Parameter Estimation in Li-ion batteries in context of Hybrid Power Plants

Master's Thesis in collaboration with Siemens AG

Aeishwarya Baviskar

Technical University of Munich

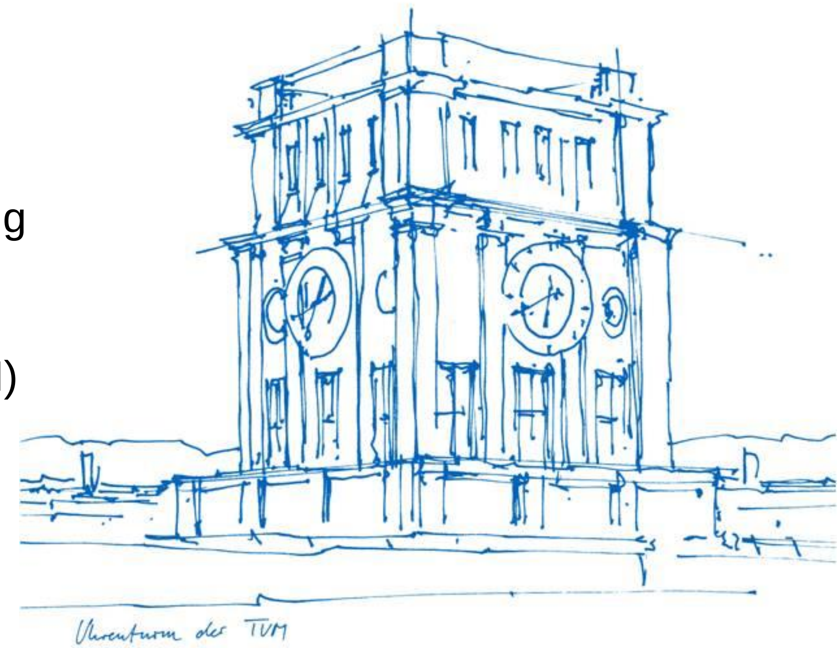
Department of Electrical and Computer Engineering

Chair of Energy Storage Technology

Supervisor: 1) Prof. Dr.-Ing. Andreas Jossen (TUM)

2) Dr.-Ing Andrei Szabo (Siemens AG)

3) Mr. Julius Schmitt (TUM)



30th October, 2019

Contents of the Presentation

Introduction to research goals

- Parameters in the BMS are calibrated at the manufacturing stage.
- Over a course of time due to battery degradation, the battery parameters may change
- Parameter deviations affect capacity estimation
- Challenge: To develop a parameter estimation algorithm to precisely estimate the battery capacity.
- Key issue: Absence of Open circuit voltage (OCV) Vs State of charge (SOC) curve.
- Only data from the BMS is available. (terminal voltage and current)

Approach towards the problem

- Model Selection
  - Literature Research about different effects and phenomena in battery
  - Choosing model that represents most significant effects
- Formulating Optimization problem concerning the model chosen
- Estimating OCV as a function of SOC
- Capacity Estimation and validation of the method

Battery Fundamentals

Battery Kinetics

Ohmic Part

Purely resistive: Linear Relationship between voltage and current

Non-Ohmic Part

Activation Polarization: Energy required to overcome activation barrier for chemical reaction to take place reaction to take place

Diffusion Polarization:

- Spatial variations in reactant concentration that can take place in the electrode or the bulk of the electrolyte.
- Faster consumption of reactance compared to the rate at which they can diffuse

- Open-Circuit voltage(OCV): determined by the electrochemical composition of the battery
- Hysteresis in the OCV: The difference in the charging and discharging potentials of the battery at the same SOC.
- $U_{OC}\ Vs\ SOC \rightarrow$ proven to be not a one-to-one mapping but a family of curves and cycling histories
- It does not correspond to the hysteresis due to overvoltage but this is the hysteresis present in the OCV curve.

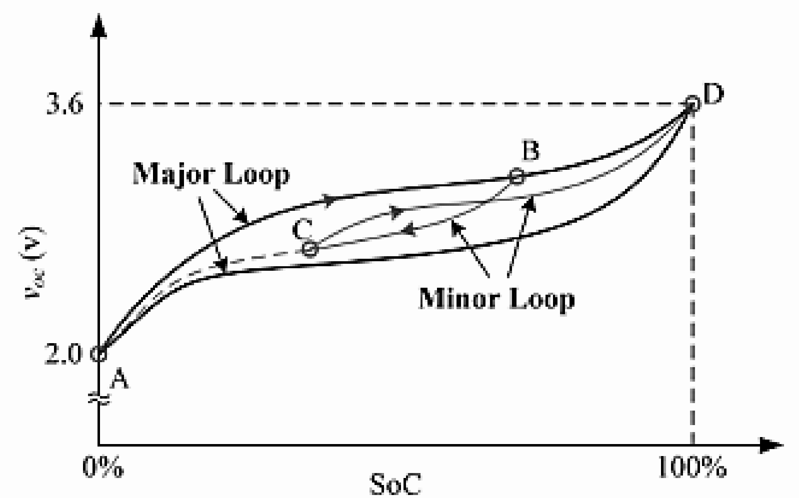


Fig1. Hysteresis in the OCV curve [1]

Electrical Circuit Model with constant maximum Hysteresis

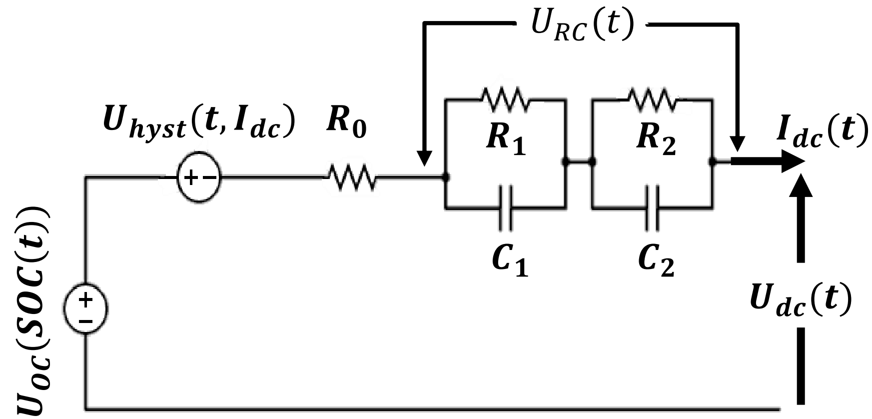
- Measured Signals: I_{dc}, U_{dc}
- State of Charge:

$$SOC(t) = \frac{1}{Q}\int_{t_0}^{t_n} I_{dc}(t)\ dt\ - SOC(t_0)$$

- Battery Equation:

$$\hat{U}_{dc}(t) = \hat{U}_{OC}(SOC(t)) - \hat{R}_0 I_{dc}(t) - \hat{U}_{RC}(t) - \hat{U}_{hyst}(t, I_{dc})$$

- Linear parameters:
  - $\hat{\theta}_{lin}^{T} = [\hat{R}_0 \quad \hat{U}_{OC}^{T}(SOC_b)]$
  - SOC_b are the base points for a piecewise-linear $OCV\ Vs.SOC$ curve.
- Nonlinear Parameters:
  - $\hat{\theta}_{nonLin}^{T} = [\hat{R}_1 \quad \hat{C}_1 \quad \hat{R}_2 \quad \hat{C}_2 \quad \hat{H}_{max} \quad \tau_h]$



- Maximum Hysteresis at every SOC is constant and given by H_{max}
- The hysteresis function provides a exponential transition between those curves.
- $SOC(t_0)$ is chosen from the BMS depending on the available data
- Temperature dependency of parameters is not modeled.

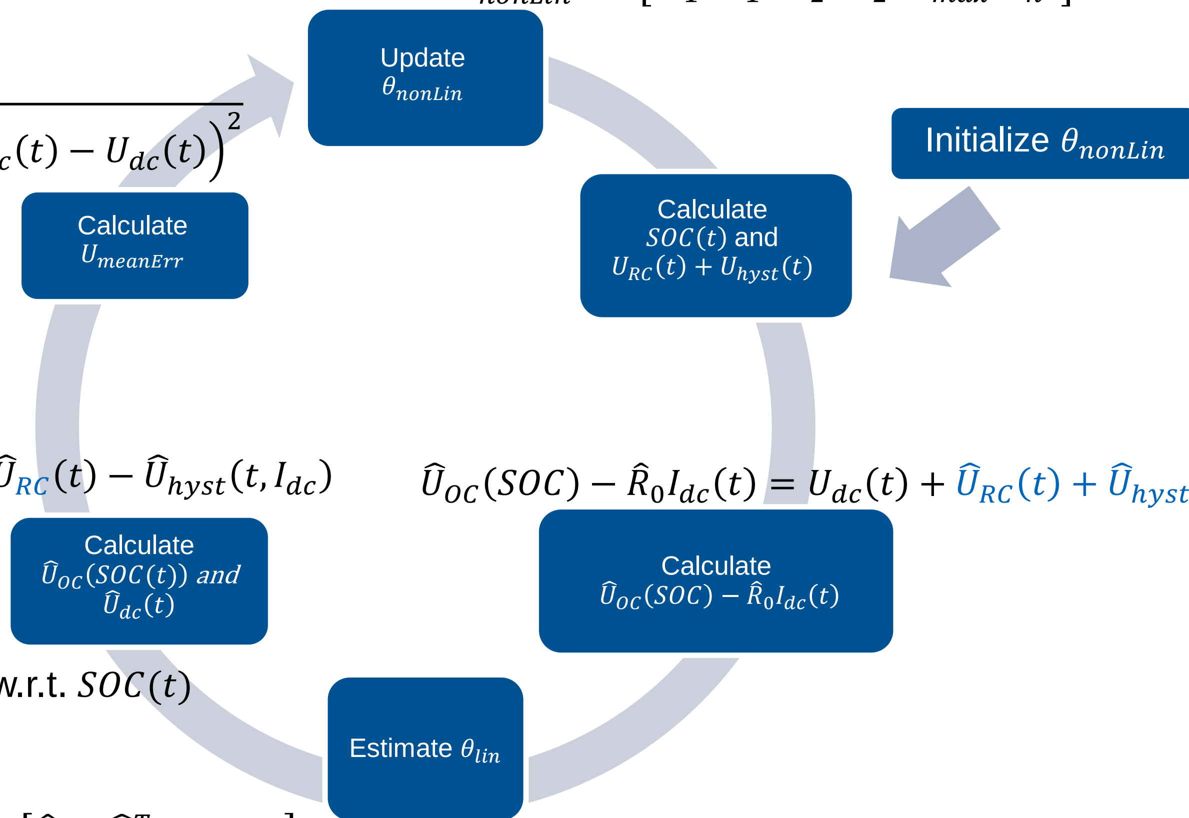
$$U_{hyst}(t) = U_{hyst}(t_{-1})e^{-\frac{dt|I_{dc}(t_{-1})|}{I_{max}\tau_H}} + H_{max}\ sign(I_{dc}(t_{-1}))\left(1 - e^{-\frac{dt|I_{dc}(t_{-1})|}{I_{max}\tau_H}}\right)$$

Optimization Problem

RMS error:

$$U_{meanErr} = \min_{[\hat{\theta}^T_{nonLin}\ \hat{\theta}^T_{lin}]} \sqrt{\sum \left(\hat{U}_{dc}(t) - U_{dc}(t)\right)^2}$$

$$\hat{\theta}^T_{nonLin} = \left[\ \hat{R}_1 \quad \hat{C}_1 \quad \hat{R}_2 \quad \hat{C}_2 \quad \hat{H}_{max} \quad \tau_h\ \right]$$



$$\hat{U}_{dc}(t) = \hat{U}_{OC}(SOC(t)) - \hat{R}_0 I_{dc}(t) - \hat{U}_{RC}(t) - \hat{U}_{hyst}(t, I_{dc})$$

$$\hat{U}_{OC}(SOC) - \hat{R}_0 I_{dc}(t) = U_{dc}(t) + \hat{U}_{RC}(t) + \hat{U}_{hyst}(t, I_{dc})$$

$\hat{U}_{OC}(SOC(t))$:
Linear Interpolation of $\hat{U}^T_{OC}(SOC_b)$ w.r.t. $SOC(t)$

$$\hat{\theta}^T_{lin} = [\hat{R}_0 \quad \hat{U}^T_{OC}(SOC_b)]$$

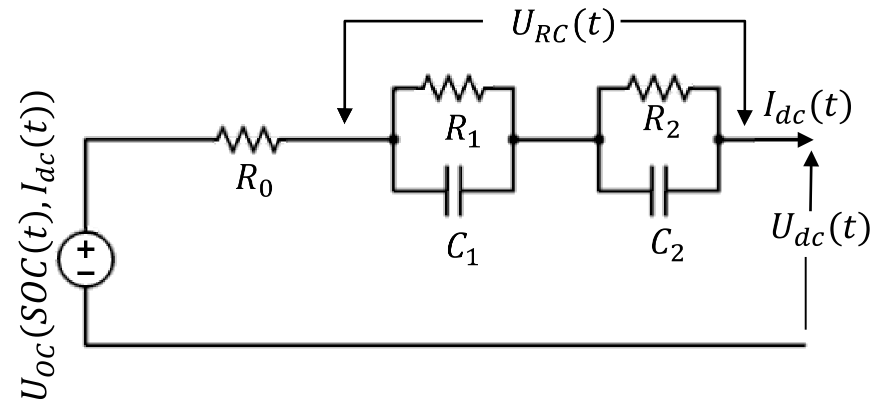
Subject to constraint,

$$\hat{U}^T_{OC}(SOC_{bj}) > \hat{U}^T_{OC}(SOC_{bi}) \ \ \forall \ \ SOC_{bj} > SOC_{bi}$$

Electrical Circuit Model with variable Hysteresis

- Measured Signals: I_{dc}, U_{dc}
- State of Charge: Coulomb Counting
- Battery Equation:

$$\widehat{U}_{dc}(t) = \widehat{U}_{OC}(SOC(t)) - \hat{R}_0 I_{dc}(t) - \widehat{U}_{RC}(t)$$



- Linear parameters:
  - $\hat{\theta}_{lin}^T = \left[\hat{R}_0 \quad \widehat{U}_{OC_{dischrg}}^T(SOC_b) \quad \widehat{U}_{OC_{chrg}}^T(SOC_b)\right]$
  - SOC_b are the base points for a piecewise-linear $OCV\ Vs.SOC$ curve.

- Nonlinear Parameters:
  - $\hat{\theta}_{nonLin}^T = \left[\hat{R}_1 \quad \hat{C}_1 \quad \hat{R}_2 \quad \hat{C}_2\right]$

- Weighting on the OCV function
  - $\widehat{U}_{OC}\big(SOC(t)\big) = w_d(t)\widehat{U}_{OC_d}\big(SOC(t)\big) + w_c(t)\widehat{U}_{OC_c}\big(SOC(t)\big)$
  - $w_c(t) + w_d(t) = 1$

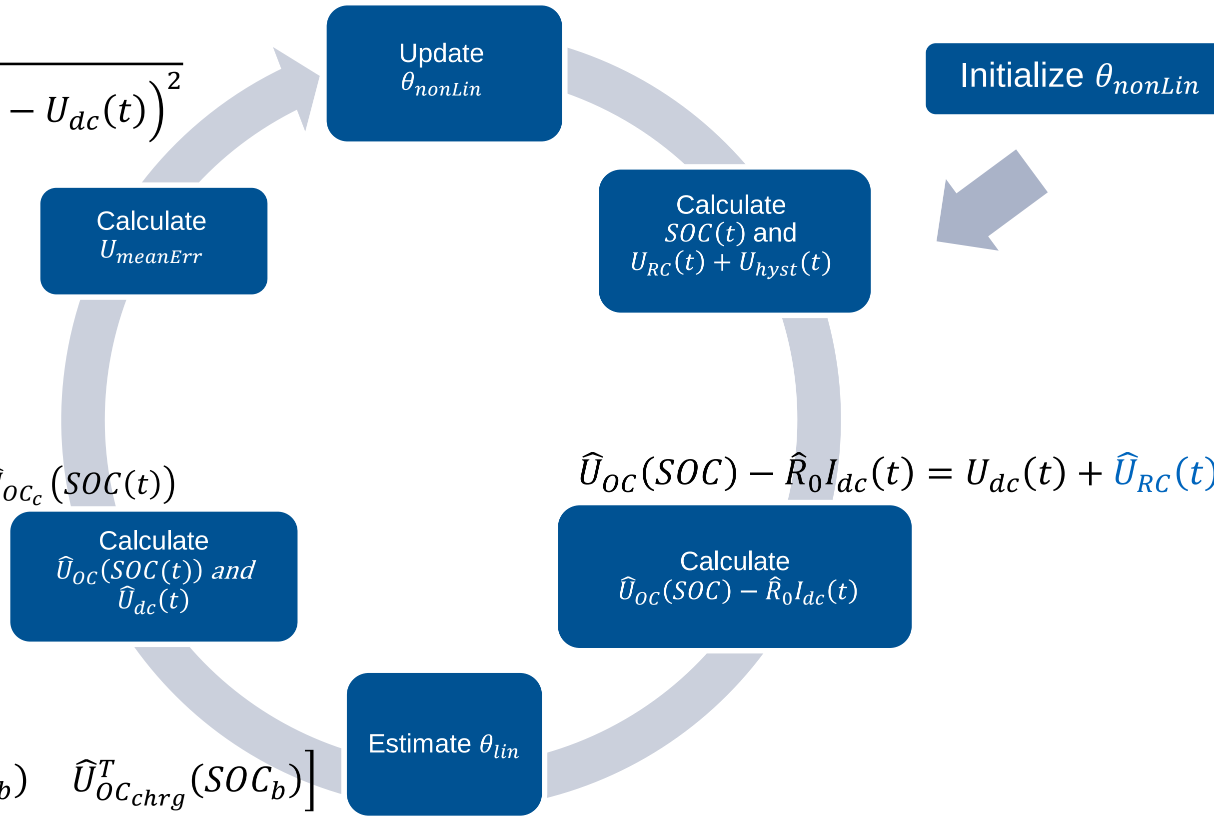
- Maximum Hysteresis is not constant w.r.t. SOC due to two different OCV Vs SOC curves for charging and discharging
- Transition between the hysteresis curves is given by a linear weighting function on the current.

Optimization Problem

$$\hat{\theta}^T_{nonLin} = \begin{bmatrix} \hat{R}_1 & \hat{C}_1 & \hat{R}_2 & \hat{C}_2 \end{bmatrix}$$

RMS error:

$$U_{meanErr} = \min_{[\hat{\theta}^T_{nonLin} \ \hat{\theta}^T_{lin}]} \sqrt{\sum \left(\hat{U}_{dc}(t) - U_{dc}(t)\right)^2}$$



$$\hat{U}_{dc}(t) = \hat{U}_{OC}(SOC(t)) - \hat{R}_0 I_{dc}(t) - \hat{U}_{RC}(t)$$

$$\hat{U}_{OC}\left(SOC(t)\right) = w_d(t)\hat{U}_{OC_d}\left(SOC(t)\right) + w_c(t)\hat{U}_{OC_c}\left(SOC(t)\right)$$

$$\hat{U}_{OC}(SOC) - \hat{R}_0 I_{dc}(t) = U_{dc}(t) + \hat{U}_{RC}(t)$$

$$\hat{\theta}^T_{lin} = \left[\hat{R}_0 \quad \hat{U}^T_{OC_{dischrg}}(SOC_b) \quad \hat{U}^T_{OC_{chrg}}(SOC_b)\right]$$

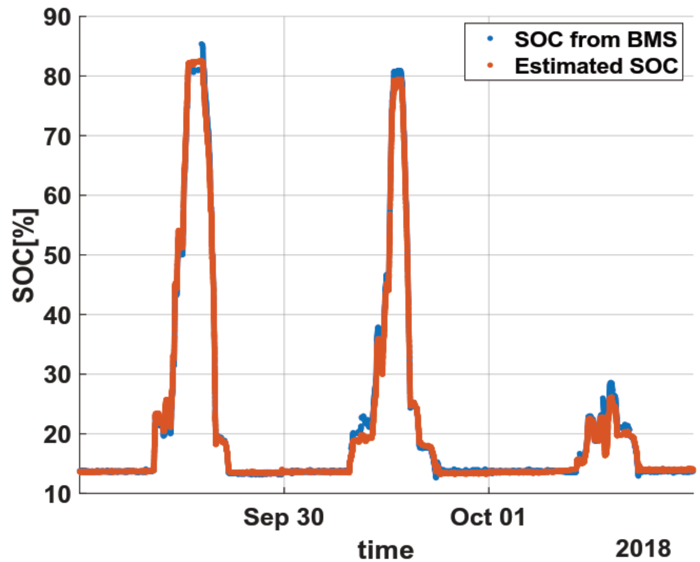
Subject to constraint,

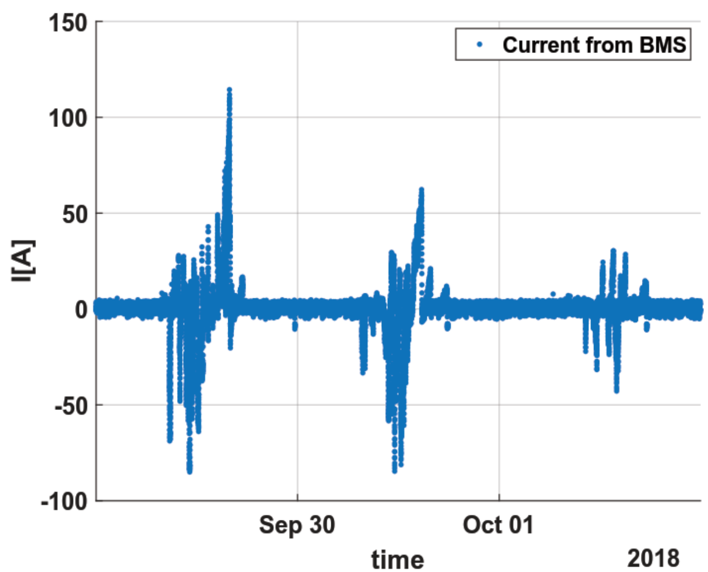
$$\hat{U}^T_{OC}\left(SOC_{bj}\right) > \hat{U}^T_{OC}(SOC_{bi}) \ \forall \ SOC_{bj} > SOC_{bi}$$

for both charging and discharging curves.

$$\hat{U}^T_{OC_{chrg}}\left(SOC_{bj}\right) > \hat{U}^T_{OC_{dischrg}}(SOC_{bi}) \ \forall \ SOC_{bj} = SOC_{bi}$$

Battery-1: Model selection





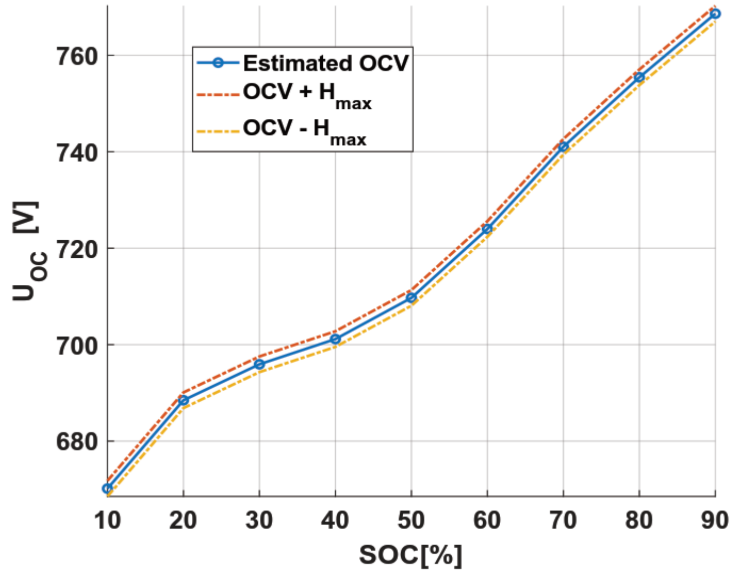
- $SOC(t_0)$ is aggregated over the initial hours of the day when current is almost 0 A.
- Parameters from model-1

R_0	0.143 Ω
R_1, R_2	0.0818 Ω, 1.08×10^{-4}Ω
τ_1, τ_2	56 s, 97 s
H_{max}	1.62 V
τ_h	67.97 s
U_{err}	**0.606 V**

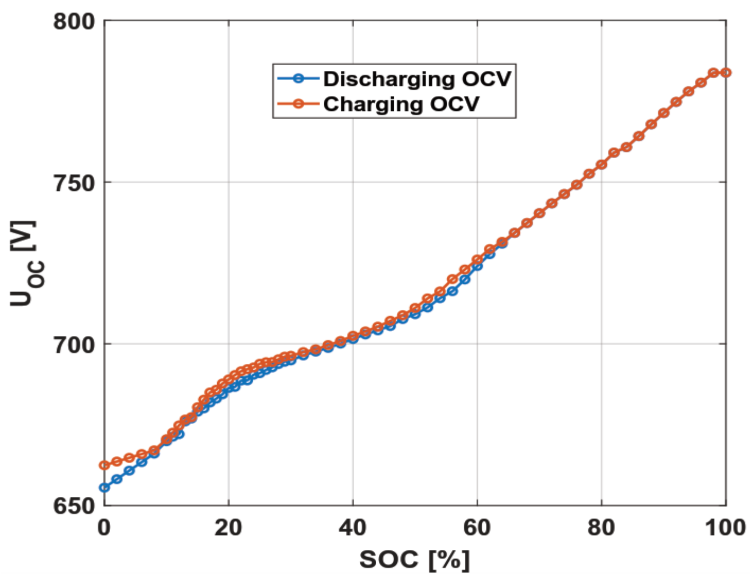
- R_2 small enough to be negligible for model-1
- Parameters from model-2

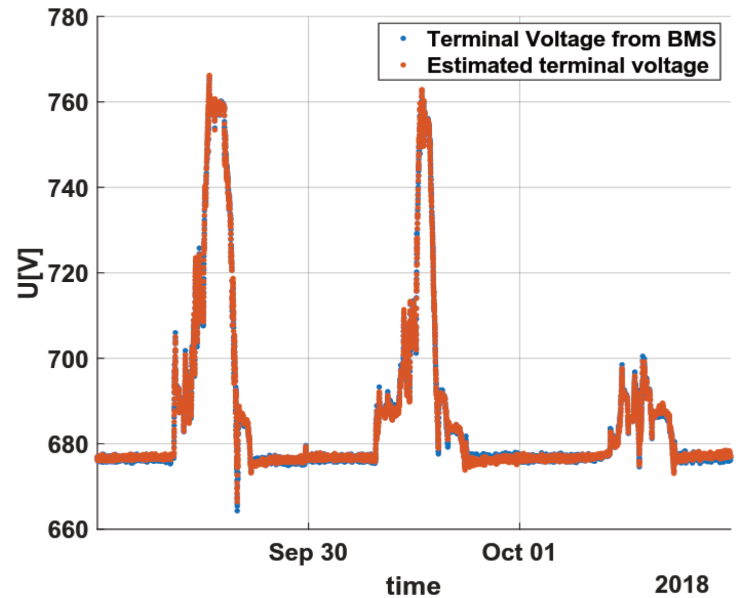
R_0	0.136 Ω
R_1, R_2	0.0619 Ω, 0.0662 Ω
τ_1, τ_2	619 s, 33 s
U_{err}	**0.463 V**

Battery-1: OCV Vs. SOC Curve



- Model-2 estimates an SOC dependent hysteresis, as shown in adjacent figure.
- The terminal voltage estimate closely follows measured terminal voltage.
- Since model-2 provides a smaller rms error, it is chosen to estimate an OCV curve.
- The OCV curve is estimated over 10 initial days of the available data, assuming constant capacity.





Battery-2: Model selection

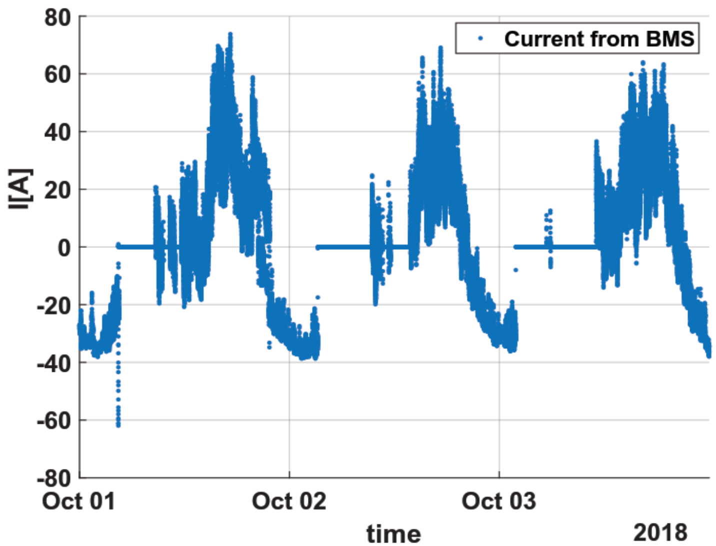
- $SOC(t_0)$ is aggregated over the hours of each day when current is 0 A.
- Parameters from model-1

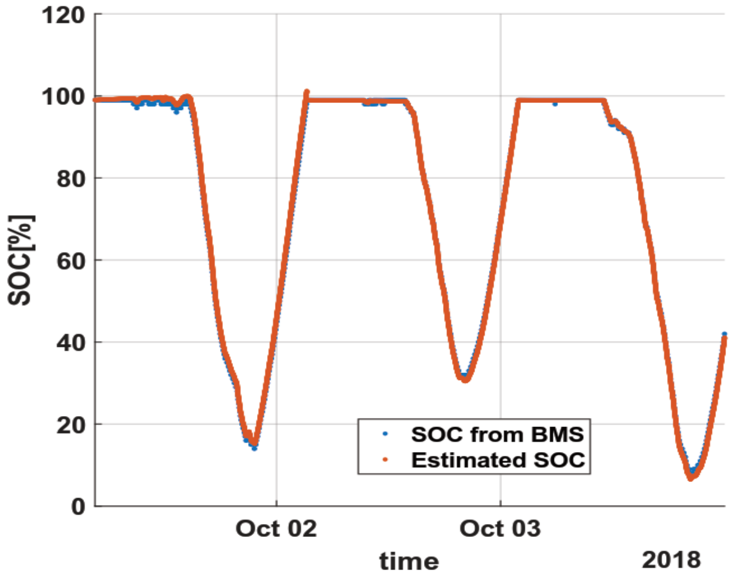
R_0	0.0637 Ω
R_1, R_2	0.135 Ω, 5.28×10^{-4}Ω
τ_1, τ_2	151 s, ≈ 0 s
H_{max}	0.521 V
τ_h	450 s
U_{err}	**0.796 V**

- R_2 is small enough to be negligible
- Parameters from model-2

R_0	0.0244 Ω
R_1, R_2	0.00235 Ω, 0.12 Ω
τ_1, τ_2	0.2 s, 30 s
U_{err}	**0.592 V**

- τ_1 is less than 1 sec which is the minimum simulation time-step.

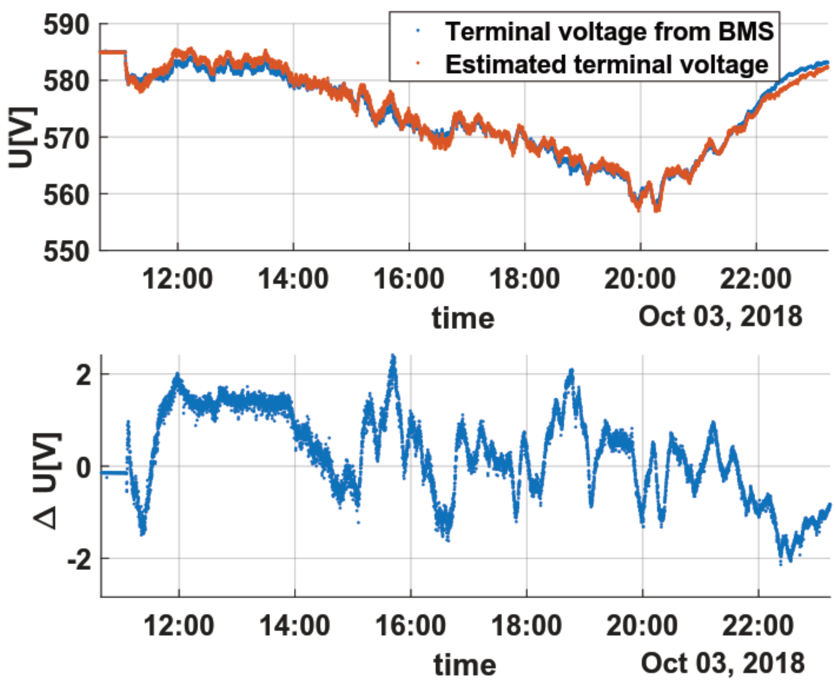




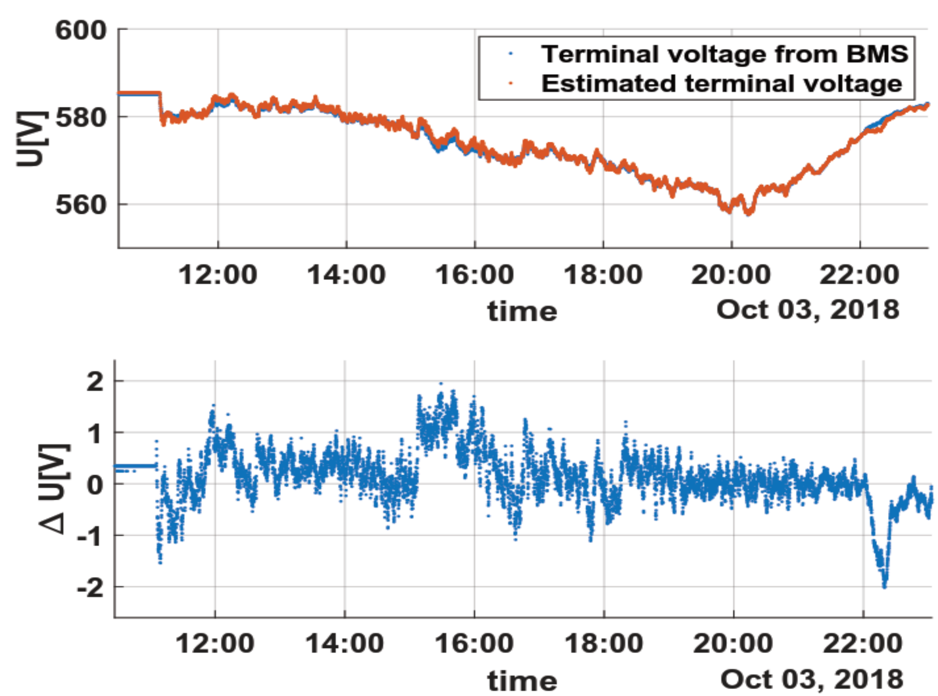
Battery-2: Model selection

- Taking a closer look at the terminal voltage estimation from model-1 and 2
- Model-2 simulates the battery kinetics better than model-1 (from the figures below)
- The peak error is reduced, as well as the systematic error from model-1 is reduced.
- Hence, model-2 is again chosen to estimate an OCV curve for battery-2

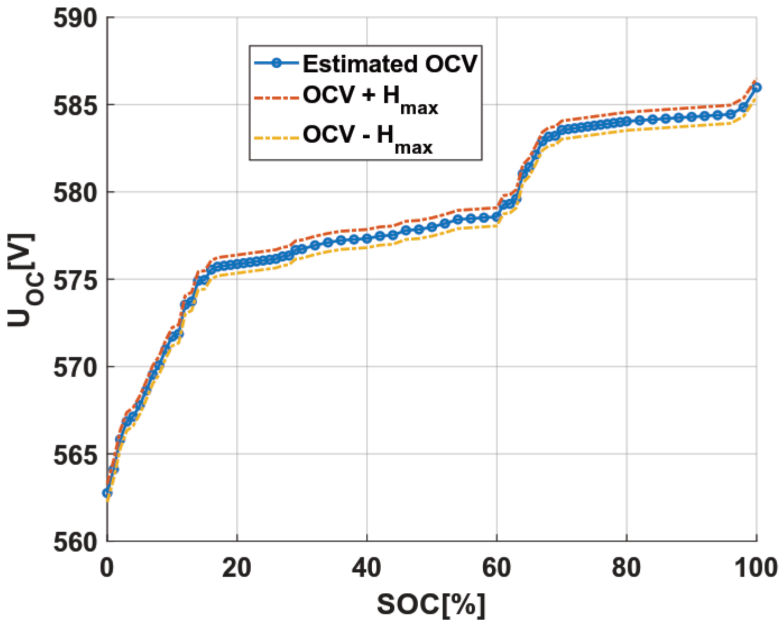
Model-1

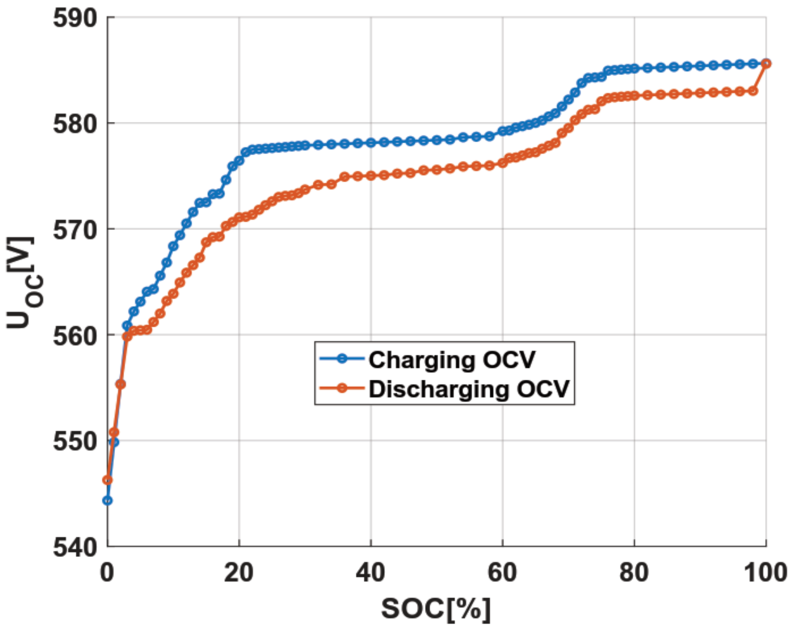


Model-2



Battery 2: OCV Vs. SOC Curve





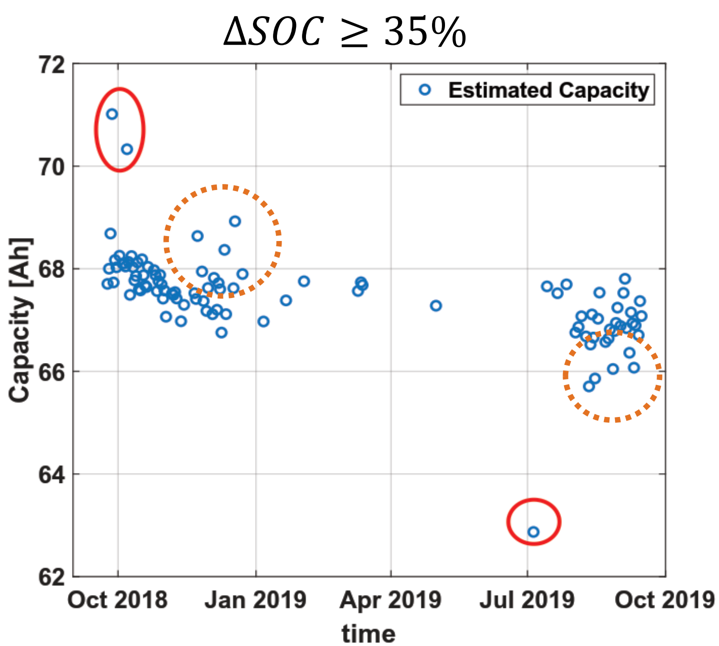
- OCV curve from model-2 sufficiently estimates a variable hysteresis.
- The OCV curves obtained for battery-2 shows characteristics similar to an OCV curve for an LFP chemistry.
- This conclusion is made by comparing the OCV curves from references [2] to the obtained OCV curve.
- Similarly on comparison OCV curve from battery-1 points towards an NMC battery chemistry. [3]

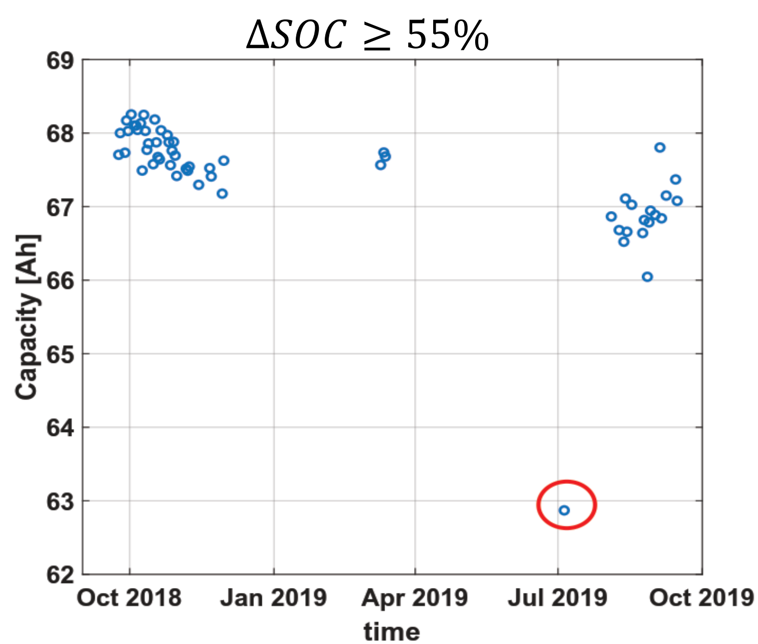
Battery-1: Capacity Estimation

- The OCV curve obtained in the previous step is used for capacity estimation.
- Estimation is done on day-to-day basis
- Optimization algorithm is the same as described for model-2, with an addition of the capacity in nonlinear parameters.

$$\hat{\theta}^{T}_{nonLin} = \begin{bmatrix} \hat{R}_1 & \hat{C}_1 & \hat{R}_2 & \hat{C}_2 & Q \end{bmatrix}$$

- With $\Delta SOC \geq 35\%$, $Q \approx 65.8\% - 69\%$ (neglecting outliers), which gives a maximum deviation of $\approx 2\%$
- With $\Delta SOC \geq 55\%$, $Q \approx 66\% - 68.4\%$ (neglecting outlier), which gives a maximum deviation of $\approx 1.5\ \%$





Battery-1: Capacity Estimation

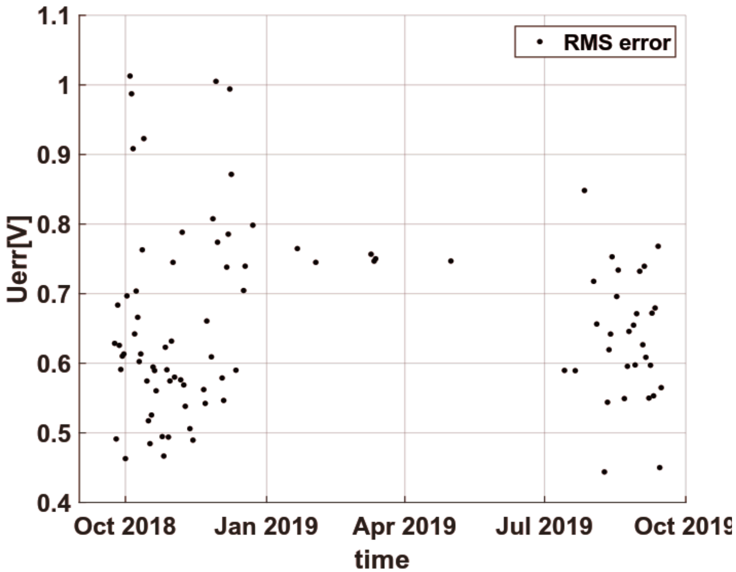


Fig.1 RMS error during capacity estimation

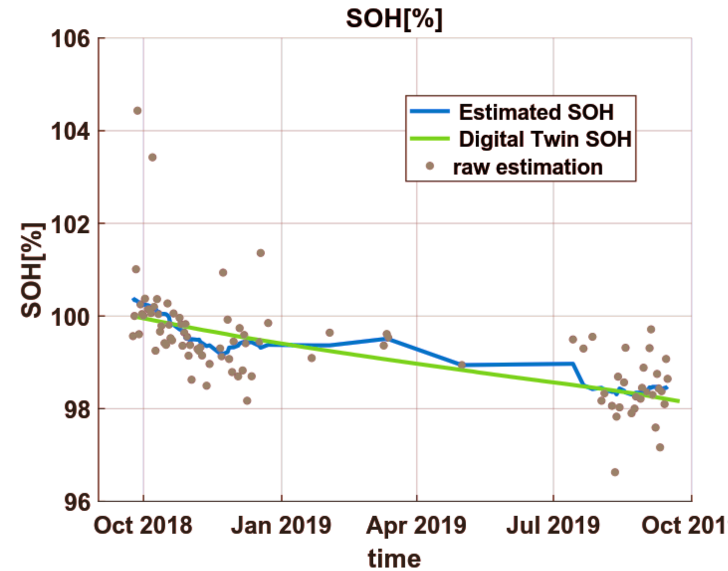


Fig.2 SOH comparison with digital twin

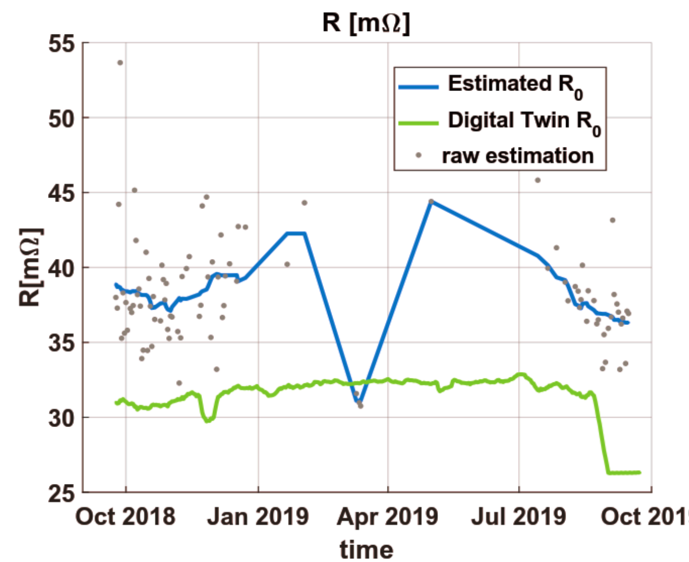


Fig.3 Internal resistance comparison with digital-twin

- The RMS error obtained during capacity estimation is less than 1V for all days except a few. (Fig.1)
- Estimated SOH in Fig.2 is a moving average of the raw data obtained.
- SOH estimate for this battery is approximately equivalent to the result from the digital-twin.
- The internal resistance estimate on three occasions in March deviates from the trend due to different operating conditions. (Fig.3)

Battery-2: Capacity Estimation and Validation

- With the exception of some outliers the estimated capacity is within bounds $\approx 200Ah - 220Ah$.
- Nominal capacity being $210\ Ah$, the estimates are within $\approx 4.7\%$ (Fig. 1)
- Possible cause is due to the flat or negligible slope zones in $OCV\ Vs.SOC$ curve. (Fig.2 Region 1 and 2).
- The capacity estimation is performed only over 40 days, hence, no degradation is expected.

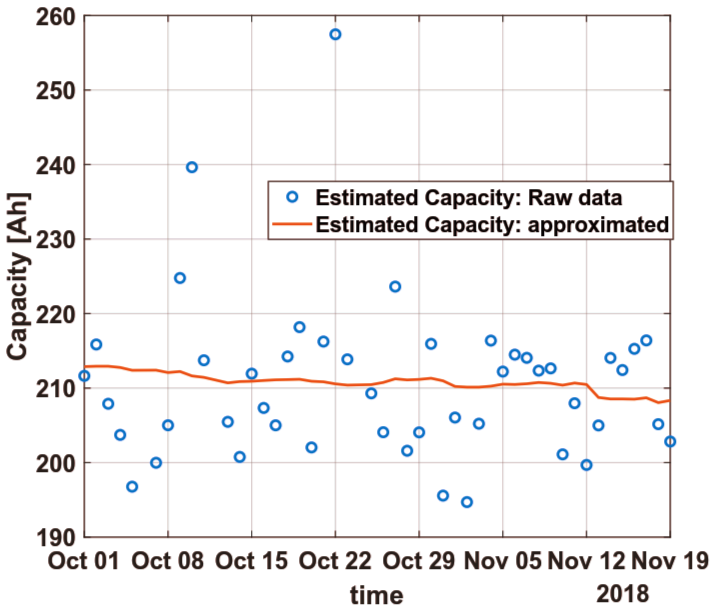


Fig.1 Capacity estimation for Battery-2

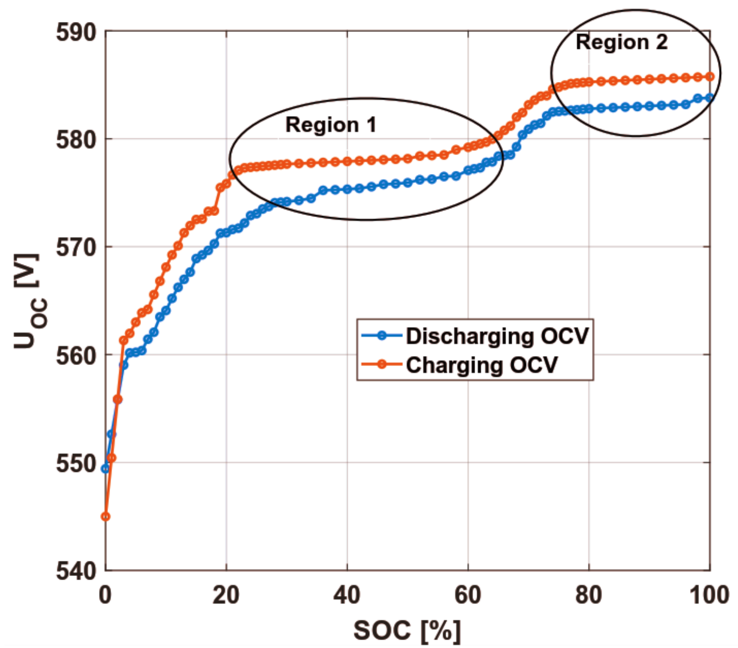


Fig.2 OCV Vs. SOC curve for Battery-2

Battery-2: Capacity Estimation and Validation

- RMS error on a day-to-day basis for capacity estimation is less than 1V. (Fig.1)
- The internal resistance estimate shows an increase of about 0.01 Ω over the period of 40 days, which is not likely over this time.

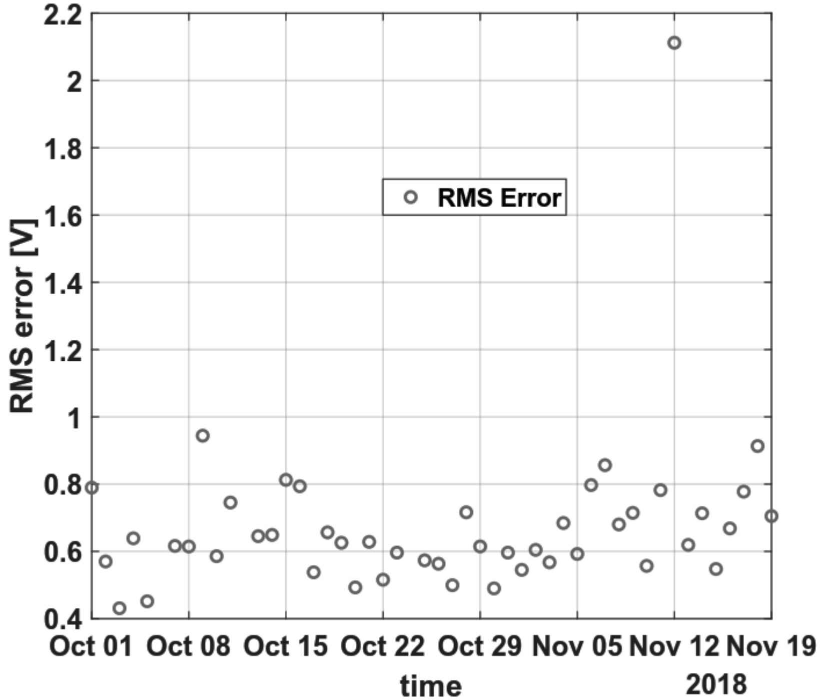


Fig.1 RMS error for capacity estimation

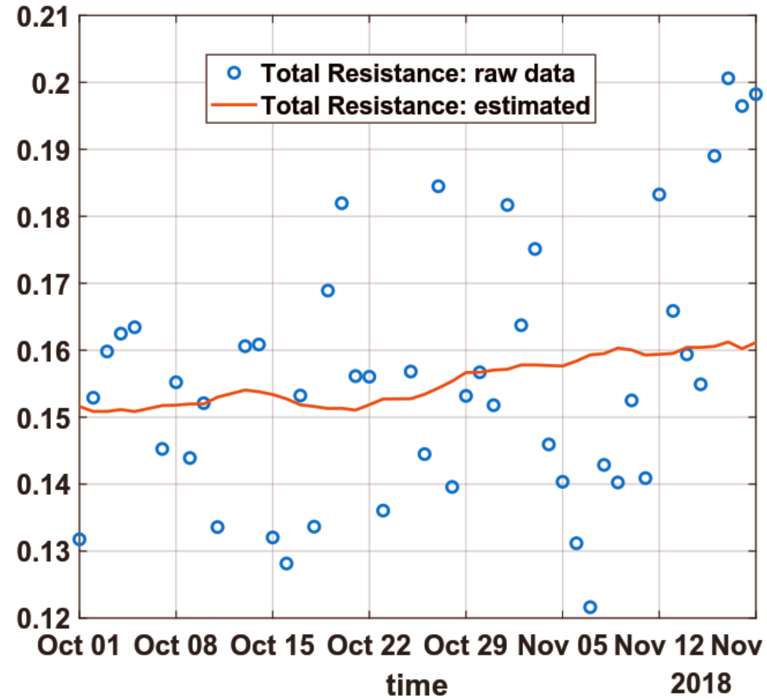


Fig.2 Internal resistance estimation over 40 days

Conclusion

- An equivalent circuit model with variable maximum hysteresis dependent on SOC provided a superior performance for both battery datasets.
- The algorithm proposed for $OCV\ Vs.SOC$ curve estimation is able to determine the OCV curve irrespective of the battery chemistry.
- It is capable of preserving the characteristic OCV curves for different batteries chemistries.
- The digital-twin is based on battery degradation characteristics in response to calendric and cyclic aging.
- Capacity estimates for battery-1 portrays $\approx 1.5\%$ deviations with $\Delta SOC \geq 55\%$
- The SOH estimation for battery-1 closely matches the results from the digital-twin.
- Battery-2 owing to the flat regions in the OCV curve has $\approx 4.7\ \%$ deviation from the nominal capacity in a period of 40 days.

Thank you for your attention.
Questions ?