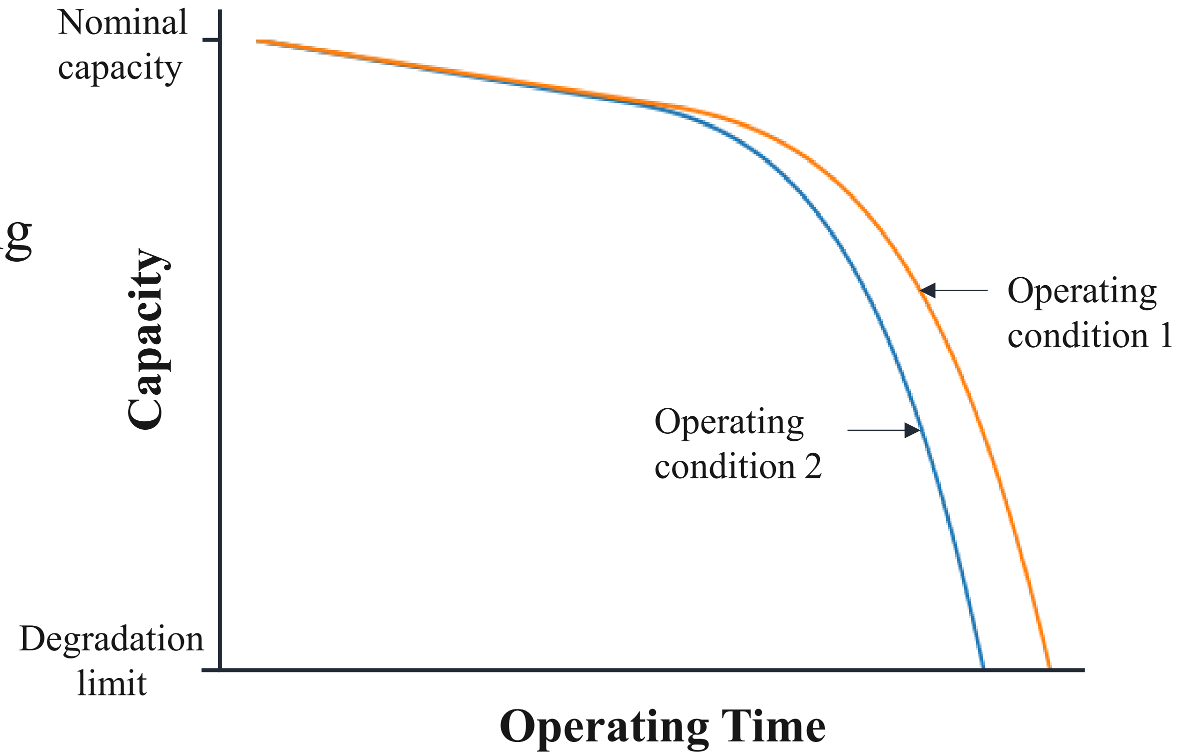
- current and voltage
- SoH
- battery temperature
- SoC
- internal resistance

Battery Specifications

- nominal capacity
- nominal voltage
- cut-off voltage
- battery chemistry
- size and weight
- max charging and discharging rate
- specific power and specific energy

Motivation

- Current lack of study on battery degradation for mining BEVs
- Study the different patterns of battery degradation in underground and surface mining vehicles
- Forecast battery longevity for mining duty cycles
- Investigate the factors that most significantly influence battery degradation



Empirical vs Machine Learning

Empirical

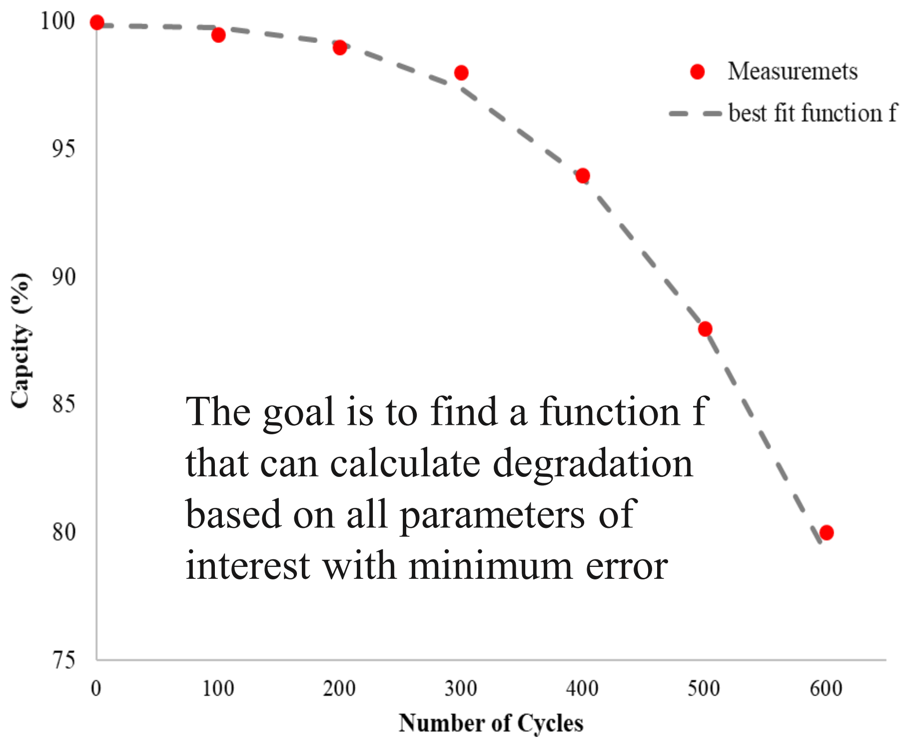
- Built on mathematical equations (like linear, exponential, or polynomial relationships). A common one found from literatures is $capacity = a \cdot number\ of\ cycles^{b}$, where a and b are functions of parameters (e.g., DoD, temperature, charging rates)
- Interpretable because the model is based on predefined equations showing how each parameter influences degradation
- Less flexible especially if they aren't designed for a broad set of operational conditions

Machine Learning

- Rely purely on data to learn patterns and relationships between the input features (e.g., DoD, temperature, charging rates) and output (e.g., capacity degradation)
- Often considered "black boxes" because it’s hard to interpret how the model makes prediction
- Adapt to complex and nonlinear patterns, making them powerful tools for capturing detailed and hidden relationships in battery behavior

Empirical vs Machine Learning

Empirical



The goal is to find a function f that can calculate degradation based on all parameters of interest with minimum error

Machine Learning

Data frame

Battery	Feature 1	...	Feature n	Life Cycle
1		…		
2		…		
3		…		
4		…		
. . .		… … …		. . .

Input features (Battery … Feature n) — Target (Life Cycle)

1 Background and Motivation

2 Degradation Modeling (Empirical and Machine Learning)

3 **Example: ML Model for LFP Cells**

4 Implementing Modeling for Mining Duty Cycles

5 Current Challenges and Future Direction

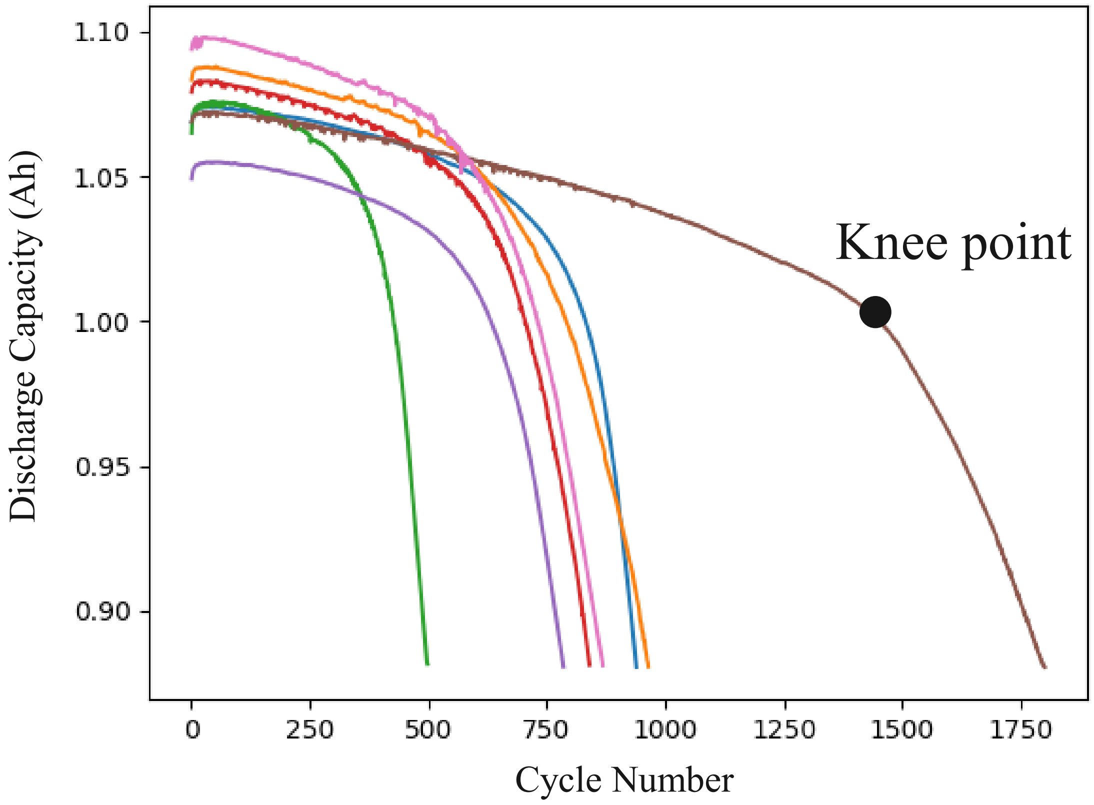
ML Modeling Example – Data Overview

- **Online public dataset***: 124 LFP/graphite cells with 1.1 Ah nominal capacity and 3.3 nominal voltage
- **Charge:** All cells charged with a one-step or two-step charging strategy from 0% to 100% SoC. There are 72 different charging strategies in total:

	SoC 0% to 80%	SoC 80% to 100%
One-step	Single C rate between 3.6C to 6C	1C CC-CV
Two-step	C1 from 0% to X% C2 from X% to 80% C1, C2 between 3.6C to 6C X between 0 to 80	1C CC-CV

- **Discharge:** 4C CC-CV
- **Cycling condition:** constant 30 °C in an environmental chamber

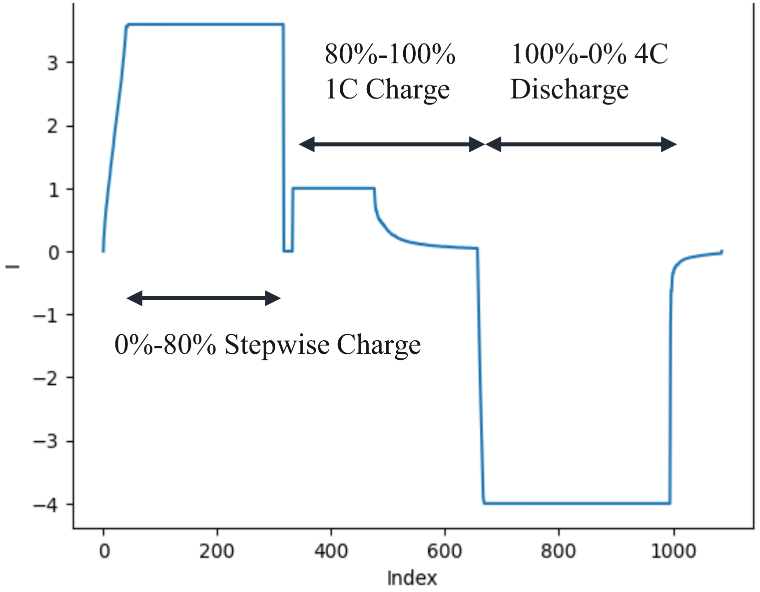
Example: Discharge capacity vs cycle number for 8 cells from the dataset



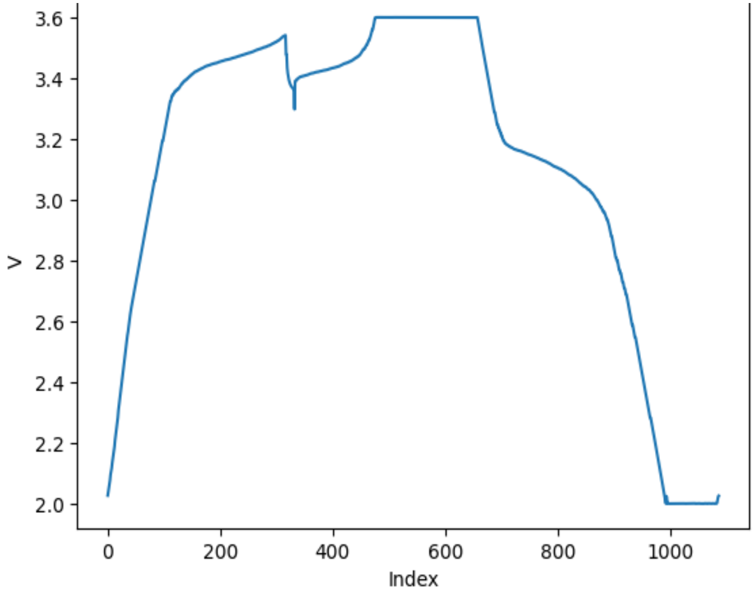
*https://data.matr.io/1/projects/5c48dd2bc625d700019f3204

ML Modeling Example – Raw Data

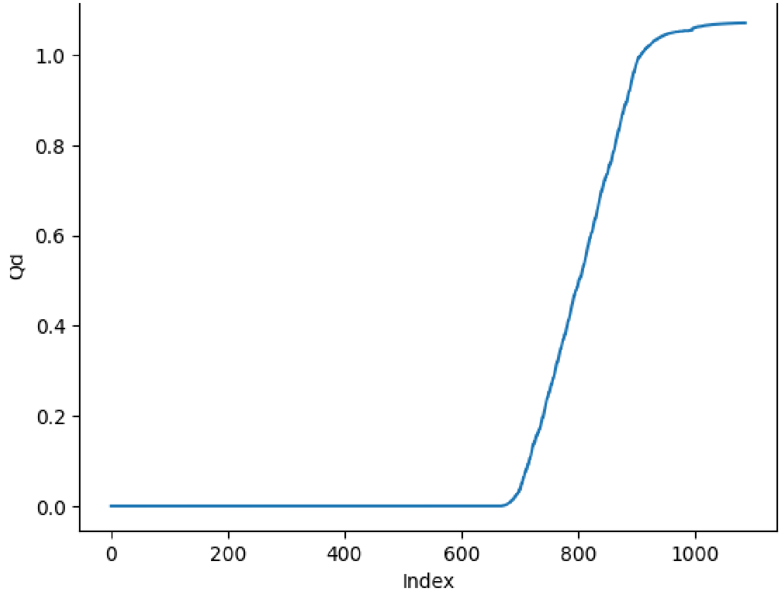
Current Profile for 1 Cycle



Voltage Profile for 1 Cycle



Discharge Capacity Profile for 1 Cycle



- Total of over 95,000 cycles for 124 cells

ML Modeling Example – Data Frame

	cell	Q_2	Q_50	Q_100	cycle#_97%	cycle#_98%	cycle#_99%	variance	min	skewness	...	min_dQdV_0	min_dQdV_20	min_dQdV_40
0	b1c0	0.974455	0.978826	0.978038	431	387	255	0.000598	-0.001839	0.007415	...	-6.683810	-6.455224	-6.483233
1	b1c1	0.978739	0.983351	0.982409	1037	786	484	0.000104	-0.006464	2.769895	...	-6.654868	-6.710725	-6.570391
2	b1c2	0.983014	0.987121	0.986313	1042	829	484	0.000084	-0.006086	2.900600	...	-6.734331	-6.820305	-6.454970
3	b1c3	0.982935	0.986984	0.986062	863	691	493	0.000038	-0.017681	-0.540710	...	-6.570647	-6.836047	-6.709819
4	b1c4	0.980920	0.985028	0.984179	878	706	497	0.000023	-0.013284	-0.436760	...	-6.453132	-6.553292	-6.545598
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
119	b3c39	0.952185	0.955540	0.954094	757	587	385	0.000036	-0.017740	-0.298655	...	-6.322670	-6.323806	-8.038724
120	b3c40	0.963021	0.966858	0.965234	526	445	323	0.000049	-0.022112	-0.331099	...	-6.622581	-11.091160	-6.457538
121	b3c41	0.955020	0.958893	0.958321	565	504	393	0.000063	-0.024614	-0.307950	...	-6.751527	-11.073138	-10.606171
122	b3c44	0.972473	0.976125	0.975389	696	610	469	0.000074	-0.026022	-0.216143	...	-6.669979	-6.576219	-6.541940
123	b3c45	0.972317	0.974677	0.973750	979	767	457	0.000031	-0.016937	-0.320753	...	-6.890425	-6.744752	-10.546980

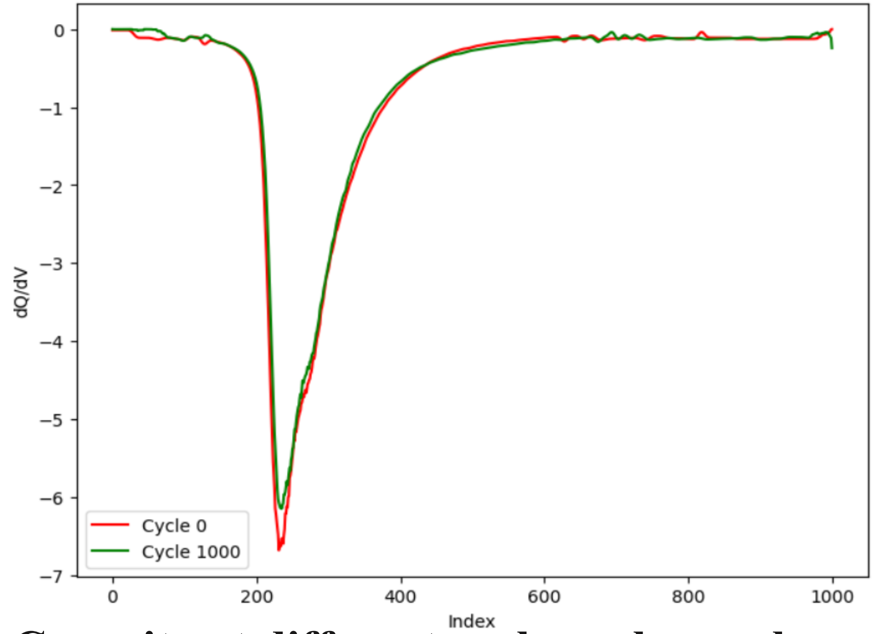
124 rows × 21 columns

cycle_life
1851.0
2159.0
2236.0
1433.0
1708.0
...
1156.0
796.0
786.0
940.0
1801.0

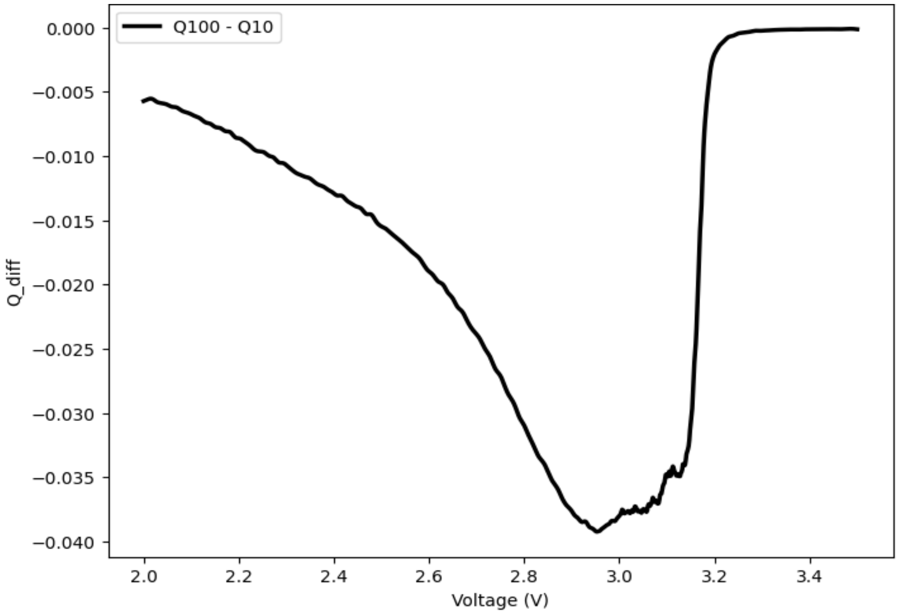
19 Features **Target**

ML Modeling Example – Feature Extraction

Incremental capacity



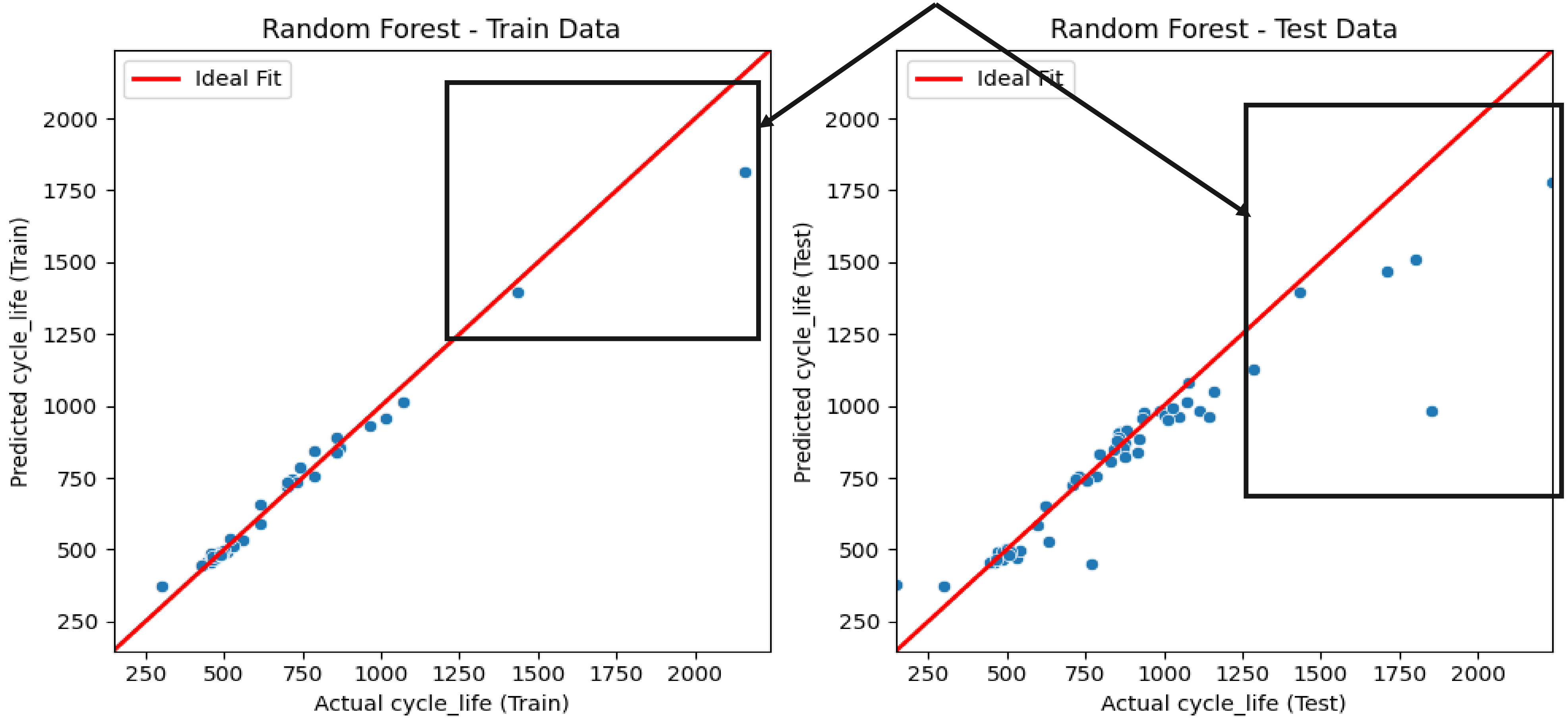
Capacity difference between cycle 100 and cycle 10



- **Capacity at different early cycle number**: capacity at cycle 2, capacity at cycle 50, capacity at cycle 100
- **Cycle number to reach small capacity drop**: cycle numbers to reach 1%, 2% and 3% degradation
- **Incremental capacity**: derivative of capacity over voltage during discharge
- **Capacity difference between cycle 100 and cycle 10**: statistics such as variance and min to define the curve
- **Charging profile**: charging rates for both one-step and two-step charging strategy

ML Modeling Example – Modeling Result

Not enough training points



ML Modeling Example – Discussion

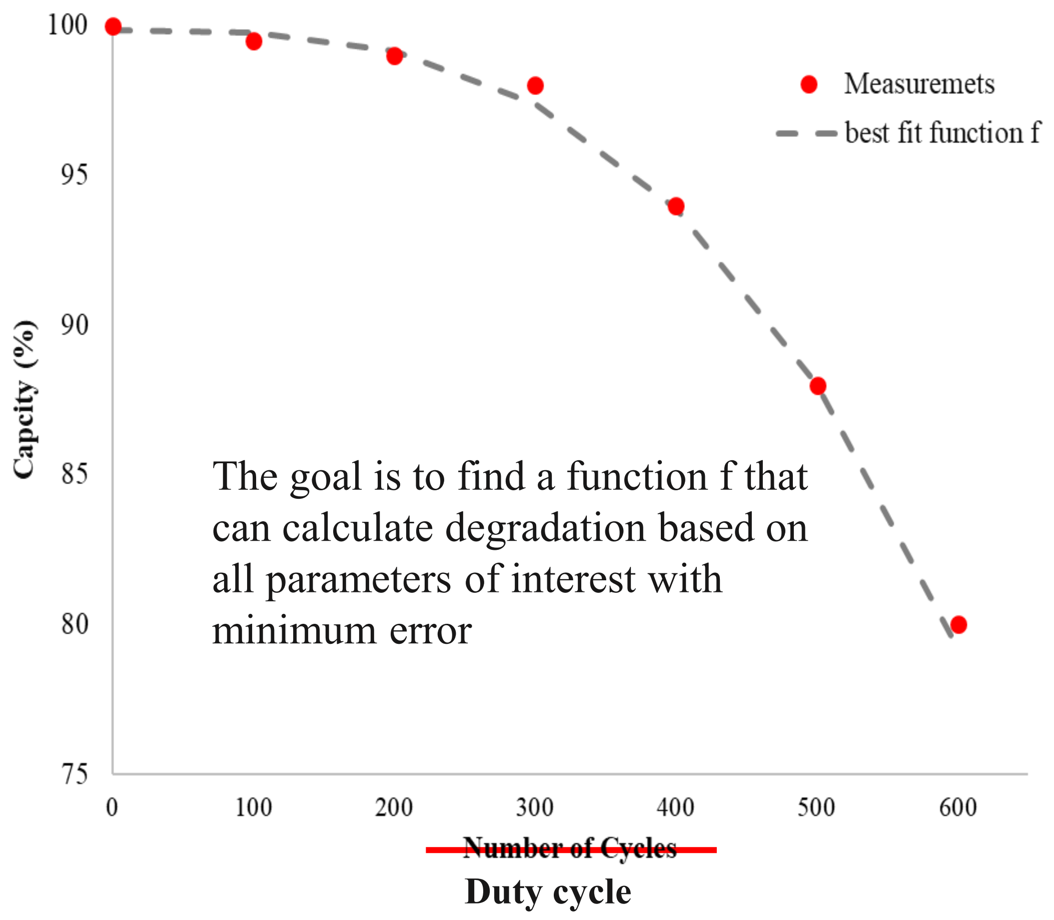
- The model utilizes early-stage degradation data (less than 3% degradation) to predict battery life. However, the results were not obtained from batteries used in mining BEVs; they were meant to demonstrate the methodology

- In Machine Learning models, the features extracted from raw data are often subjective. Additional features may be discovered later to improve model performance

- The ML model demonstrates good accuracy for batteries with fewer than 1250 cycles. For batteries with higher life cycle counts, the accuracy dropped due to not having enough data points for model training

- Currently, an empirical model is being developed to establish a mathematical relationship between step-wise charging rates and battery degradation

Implement Modeling for Mining Duty Cycles



- The general idea remains the same: fit mathematical equation such as $capacity = a \cdot number\ of\ cycles^{b}$. However, instead of using a typical cycle from a controlled laboratory environment, the duty cycle should be applied
- The charging profile can be obtained from the BMS data during charging, while the discharging profile can be extracted from the BMS data during tasks (loading, hauling, dumping) for each duty cycle. A similar stepwise approach for discharging, as demonstrated in the earlier public dataset, can be applied to modeling

Implement Modeling for Mining Duty Cycles

	cell	Q_2	Q_50	Q_100	cycle#_97%	cycle#_98%	cycle#_99%
0	b1c0	0.974455	0.978826	0.978038	431	387	255
1	b1c1	0.978739	0.983351	0.982409	1037	786	484
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4	b1c4	0.980920	0.985028	0.984179	878	706	497
...	...	...	...	...	...	...	...
119	b3c39	0.952185	0.955540	0.954094	757	587	385
120	b3c40	0.963021	0.966858	0.965234	526	445	323
121	b3c41	0.955020	0.958893	0.958321	565	504	393
122	b3c44	0.972473	0.976125	0.975389	696	610	469
123	b3c45	0.972317	0.974677	0.973750	979	767	457

- In Machine Learning, the focus is on identifying key features. Beyond the typical capacity-related features, such as those shown in the left graph of the previously seen dataset, features that characterize each task in the duty cycle should be extracted

- For instance, brake regeneration is crucial in mining duty cycles, and studying its pattern as the battery degrades could be valuable. Features like the difference in regeneration energy between duty cycle 1 and duty cycle 100 can be extracted as a feature for further analysis

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Current Challenges and Future Work

Challenges

- Due to the lengthy process of conducting battery life cycle tests, it is challenging to gather a dataset with enough battery cells tested under each condition
- Life cycle data from batteries used in mining duty cycles is needed to validate whether the models being developed from controlled lab cycling tests remain applicable in real-world condition

Future Work

- Gather data on common mining duty cycles and convert it into corresponding testing conditions
- Conduct cycling tests with battery cells or packs used in mining vehicles to obtain data that accurately reflects the stress levels of mining duty cycles
- The development of both empirical and Machine Learning models is still in the early stages. The models will continue to evolve as new datasets become available

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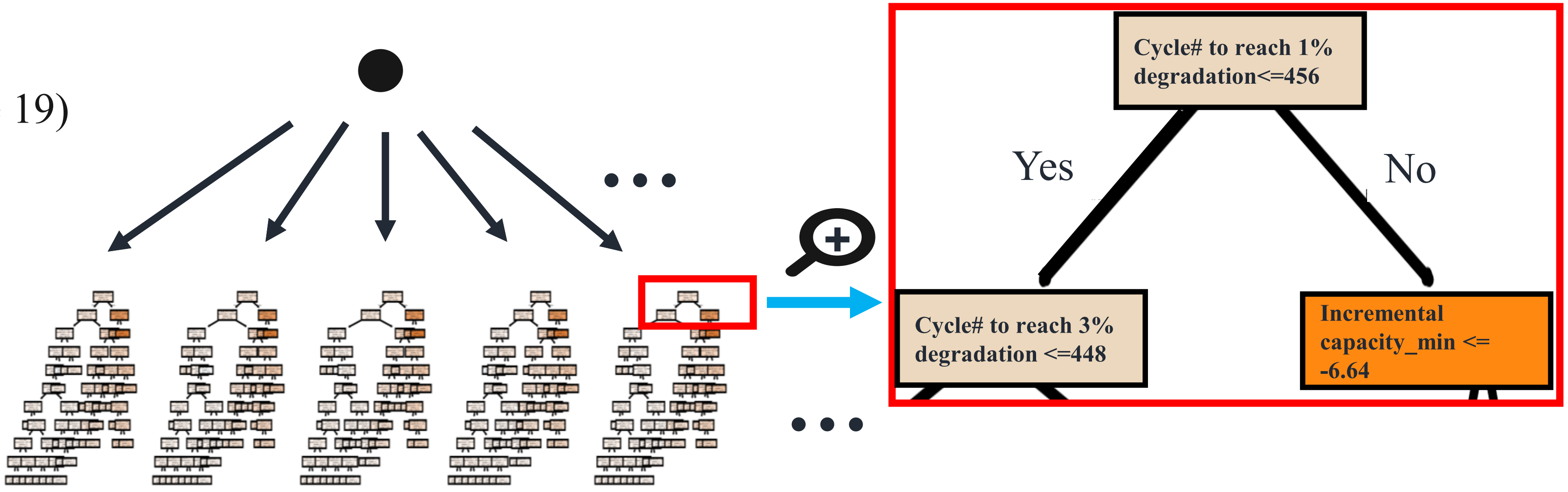
Q&A

THANK YOU!

Appendix: Random Forest

Data point x
(feature 1, feature 2 ,…, feature 19)



Forest: 200 tree models

Prediction from each tree: $y_1, \ldots y_{200}$

y_1 y_2 y_3 y_4 y_5 …

Final model prediction y

$y = \text{average}\,(y_1, y_2, \ldots y_{200})$