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# Physics-Informed Data-Driven Approaches to State of Health Prediction of Maritime Battery Systems

PHM 2024,
Nashville, Tennessee, USA

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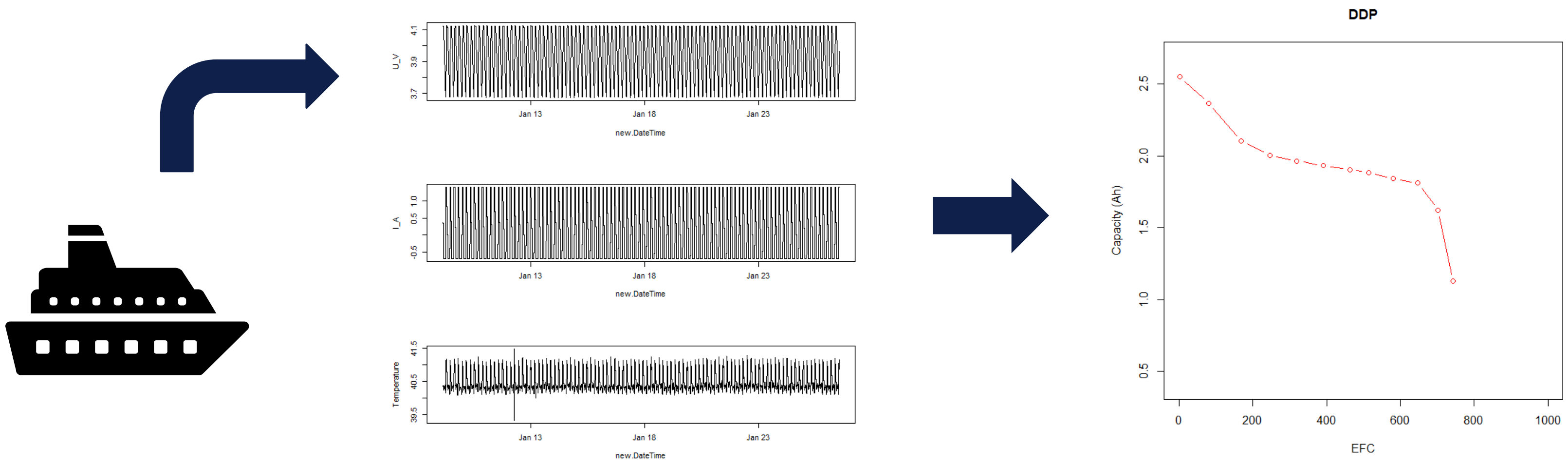
13 November 2024

# Introduction and motivation

- Available energy information is important for the safety of electric ships → Need to monitor SoH
- SoH estimated by BMS, but difficult to assure accuracy
- Class requirement that SoH from BMS should be verified by an independent method
  - Typically done by an annual capacity test
  - Annual capacity test is time consuming and costly → want to go for data-driven verification of SoH



# Background

- Previous attempts with purely data-driven methods failed to meet expectations*

**Cumulative models:**

- Estimate contribution to degradation from each cycle and add up to get current SoH

$$SOH(c_n) = 100 - \sum_{i=1}^{n} \Delta SOH(c_i)$$

- Computationally expensive – do not scale well to large battery systems
- Requires full operating history of the batteries

**Snapshot methods**

- Based on extracting features from charge/discharge curves
- Establish models for the relationship between these features and SoH
- Results OK for about 40% of the cells
- Possibly because lack of representative training data

**Semi-supervised learning**

- Train models on pseudo-capacity extracted from operational data; but do only have SoH from annual tests
- Assume constant SoH in a time-window around annual tests and look for "similar" cycles
- Build a statistical model on newly labelled data
- Dependent on previous vessels having relevant data; experienced similar conditions and degradation

* See papers presented at previous PHM conferences, PHM 2021, PHM 2022 and PHM 2023

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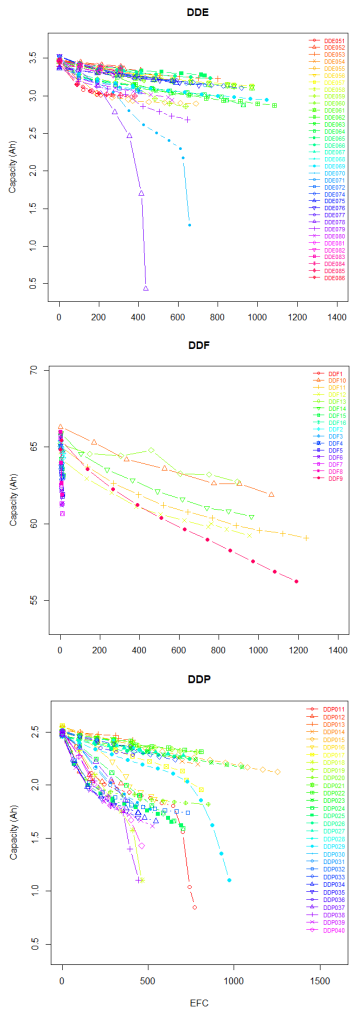
# Available data sources




- Battery cells have been cycled within the project to obtain lab data
  - Fraunhofer and Corvus labs; DDE, DDP and DDF cells
  - Time-series of current, voltage and temperature with regular check-ups
- Operational data have been collected from several vessels
  - Vessels A – F; similar cells as DDF (pouch cells)
  - Time-series of current, voltage, temperature and SOC + annual test results
  - Ferries and offshore vessels: all-electric and hybrid
- Some publicly available dataset

- One problem is that different chemistries and cell types have very different degradation.
  - Need training data from the *same cell types* as the ones to monitor with data-driven approaches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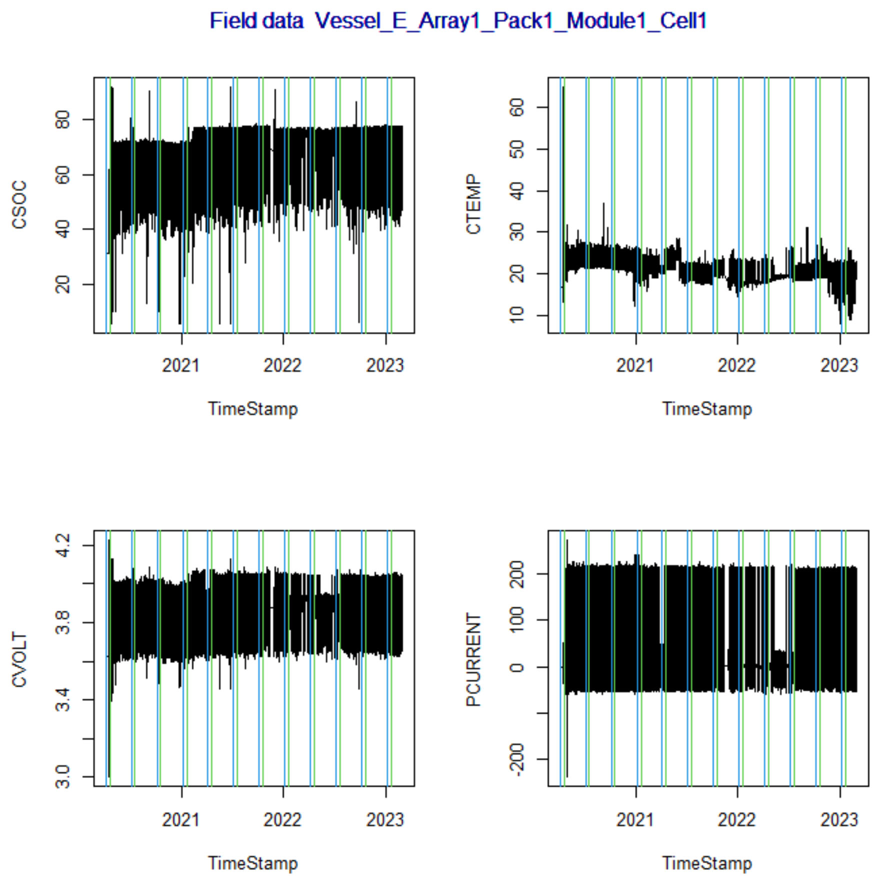
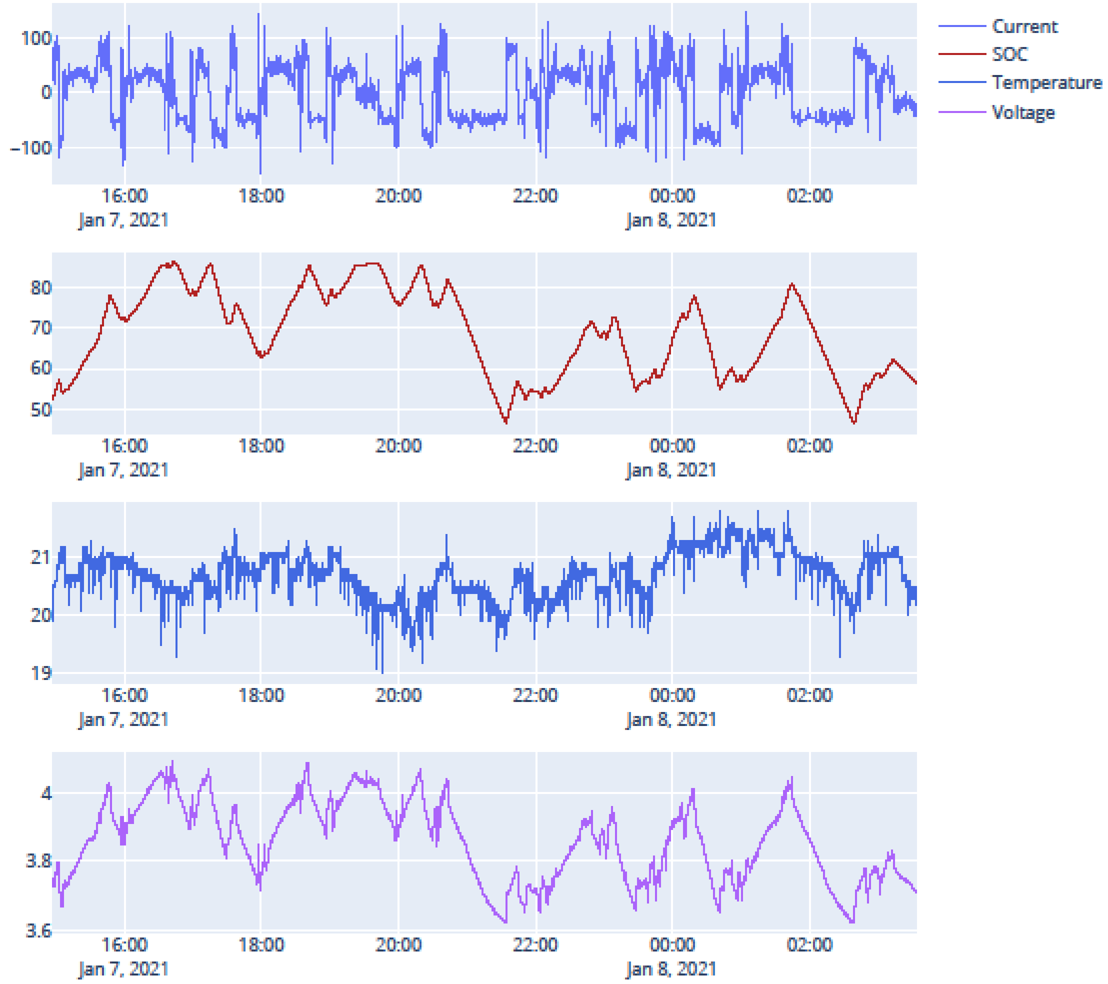
# Example of operational data from ships in service



# Data-driven SoH estimation

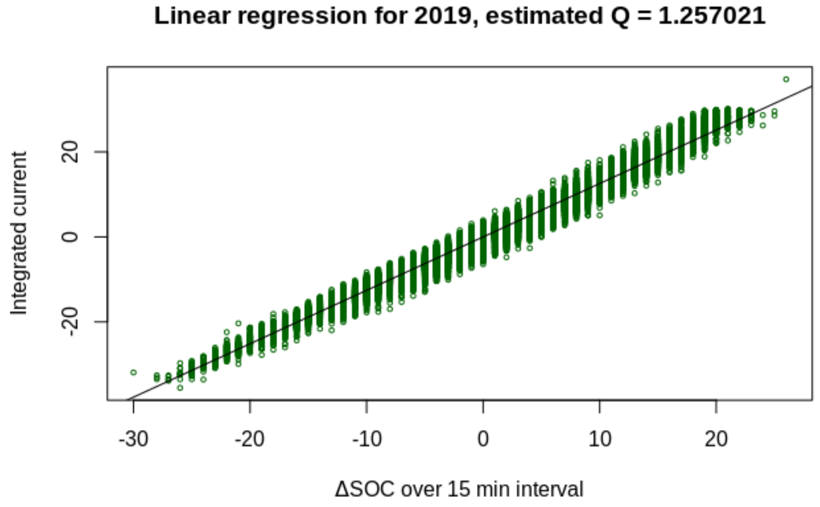
- Earlier attempts on pure data-driven methods did not meet expectations
  - Accuracy and robustness
  - Computational cost and scalability to very large battery systems
  - Data requirements; full operational history and need for high-quality representative training data
    - Accounting for all perceivable operating conditions
  - Different approaches were encouraging but not quite good enough
- Concluded that data alone is not enough!
  - Purely data-driven models not sufficient, need to utilize physical insight
  - Explore physics-informed data-driven models, combining simple physical principles with sensor data

# Data-driven SoH estimation utilizing physical principles

- Exploits fundamental relationship between integrated current and change in SoC
  - Model for degradation without the need for training data
  - Capacity, Q, is regression coefficient between integrated current and change in SOC

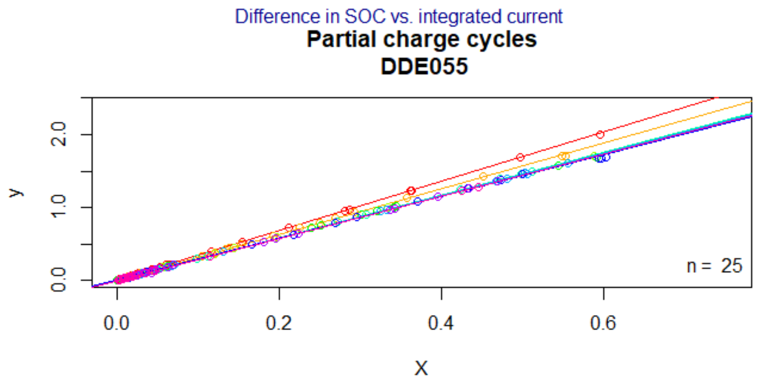
$$\int_{t_1}^{t_2} \eta I(\tau)d\tau = Q\big(SoC(t_2) - SoC(t_1)\big) \rightarrow Y = QX$$

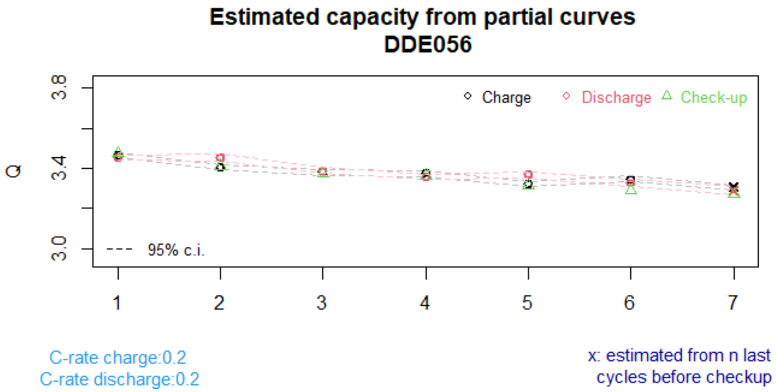
  - May be solved by OLS: $Y = QX + \varepsilon$
  - Or by TLS, accounting for measurement error in both Y and X to remove attenuation bias: $Y + \Delta Y = Q(X + \Delta X)$



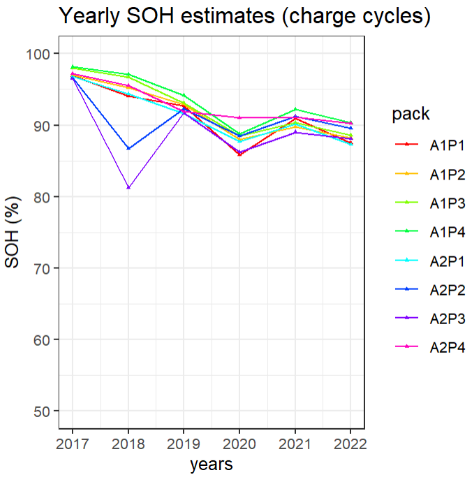
# Simple linear model based on Coulomb counting

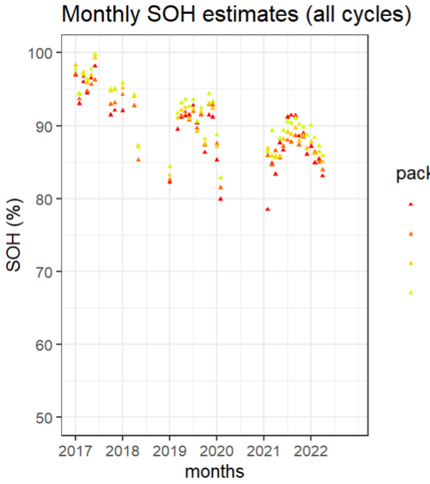
- Performs well on lab-data

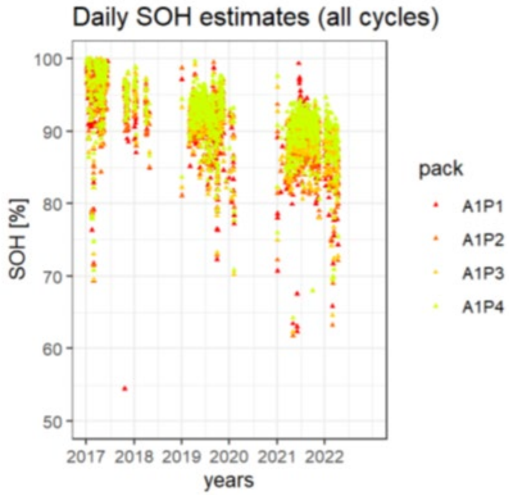



- More challenging on operational data
  - More noise; more variable conditions
- Variable results
  - Initial attempts did not appropriately account for changes in loading conditions



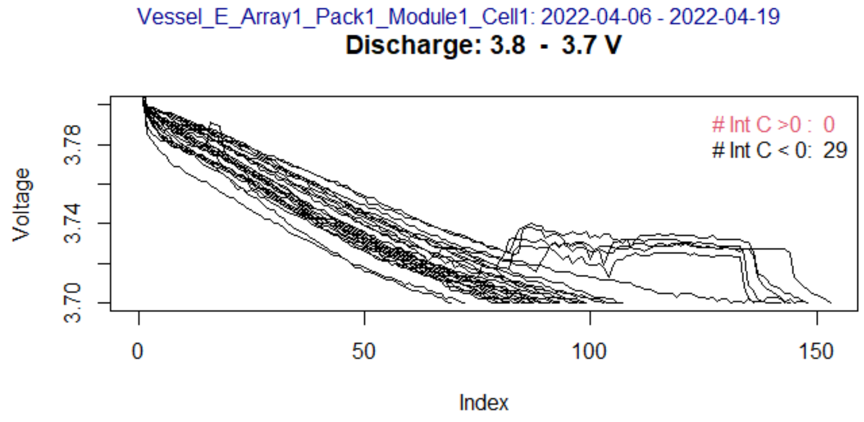



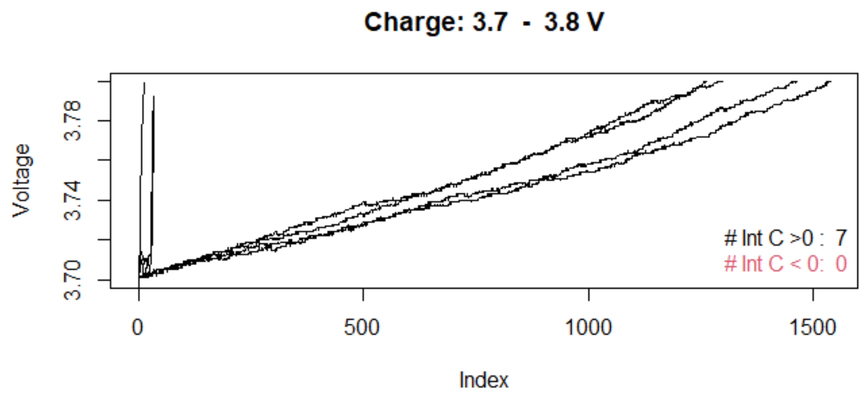
# Ensembles of simple linear models

- Use an ensemble of simple linear models to account for variable operating conditions
  - Apply the model on various subsets of the data; filtering and pre-processing
  - Apply the model to segments of the charge and discharge curves between specified voltage ranges
  - Individual estimates from pure charging and discharging; and both
  - Final estimate based on average of individual estimates; normal and weighted average
- Four voltage ranges specified (between cut-off voltages of 3.0 and 4.2 V):
  - 3.65 – 3.7 V
  - 3.7 – 3.8 V
  - 3.8 – 3.9 V
  - 3.9 – 4.0 V
- This yields 8 point-estimates for each selected time period
- Use 14-days snapshots 3 months apart

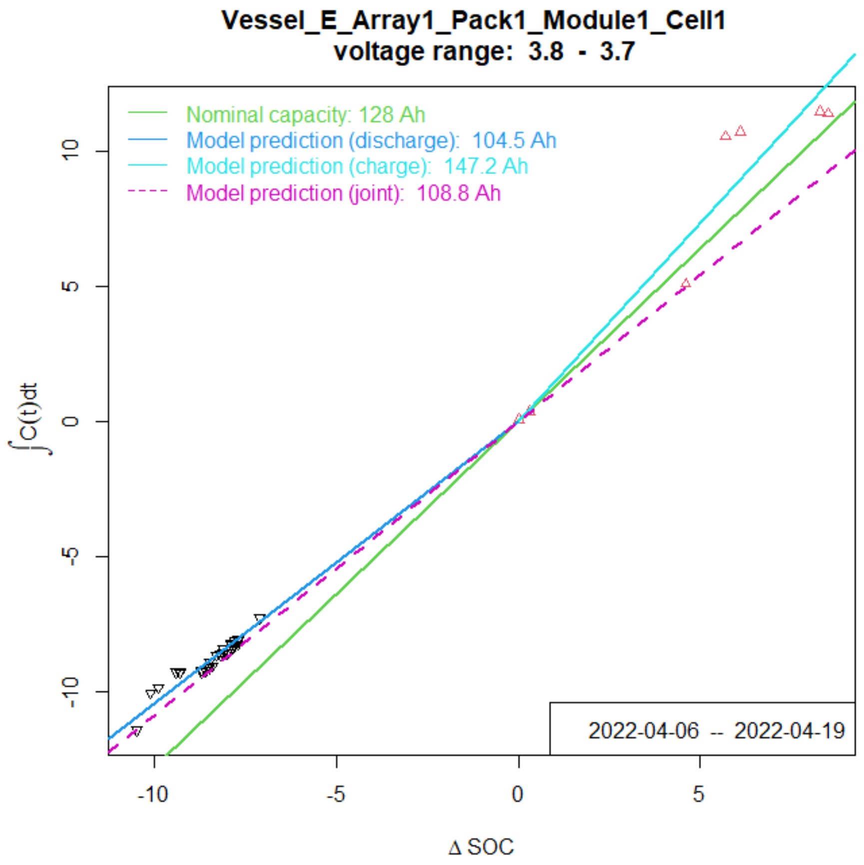
# Ensembles of simple linear models

## Segments of charge/discharge curves

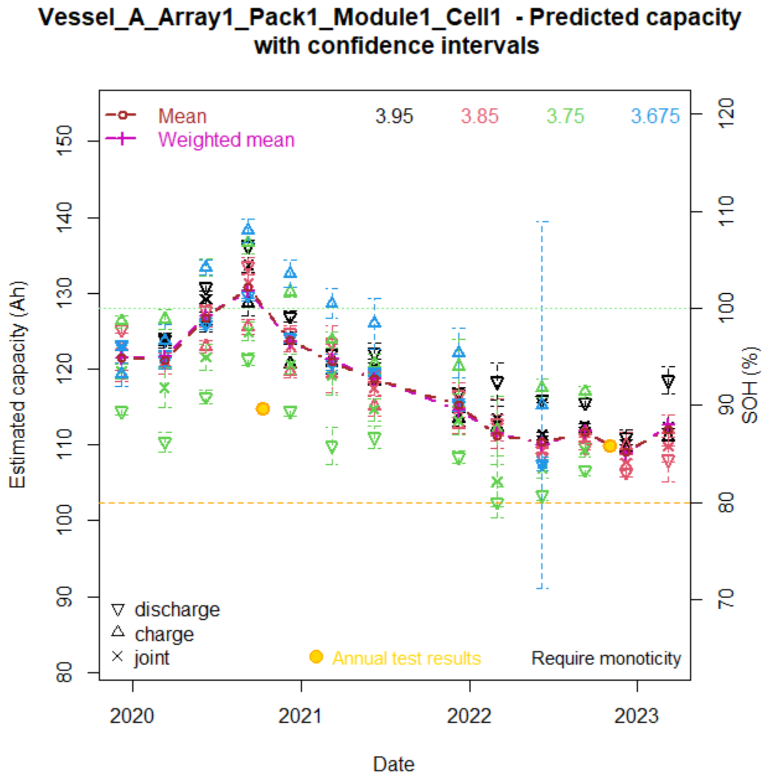


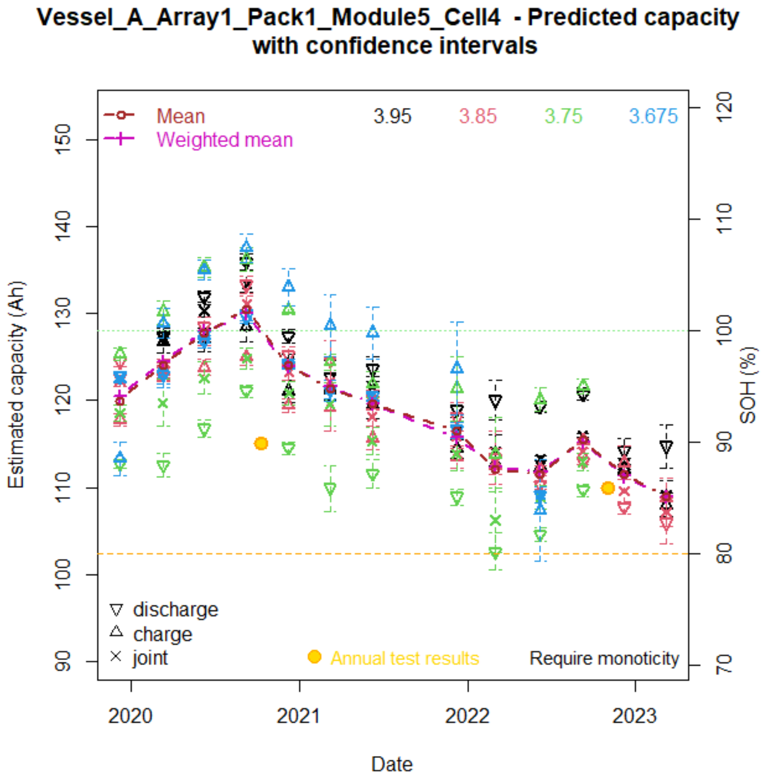



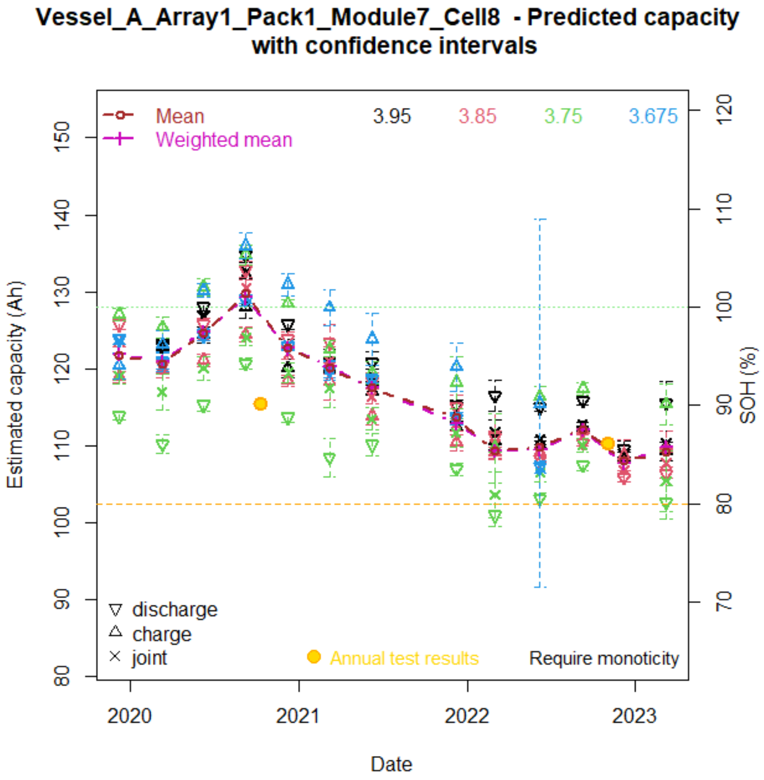

## Extracted data and fitted linear models



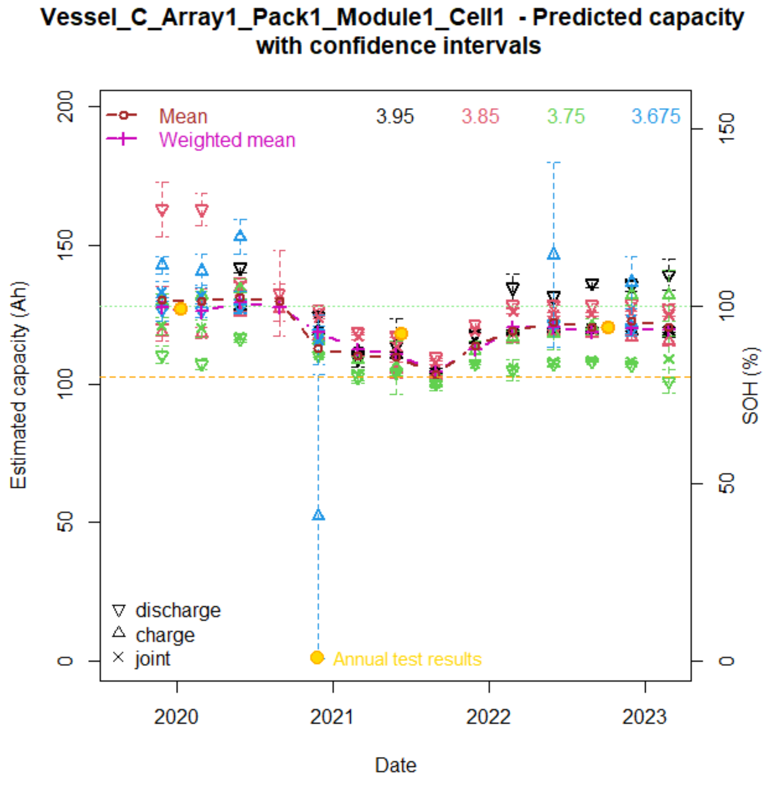
# Ensemble of simple linear models – capacity prediction examples (vessel A)

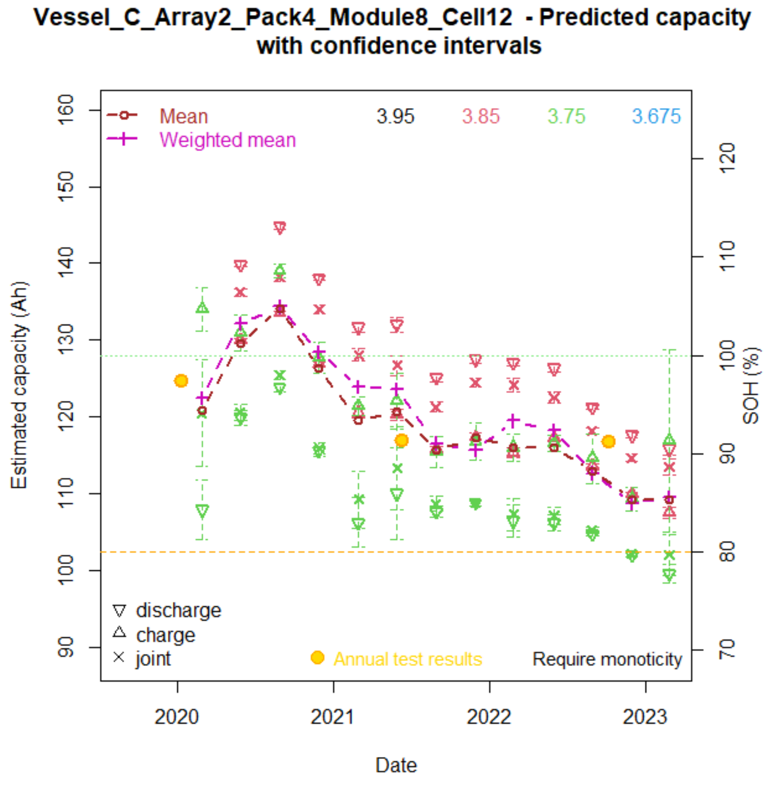


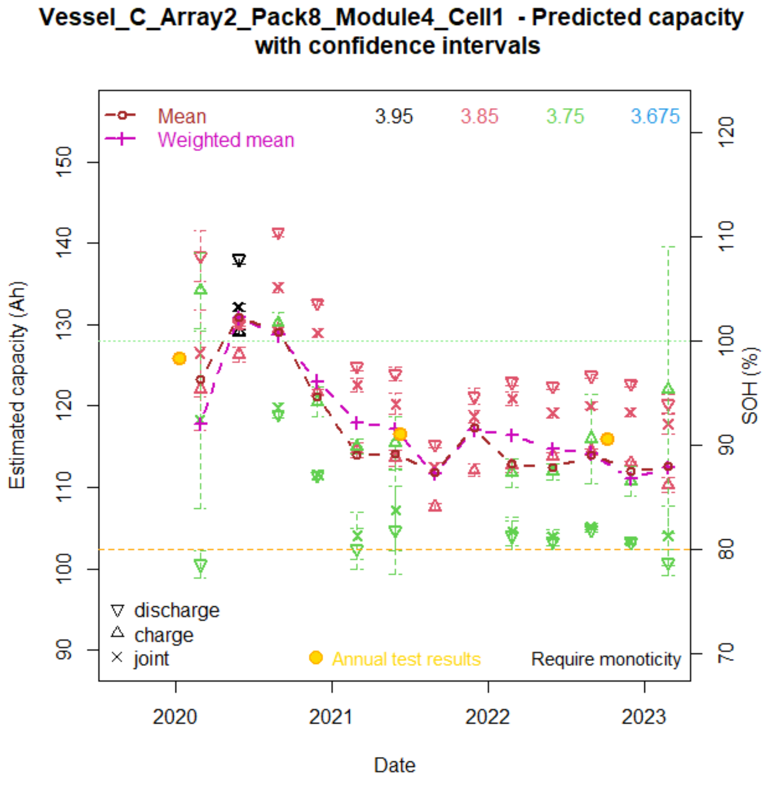



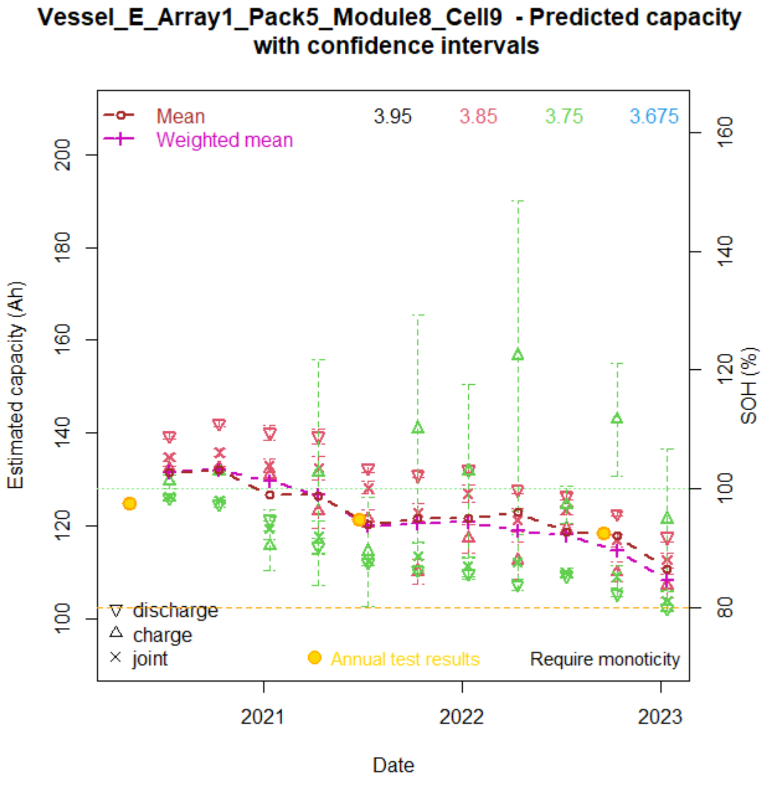
# Ensemble of simple linear models – capacity prediction examples (vessel C)

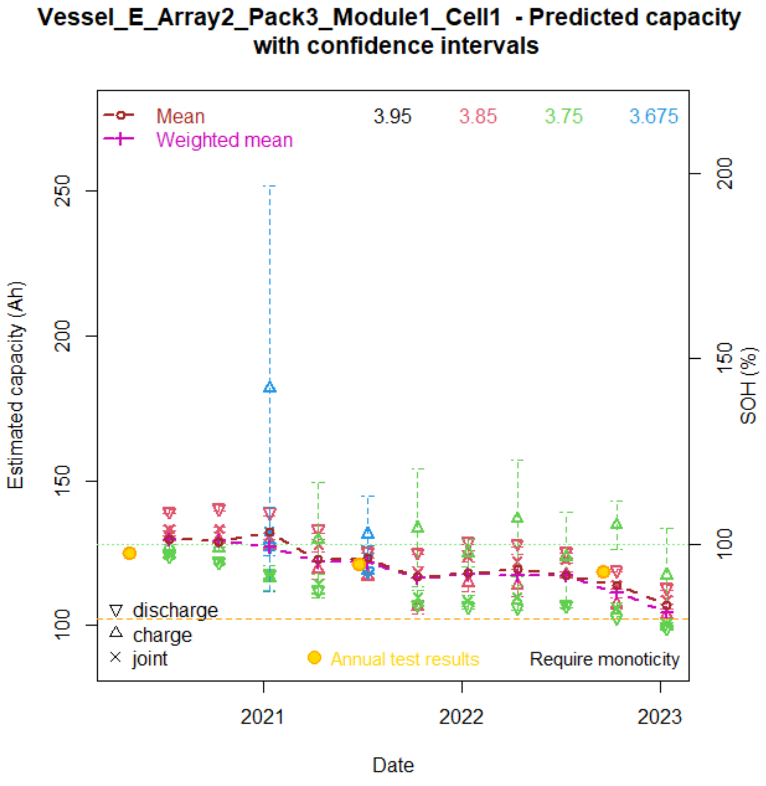


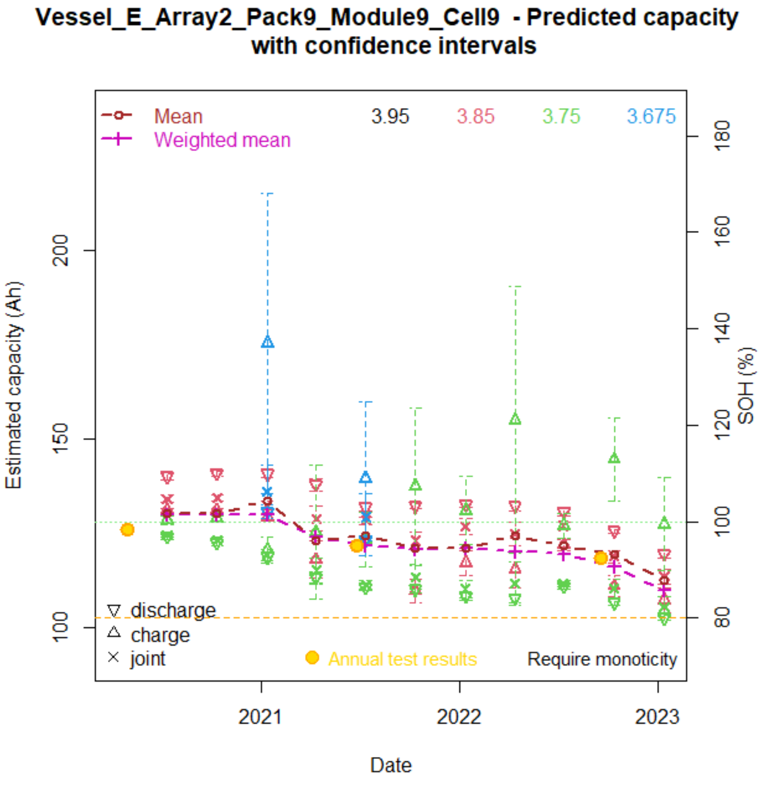



# Ensemble of simple linear models – capacity prediction examples (vessel E)



# Ensemble of simple linear models

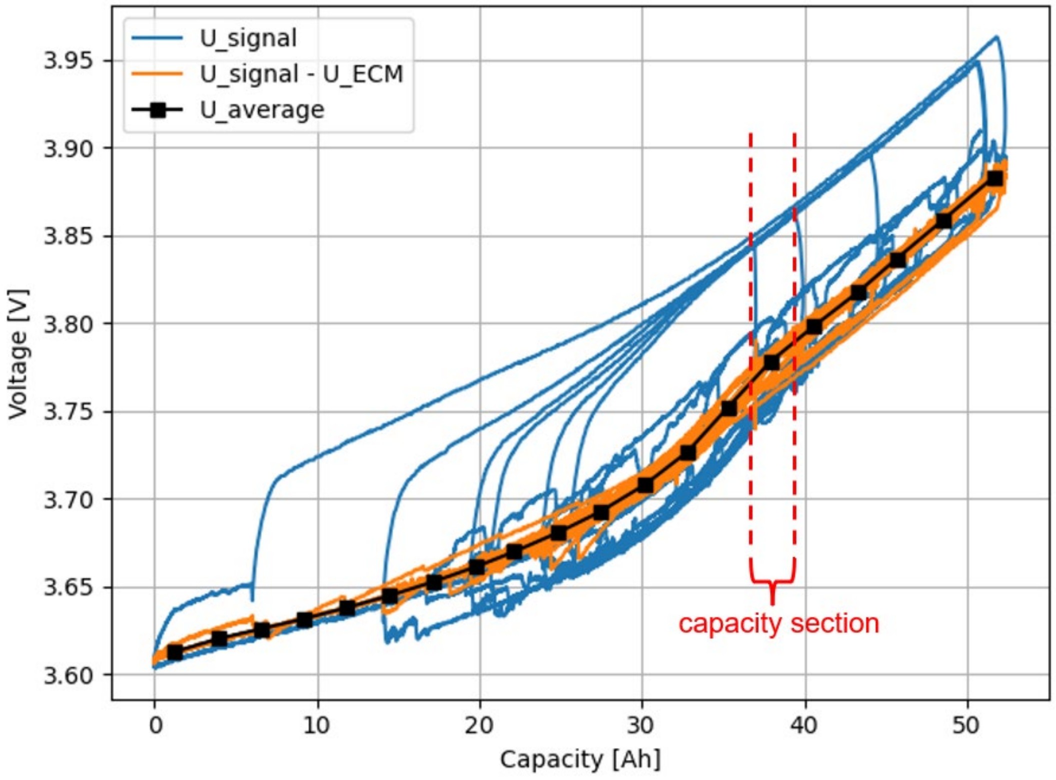
- Results generally better for Vessels C and E compared to A
  - Vessel A is hybrid; vessels C and E are fully electric
- One problem with the simple linear model is the reliance on SoC
  - SoC is a derived quantity not directly measured – it may not be accurate enough
  - More accurate algorithms for SoC calculation can improve capacity estimation
- A possible remedy for this is to rather use open circuit voltage (OCV)
  - Need to obtain an estimate of the OCV from the data

# Methods based on open circuit voltage (OCV)

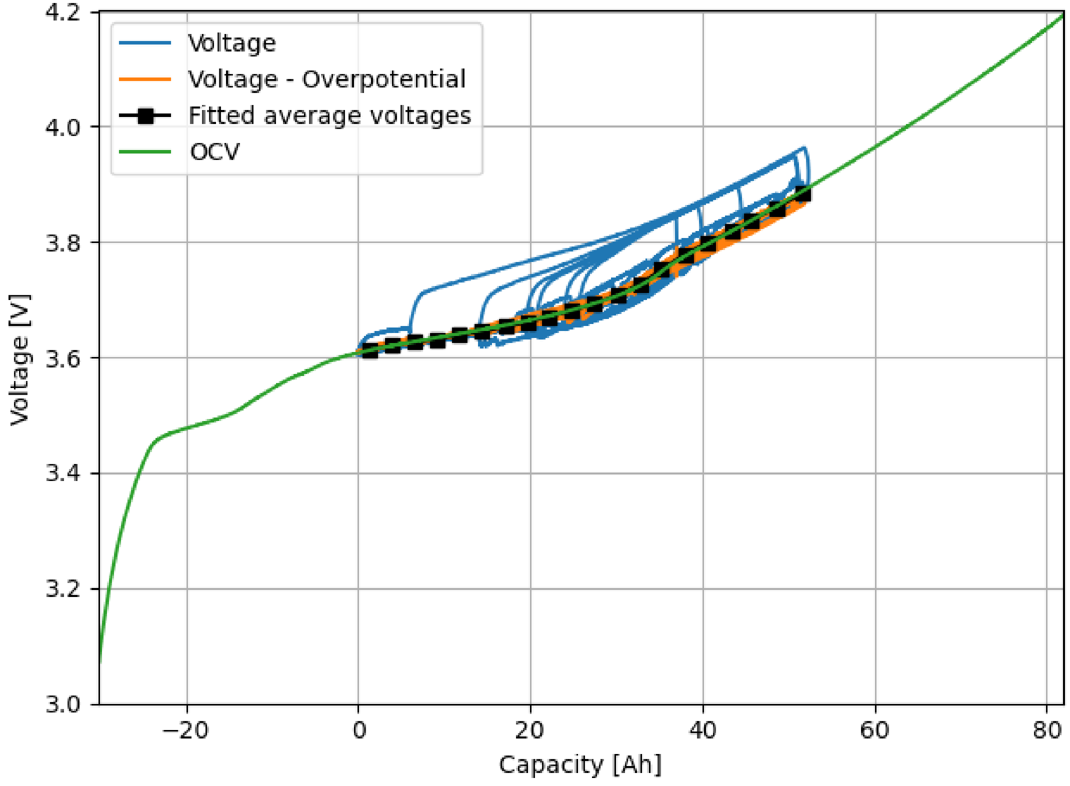
- This approach utilizes the correlation between capacity and open circuit voltage
  - OCV is increasing with SoC, but the relationship is not linear
  - There is also a small influence of temperature and SoH
  - The challenge is to estimate OCV when the cell is not at rest
- An equivalent circuit model (ECM) can be used to describe the overpotential
  - OCV can be obtained by subtracting the overpotential from measured voltage
  - OCV can then be related to the capacity at 100% SoC using a **known** OCV-SoC curve
- The only necessary prior knowledge is the OCV-SoC curve
  - May be obtained from initial laboratory testing
- In this study, an ECM with a serial resistance and 3 RC elements is assumed
  - Parameters are estimated by least squares to minimize voltage fluctuations within a narrow capacity range

# Methods based on open circuit voltage (OCV)

## Subtracting overpotential from measured voltage

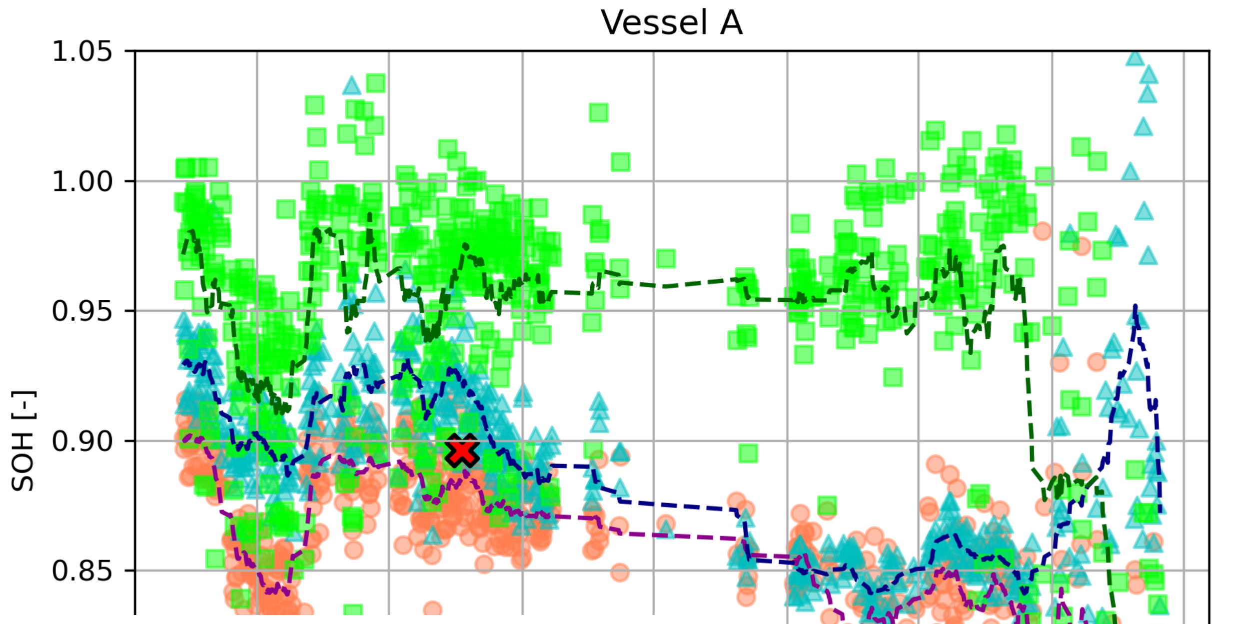


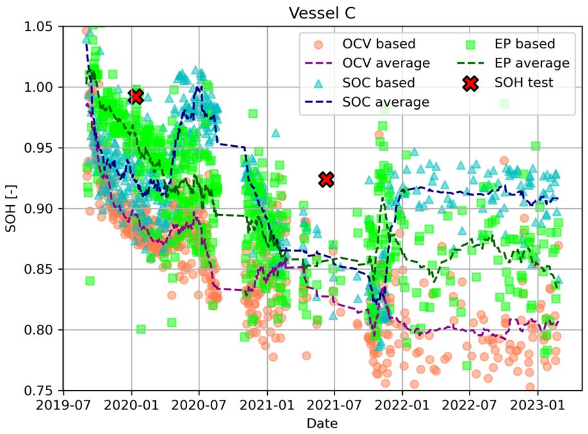

## Fitting to known OCV curve

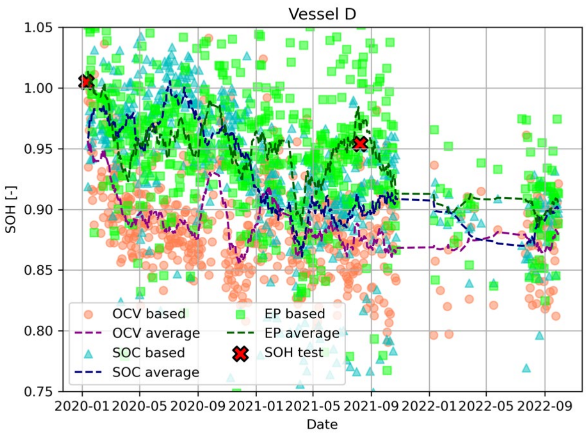


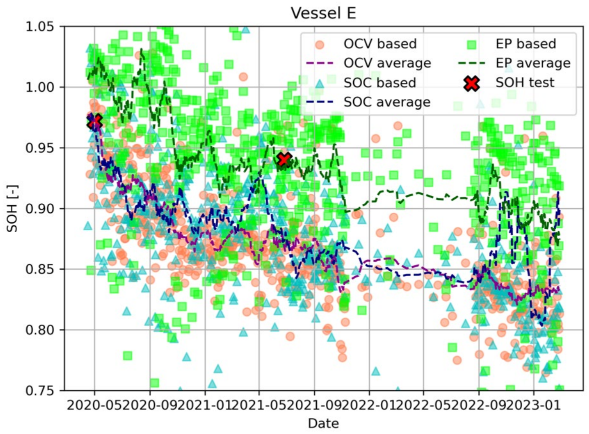
# Methods based on open circuit voltage (OCV)

- Results are found to have questionable accuracy and low precision
  - Voltage signal might not provide sufficient significant information
  - Large variability indicates overfitting
    - Might be improved by regularization



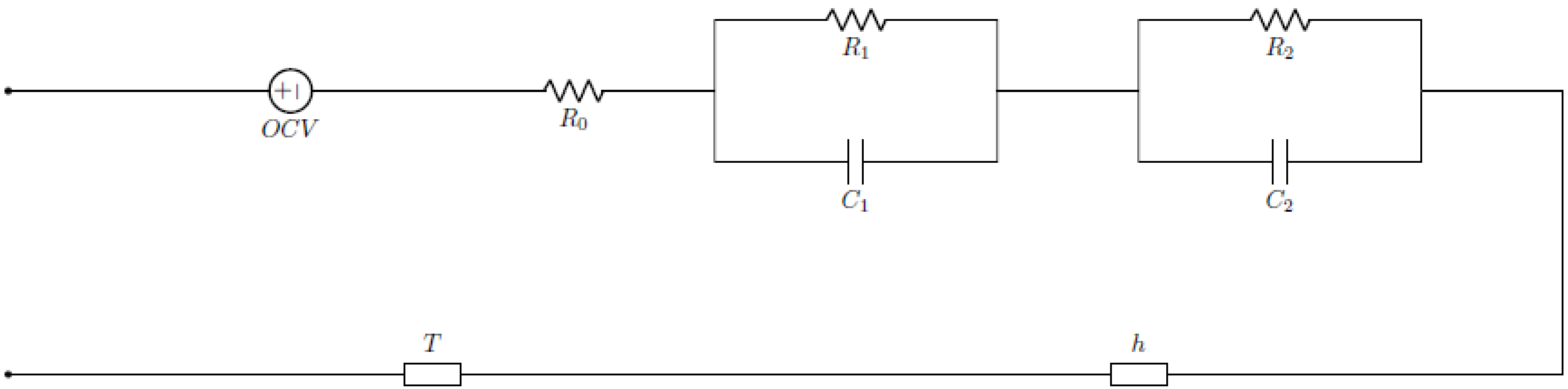



# Methods based on equivalent circuit models (ECM) and extensive characterisation tests

- The previous method is extended with a more complicated ECM model and extensive characteristics testing to account for variations in current and temperature
  - ECM with serial resistance, 2 RC elements and a thermal and a hysteresis model



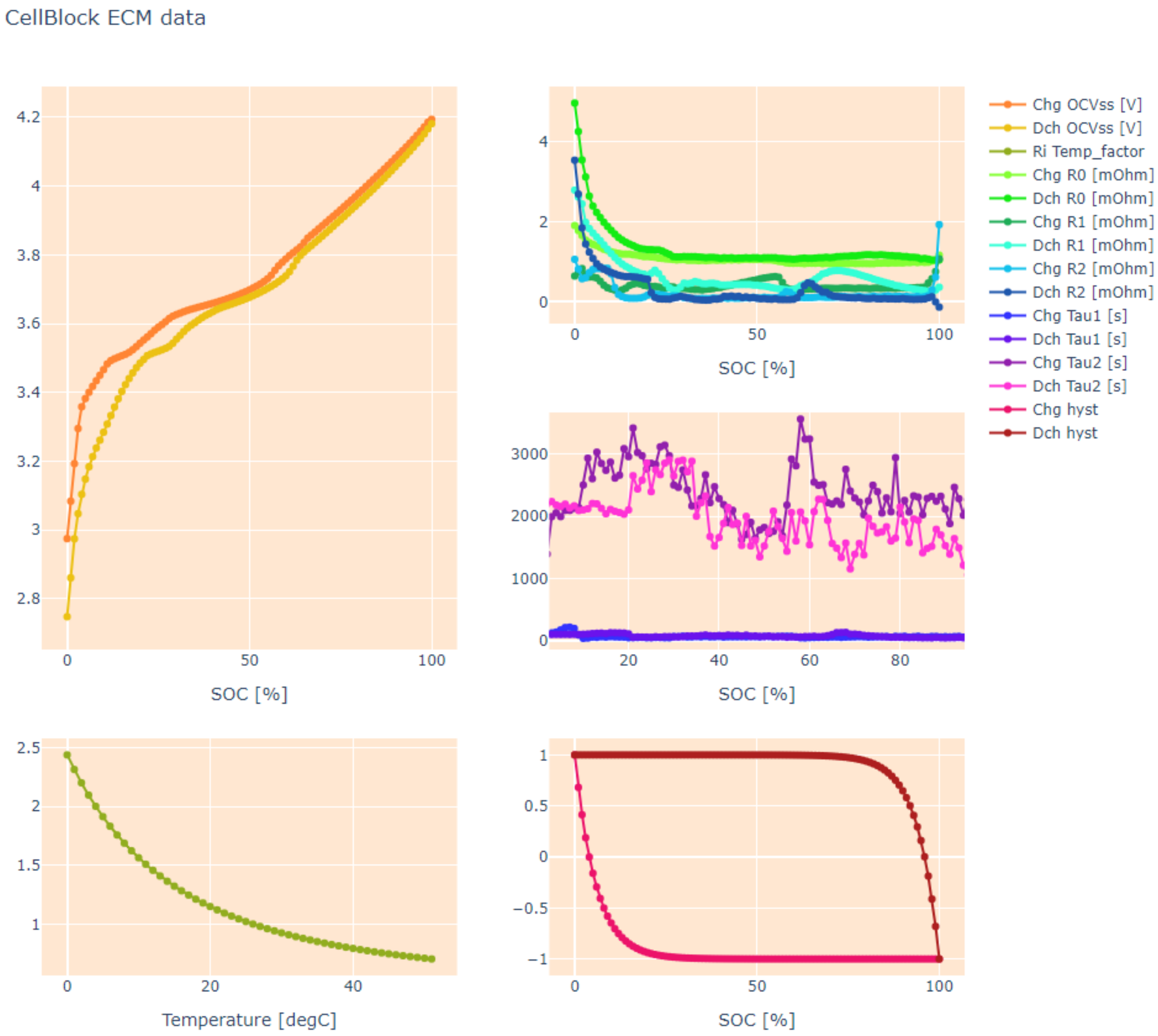

  - ECM defines a set of five states: $x = \begin{bmatrix} SoC \\ U_1 \\ U_2 \\ h \\ T \end{bmatrix}$. Cell voltage and overpotential given by $$V = OCV(x) + OP$$ $$OP = IR_0(x) + U_1 + U_2$$

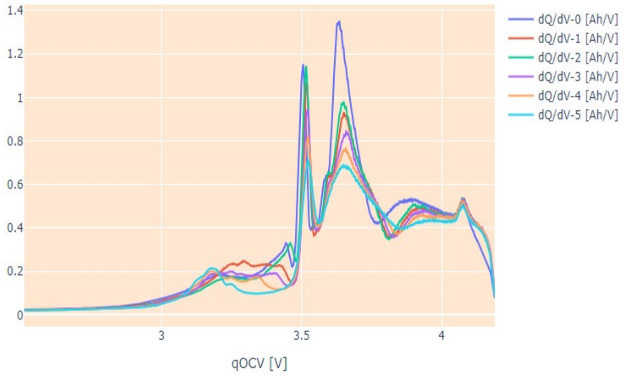
# Cell states and state change

- Each of the circuit elements depend on cell states and conditions
  - E.g. OCV and internal resistance depend on SoC, SoH, T and h
- The state change according to a set of differential equations: $\frac{\partial x}{\partial t} = \begin{bmatrix} \eta \frac{I}{SoH \times C_{nom}} \\ \frac{IR_1(x) - U_1}{\tau_1(x)} \\ \frac{IR_2(x) - U_2}{\tau_2(x)} \\ f_h(x, I) \\ \alpha R_0(x) I^2 - \beta (T - T_\alpha) \end{bmatrix}$
- Integrating between two SoC values gives: $SoH \times C_{nom} \times (SoC_2 - SoC_1) = \eta \int_{t_1}^{t_2} I \, dt$

# Method overview

- The method is based on estimating the states OP and h, which allows the lookup of SoC and calculating depth of discharge and comparing with actual capacity from Coulomb counting.
- Lookup tables established based on extensive characterization testing
  - Establish dependence on temperature, current, hysteresis, etc…



# Verification on operational field data

- Verification and validation based on
  - Calculate SoH from operational data for selected modules
  - Send modules to the lab and perform lab capacity check-up
  - Compare SoH calculated from operational data with SoH from laboratory check-up
  - Note: there may be some delay between operational calculation and lab; calendar aging
- Module SoH is assumed to be the lowest cell SoH within the module
- In total 6 validation scenarios reported in the paper
  - Scenario 1: hybrid ferry with 79.7% SoH from lab and 79.7% SoH from field measurements
  - Scenario 2: hybrid bulk carrier with 93.25% SoH from lab and 93.50% from field data
  - Scenario 3: same vessel as Sc.2; lab = 92.38% and field = 92.85%
  - Scenario 4: Shore station. SoH difference in the range of 1 – 2 %
  - Scenario 5: fully electric ferry. Lab = 83.8%; field = 85.2%. (1 year lag; defect cell)
  - Scenario 6: Shore station. Lab = 73.7%; field = 76.1% (1 year lag; DoD about 40%)

# Discussion

- Attempts with purely data-driven models for capacity estimation failed on actual operational data
  - Although they can perform well on laboratory data
- A simple linear model based on Coulomb counting is attractive; it does not need training data
  - Not accurate enough, probably due to reliance on SoC
  - Ensemble methods can improve results, but dependence on SoC remains
- A modified method relating capacity to OCV was developed, utilizing a simple ECM
  - Initial results highly variable, although average predictions are somewhat reasonable
- Supplementing this approach with comprehensive lookup tables from characterization tests to account for temperature, hysteresis and current effects yields reasonable results
  - Still requires “deep enough” cycles to have been experienced in the operational data
  - This method has already been used in actual verification of capacity for electric ships in operation, as announced in a recent press release

# Summary and conclusions

- Purely data-driven models for capacity and SoH estimation for operational conditions is challenging
- Carefully constructed physics-informed, data-driven models may improve this by utilizing fundamental physical knowledge
  - Final model is based on Coulomb counting, ECM, extensive characterization tests and snapshots of sensor data collected during normal operation
  - But requires some “relatively deep” charge and discharge cycles
- Further validation is recommended – particularly for batteries approaching their end of life
  - And for other battery chemistries
- Facilitates continuous verification of SoH without disrupting normal operations
  - Considerable benefit for operators of electric ships
  - Can relax strict requirements of test protocols for annual tests

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# Get in touch!

Questions and comments are welcome!

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