COLLEGE OF ENGINEERING & COMPUTER SCIENCE
DEARBORN | UNIVERSITY OF MICHIGAN-DEARBORN

AENG 576 – Modeling and Control of Battery Systems

Final Project Presentation

STATE OF CHARGE ESTIMATION USING KALMAN FILTER

Fall 2023

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Presentation Outline

- Project motivation and goal
- Background of NMC Battery
- Battery Plant Model
    - Electrical Equivalent circuit model of NMC Battery(OCV-R-2RC)
- Overview of Simulink Model
- Observer Design
    - Kalman Filter Algorithm
        - Extended Kalman Filter Model (OCV-R-RC)
        - Linear Kalman Filter Model (OCV-R-RC)
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- Dual Extended Kalman Filter – Parameter Estimation
- Results and Observations

Project Motivation and Goal

MOTIVATION

- Accurate State of Charge (SoC) estimation is critical for battery management systems, particularly in electric vehicles, to optimize battery performance, extend battery life, and ensure safe operation.
- Kalman filters have emerged as a reliable and efficient method for SoC estimation, especially for complex battery chemistries, and have gained increasing attention in the literature.

GOALS

- Estimate the current demand of a Tesla Model X vehicle, based on two driving cycles (UDDS and US06), using AVL Cruise software and the Quasistatic battery model.
- Estimate the battery's SoC level using various Kalman filters and input parameters, assuming full battery charge at the start.
- Determine the accuracy of SoC estimation by comparing the results with experimental values, which can help in the development of efficient battery management systems for electric vehicles.
- Evaluate the performance of various Kalman filter types for SoC estimation, offering insights for future research on battery chemistries and driving cycles.

Background of NMC Battery

- NMC (Lithium Nickel Manganese Cobalt Oxide) batteries are commonly used in electric vehicles due to their high energy density, power capability, and long cycle life.
- NMC Battery uses combination of nickel, manganese, and cobalt as cathode materials, which provide several advantages over other battery chemistries.
- The optimal performance and lifespan of an NMC battery, accurate estimation of its State of Charge (SoC) is crucial.
- Various methods can be used to estimate the SoC of an NMC battery, including Coulomb counting, model-based estimation, and Kalman filters.
- The development of accurate SoC estimation techniques for NMC batteries is of great importance in the field of battery management systems.

Background of NMC Battery

First-Order Model Parameters	5°	15°	25°	45°
C_{nom} (Ah)	17.17	19.24	20	21.6
R_i (Ω)	0.007	0.0047	0.003	0.0019
R_{df} (Ω)	0.0042	0.0018	0.00065	0.00054
τ_{df} (s)	21	19.3	16.5	15.2

The extracted parameters of the battery model of the charge at different temperatures.

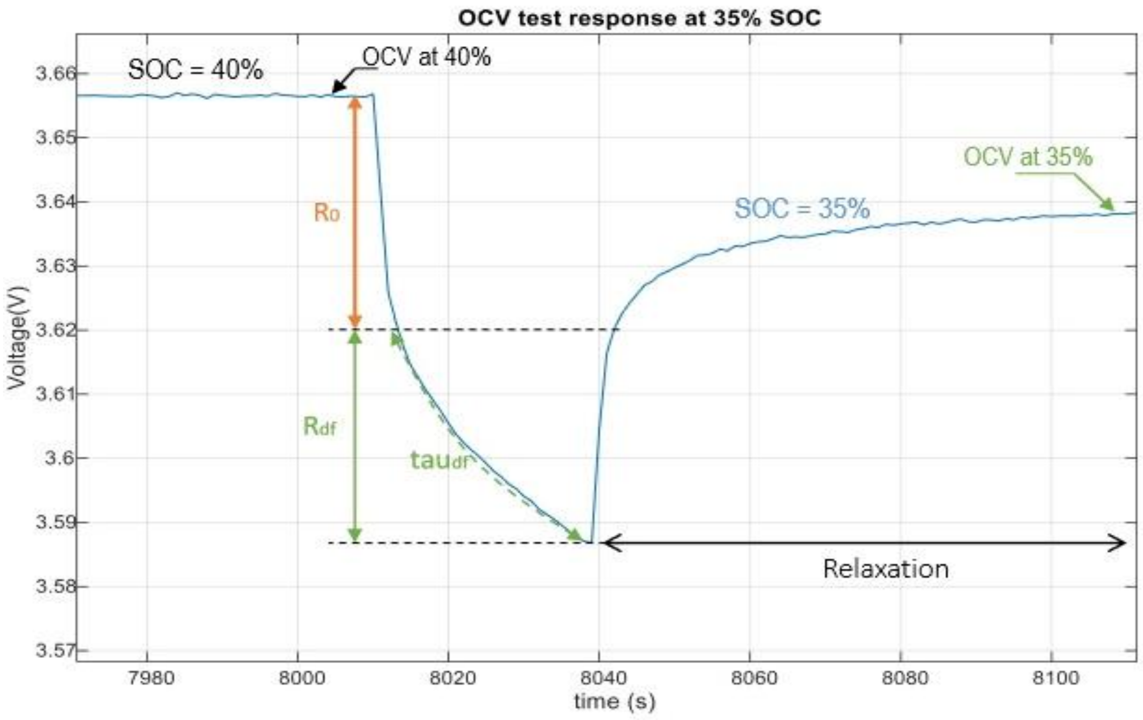
- The Thevenin first-order model has parameters Ri, Rd f, and τdf.
- These parameters are approximated to constant values as their observed variation is not extremely considerable.
- Simplifying the model in this way makes it easier to use online and for eventual implementation.
- Charge parameters were extracted at different temperatures and are available in a table (which was not included in the question).

Capacitance calculation:-

$$\tau_{df} = 4 * R_{df} C$$

$$C = \frac{\tau_{df}}{4 * R_{df}}$$

C = 6346.15 F

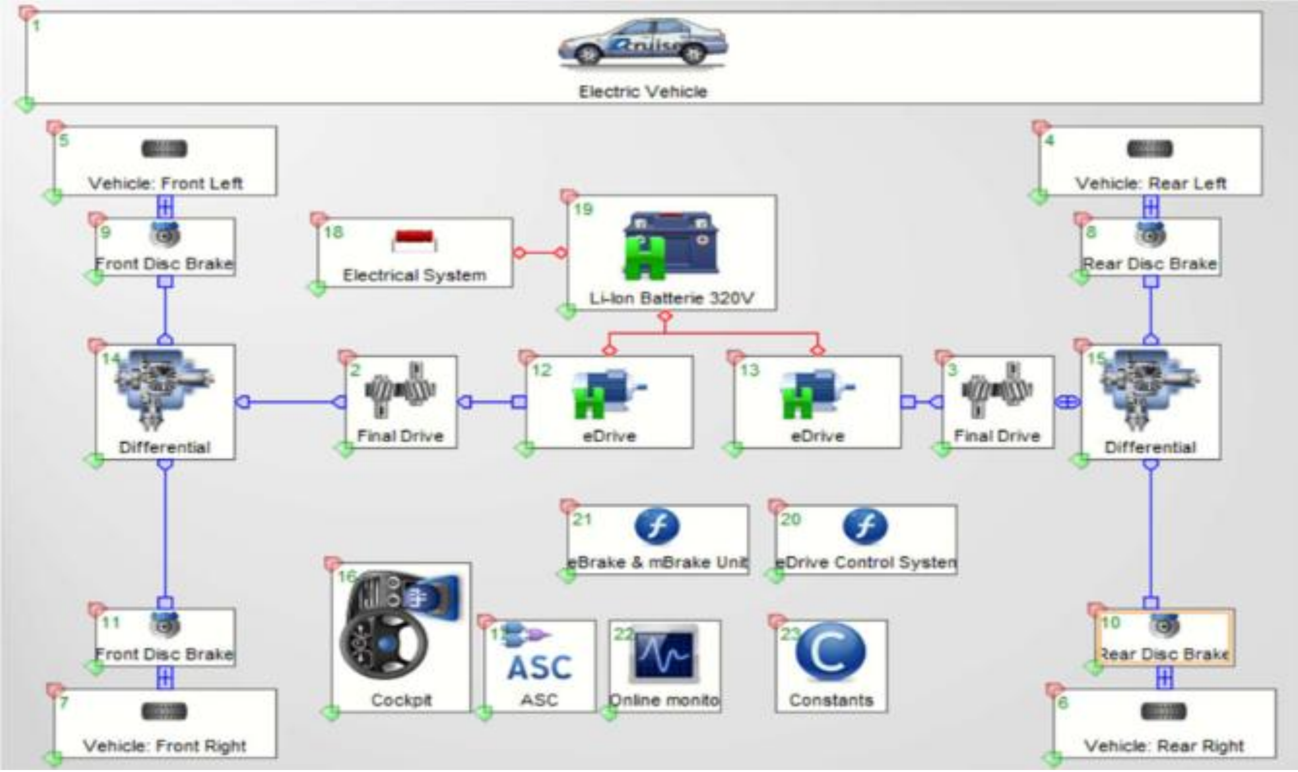


In Battery plant model we are not using Thermal Model ; keeping the temperature as 25℃ constant.

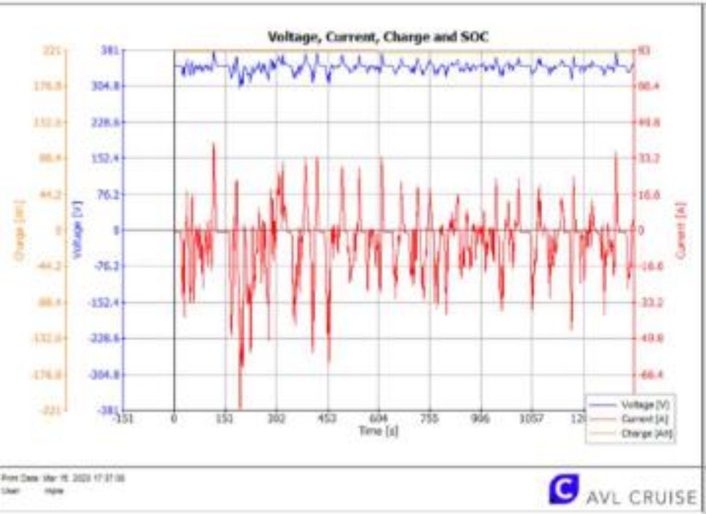
AVL Cruise software

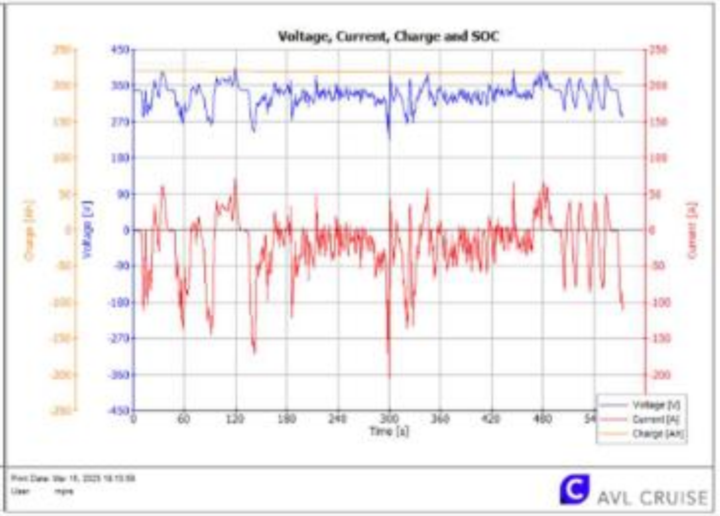
The current demand was calculated from AVL Cruise software by importing specifications such as

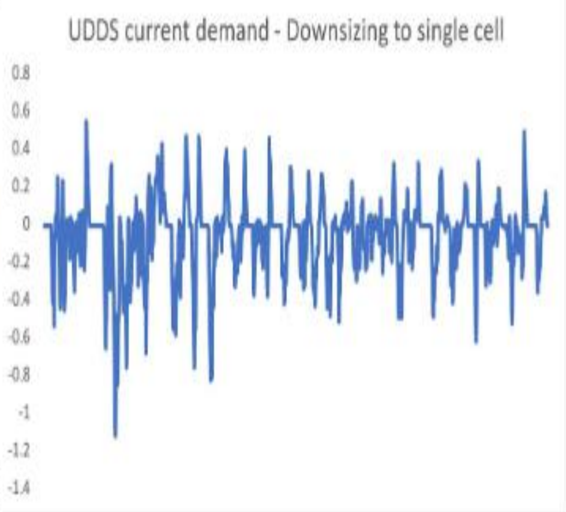
- Vehicle mass and road load based data
- Front and rear motor torque characteristics
- battery (1 module specs – 232 Ah, 21.96V) data

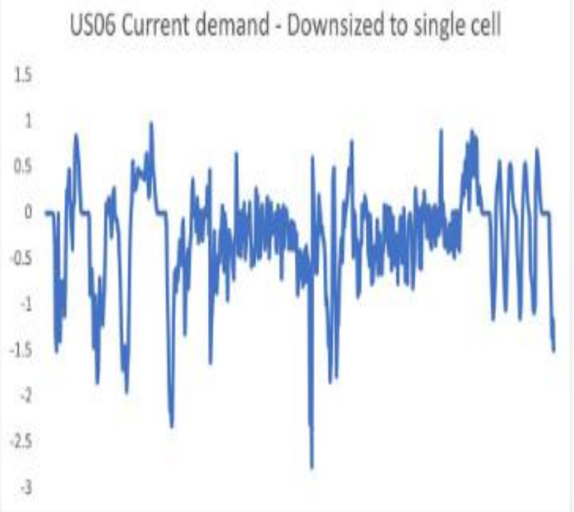


The model was run for the UDDS and US06 driving cycles with a 200-second pause between each cycle. The cycles were run



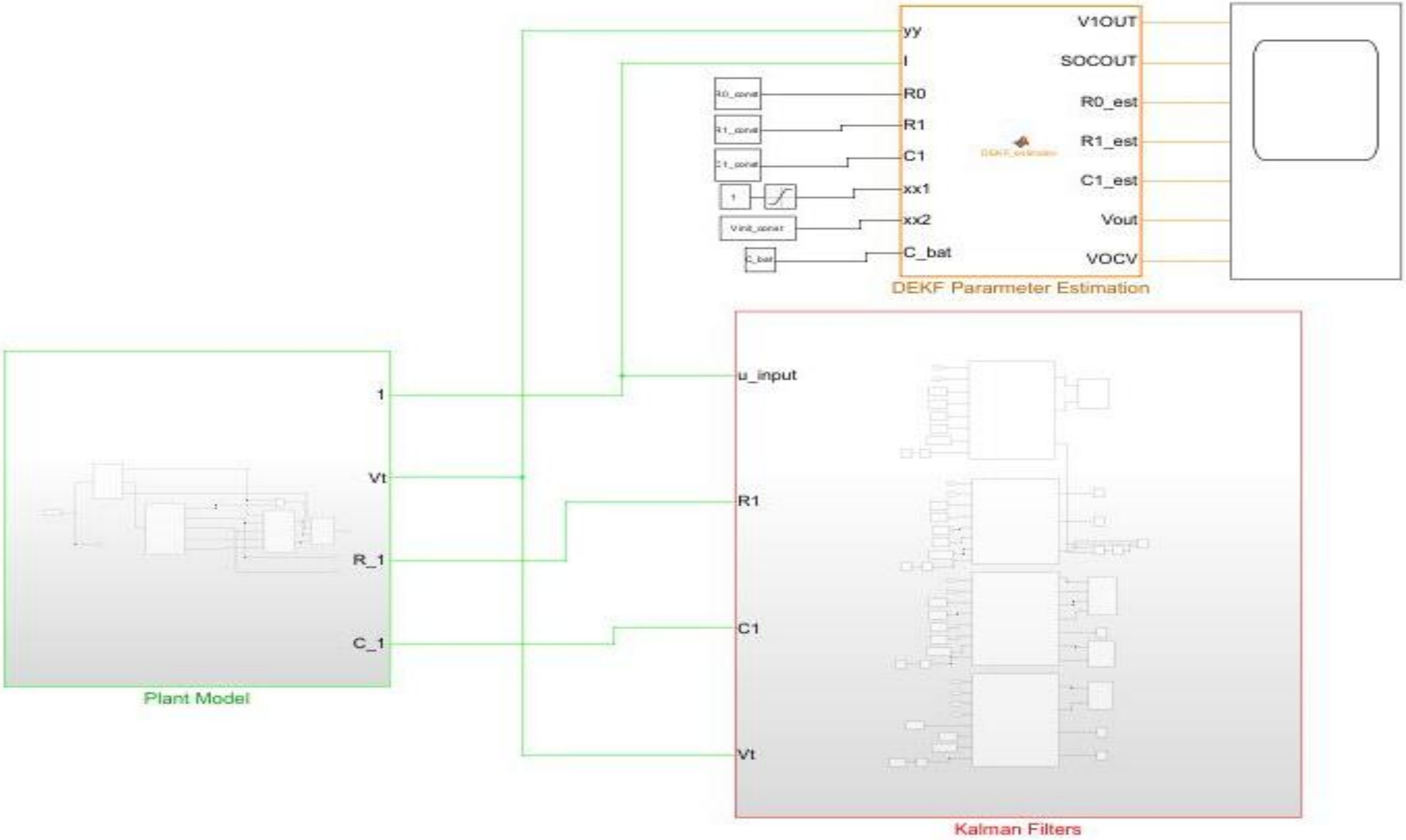






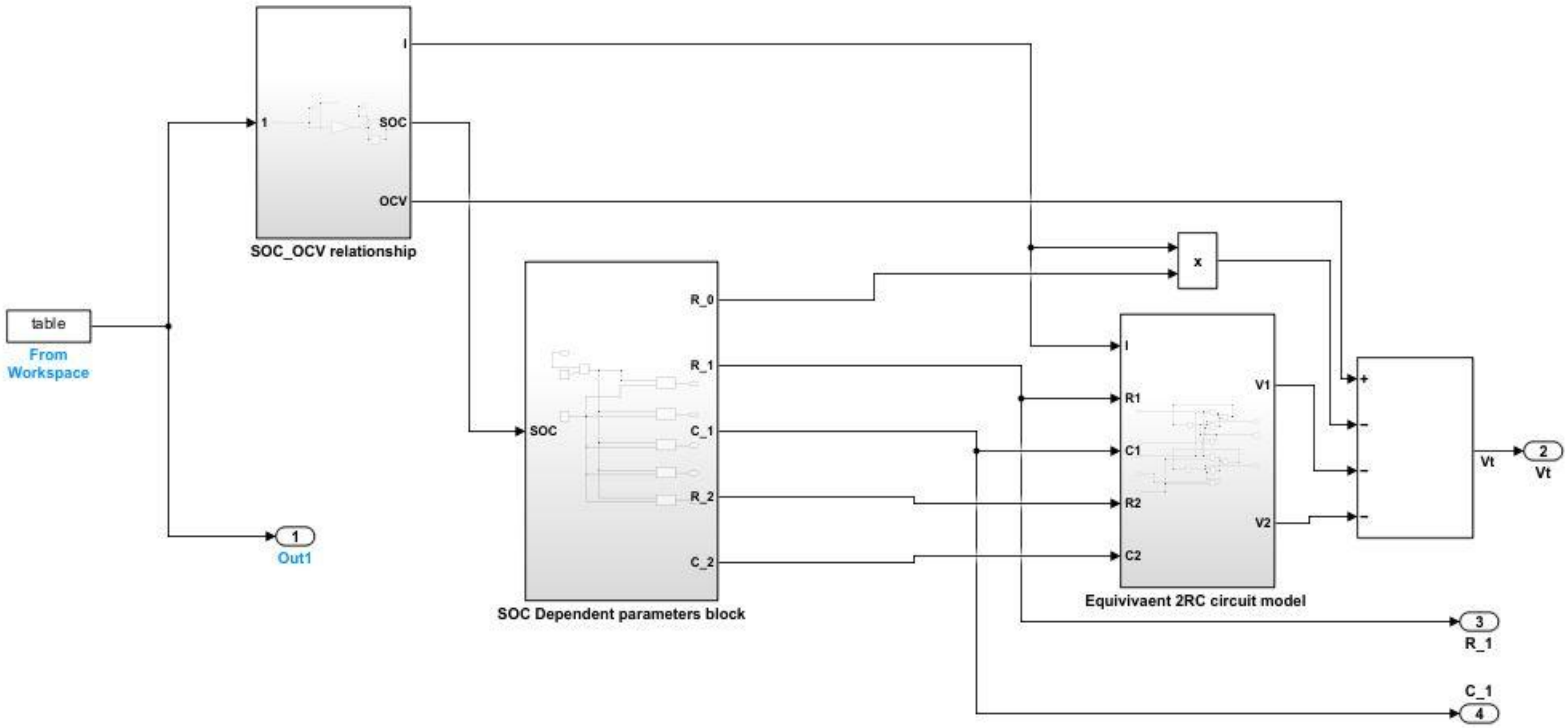
Simulink model

Overall Simulink Model



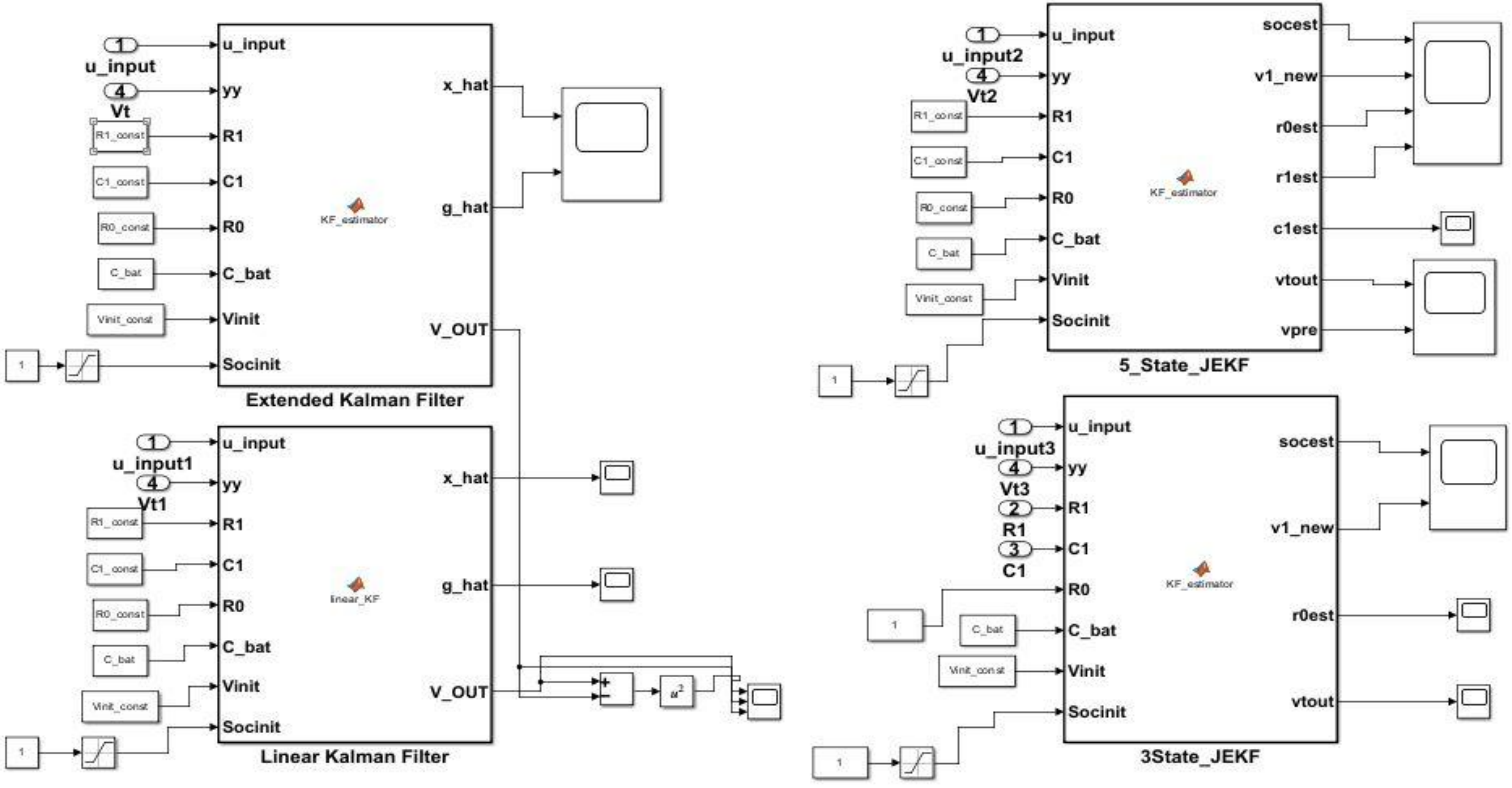
Simulink model

Plant Model



Simulink model

Kalman Filters – Linear, Extended & Joint estimation



Battery Plant Model

Electrical Equivalent circuit model of NMC Battery(OCV-R-2RC)

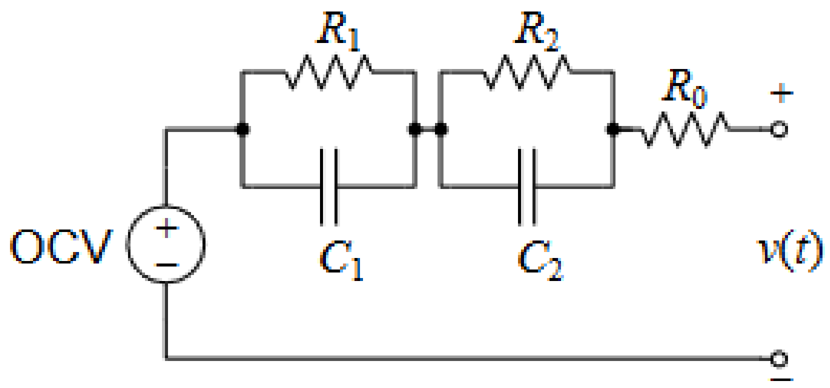
➢ **Second order model equation**

i. $SOC(t) = SOC(0) + 1/C_{actual}\left(\int_0^t \eta_i I(t)dt\right)$

ii. $u_{1,j+1} = \exp\left(-\frac{\Delta t}{R_1 c_1}\right) u_{1,j} + R_1\left[1 - \exp\left(-\frac{\Delta t}{R_1 c_1}\right)\right] I_j$

iii. $u_{2,j+1} = \exp\left(-\frac{\Delta t}{R_2 C_2}\right) u_{2,j} + R_2\left[1 - \exp\left(-\frac{\Delta t}{R_2 C_2}\right)\right] I_j$

iv. $V_j = OCV - R_0 I_j - u_{1,j} - u_{2,j}$



- U1 and U2 represent voltage across RC1 and RC2
- Vj represent terminal voltage of Battery
- R1C1 AND R2C2 parameters across RC1 and RC2 circuit
- R0 represent initial resistant of Battery

Linearization and Observability check

Linearization of OCV-SOC Relationship

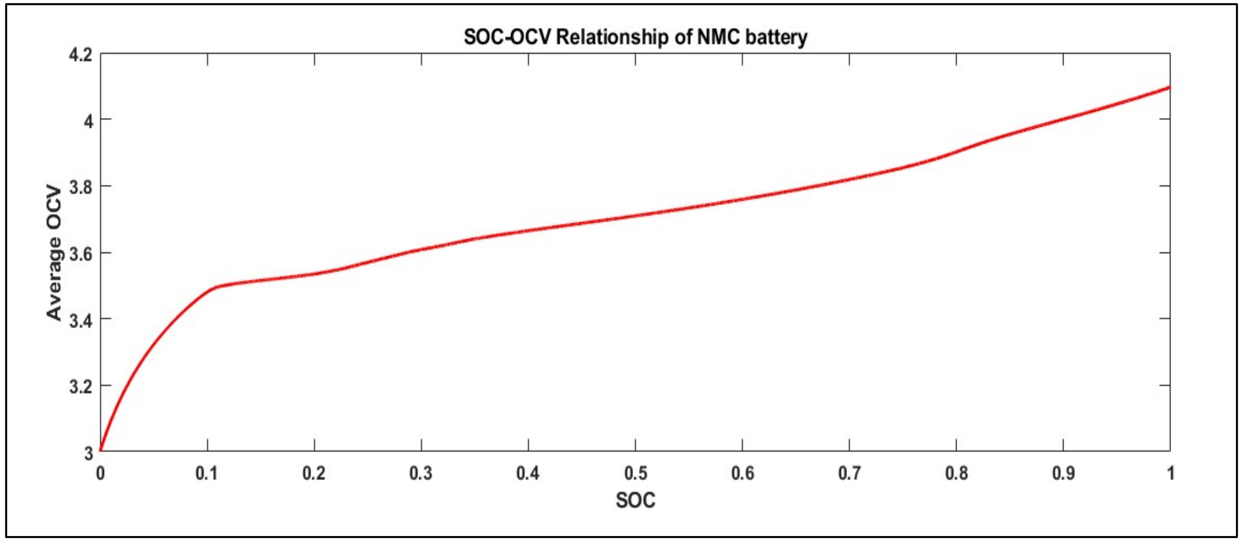
Linear relation between OCV and SOC and calculated the parameters of the curve by using single polynomial function.

By using polyfit linearized the graph such that:

$$\frac{dOCV}{dz} = \alpha x + \beta$$

a = 0.7160

β = 3.3503

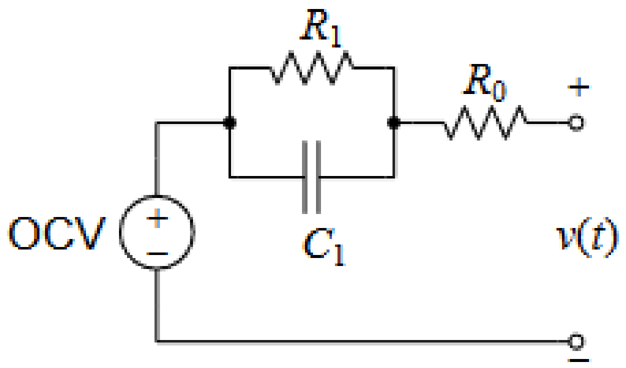


Observability check

Observability refers to the ability to understand the internal states of the model based on its output or behavior.

- **A model is to be observable if the rank of observability matrix equals the n of the matrix.**
- **O(A,C) = [C; CA ; CA^2; CA^3 ………….. CA^n]**
- **It is observed that the rank of the observability matrix and the n of the matrix are equal, and it is good to design an observer to estimate the internal states of the battery.**

Kalman filter Algorithm



I. Extended Kalman Filter Model (OCV-R-RC)

i. **Step1 State-prediction Time Update:** $\hat{x}_{\bar{k}} = A_{k-1} + \hat{x}^{+}_{k-1} + B_{k-1}U_{k-1}$

ii. **Step2 Error-Covariance Time Update:** $\boldsymbol{P}_1 = A_{k-1}P^{+}_{k-1}A^{T}_{k-1} + \Sigma_{\omega}$

iii. **Step 3 Output Prediction:** $\hat{y}_k = C_k\hat{x}^{-}_{k} + D_kU_k$

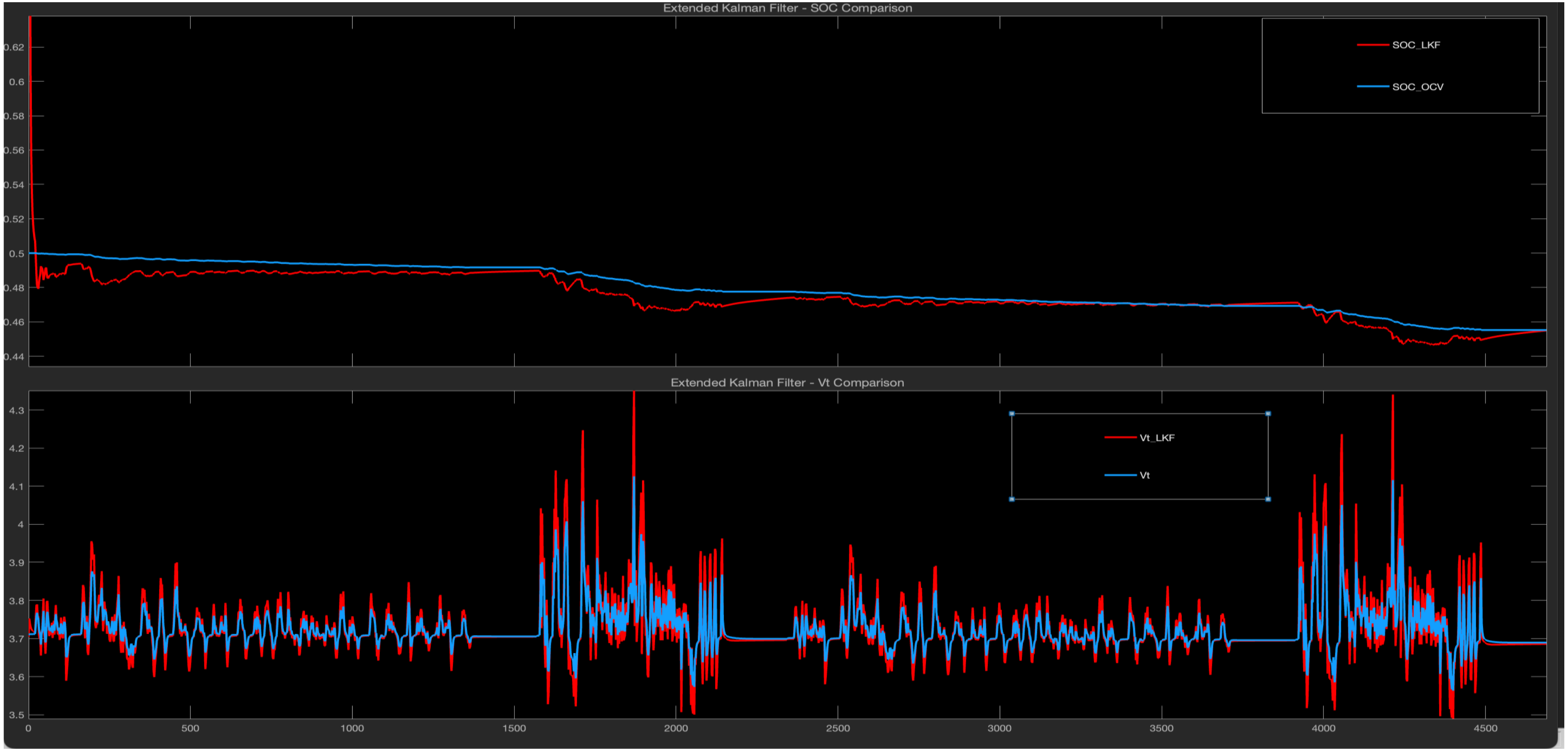
iv. **Step 4 Kalman Gain Computation:** $k_k = P^{-}_{k} * C^{T}_{k}\left[C_kP_{\bar{k}}C^{T}_{k} + \Sigma_v\right]^{-1}$

v. **Step 5 State-estimate Measurement Update:** $\hat{x}^{+}_{k} = \hat{x}_{\bar{k}} + k_k[y_k - \hat{y}_k]$

vi. **Step 6 Error-covariance Measurement Update:** $P^{+}_{k} = [I - k_kC_k]P^{-}_{k}$

- A = $\begin{bmatrix} 1 & 0 \\ 0 & \mathrm{e}^{\frac{-\Delta t}{R_1 * C_1}} \end{bmatrix}$
- B = $\begin{bmatrix} \dfrac{-1}{(3600 * C)} \\ R_1 * \left(1 - \mathrm{e}\left(\frac{-\Delta t}{R_1 * C_1}\right)\right) \end{bmatrix}$
- C = $[0.7160 \quad -1]$
- D = - R0

I. Extended Kalman Filter Model (OCV-R-RC) - Results



SOC and Vt comparison with experimental data

RMSE Calculation:

- SOC = 0.043527
- VT = 0.02978

Kalman filter Algorithm

II. Linear Kalman Filter Model (OCV-R-RC)

i. **Step1 State-prediction Time Update:** $\hat{x}_{\bar{k}} = A_{k-1} + \hat{x}^{+}_{k-1} + B_{k-1}U_{k-1}$

ii. **Step2 Error-Covariance Time Update:** $\boldsymbol{P}_1 = A_{k-1}P^{+}_{k-1}A^{T}_{k-1} + \Sigma_{\omega}$

iii. **Step 3 Output Prediction:** $\hat{y}_k = C_k\hat{x}^{-}_{k} + D_kU_k$

iv. **Step 4 Kalman Gain Computation:** $k_k = P^{-}_{k} * C^{T}_{k}\left[C_kP_{\bar{k}}C^{T}_{k} + \Sigma_v\right]^{-1}$

v. **Step 5 State-estimate Measurement Update:** $\hat{x}^{+}_{k} = \hat{x}_{\bar{k}} + k_k[y_k - \hat{y}_k]$

vi. **Step 6 Error-covariance Measurement Update:** $P^{+}_{k} = [I - k_kC_k]P^{-}_{k}$

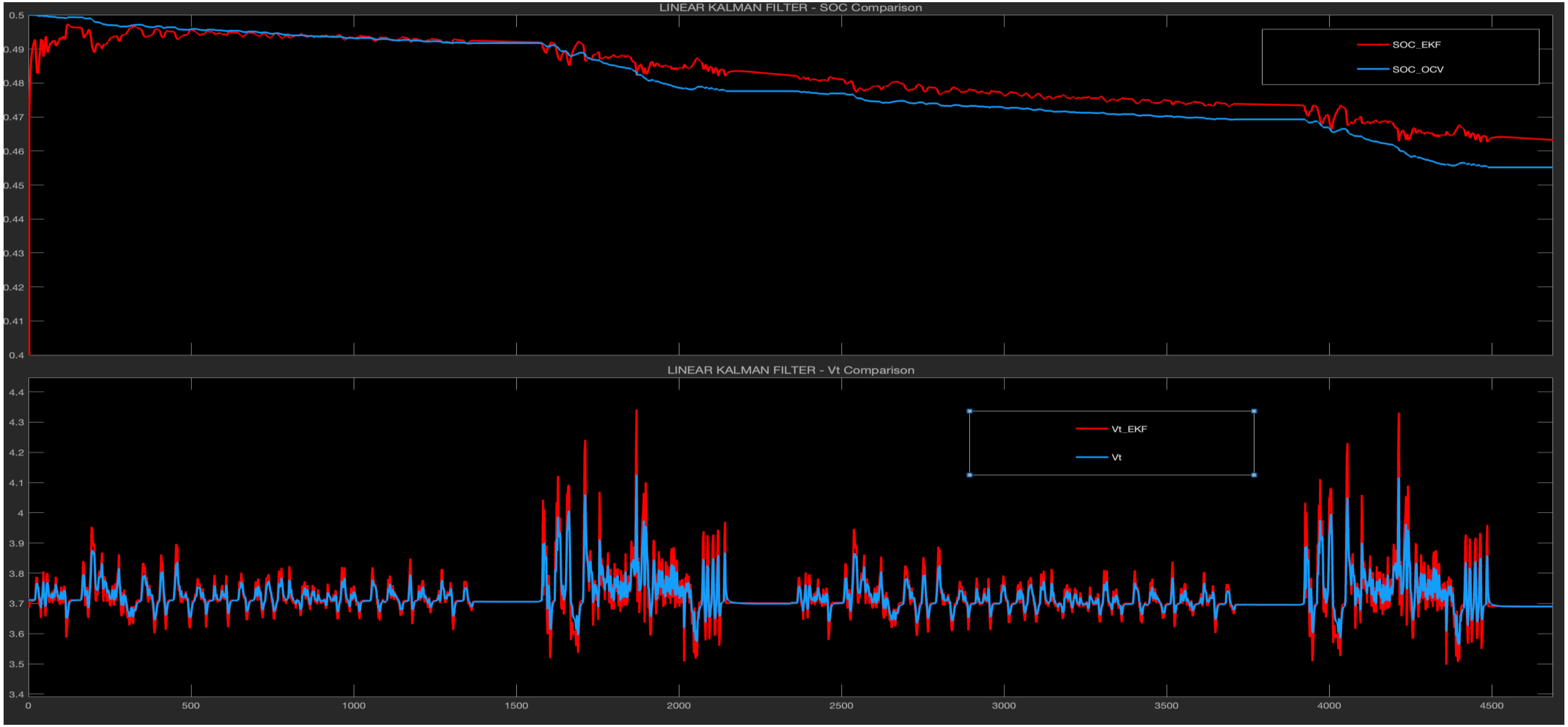
- **A =** $\begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \frac{-\boldsymbol{\Delta t}}{\boldsymbol{R_1 * C_1}} \end{bmatrix}$

- **B =** $\begin{bmatrix} \frac{-\boldsymbol{\Delta t}}{(\mathbf{3600} * \boldsymbol{C})} \\ \frac{-\boldsymbol{\Delta t}}{\boldsymbol{C_1}} \end{bmatrix}$

- **C =** $[\mathbf{0.7160} - \mathbf{1}]$

- **D = - R0**

II. Linear Kalman Filter Model (OCV-R-RC) - Results



SOC and Vt comparison with experimental data

RMSE Calculation:

- SOC = 0.0253
- VT = 0.030111

Kalman filter Algorithm

II. 3-state Joint Extended Kalman Filter Model (OCV-R-RC)

i. **State – predication Time Update** $\hat{x}_{a,k} = \bar{A}_{a,k-1}\hat{x}^{+}_{a,k-1} + \bar{B}_{a,k-1}u_{k-1}$

ii. **Error- Covariance Time Update** $P^{-}_{k} = \bar{A}_{a,k-1}P^{+}_{k-1}\bar{A}^{T}_{a,k-1} + \Sigma_{\omega}$

iii. **Output Prediction** $\hat{y}_{k} = f(\hat{x}_{a,k}, \mu_{k})$

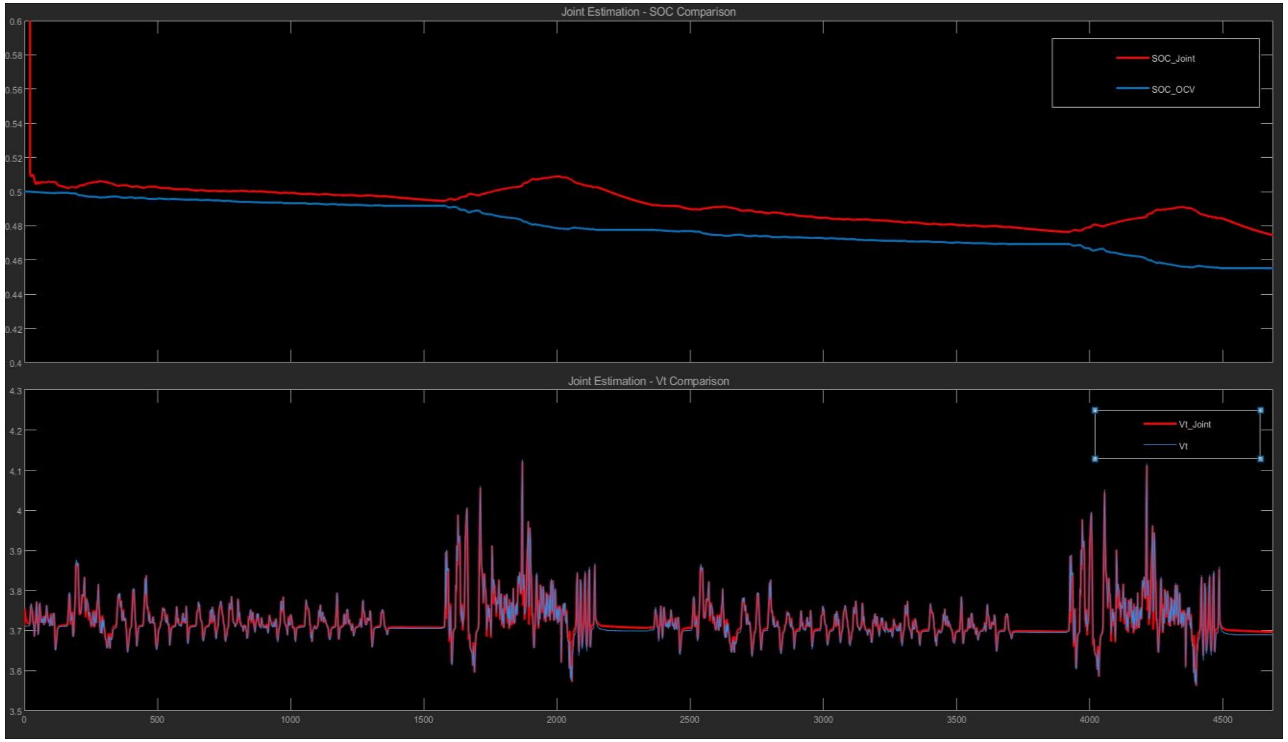
iv. **Kalman Gain Computation** $K_{k} = P^{-}_{k}{C^{x}_{a,k}}^{T}\left[C^{x}_{a,K}P^{-}_{k}{C^{x}_{a,k}}^{T} + \Sigma_{v}\right]^{-1}$

v. **State-estimation Measurement Update** $\hat{x}^{+}_{a,k} = \hat{x}_{a,k} + K_{k}[y_{k} - \hat{y}_{k}]$

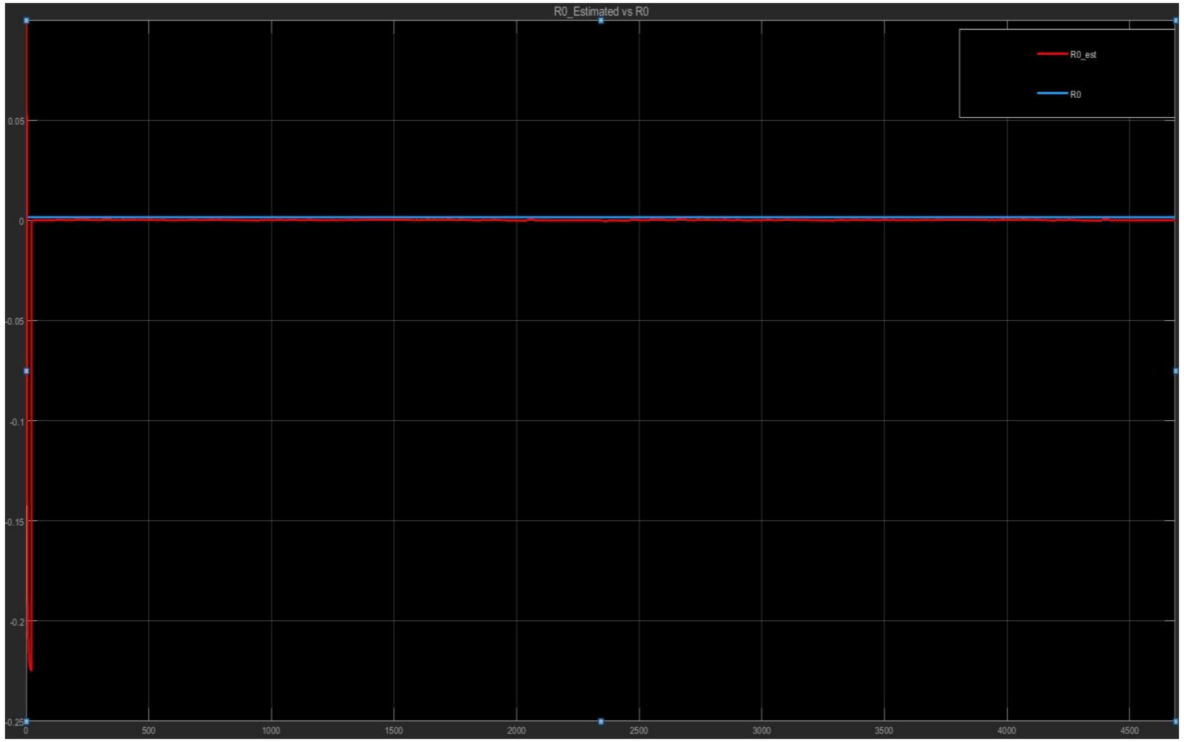
vi. **Error-covariance Measurement Update** $P^{+}_{k} = [I - K_{k}\, C^{x}_{a,k}]\, P^{-}_{k}$

- **A =** $\begin{bmatrix} 1 & 0 & 0 \\ 0 & e\left(\frac{-\Delta t}{(R_1 * c_1)}\right) & 0 \\ 0 & 0 & 1 \end{bmatrix}$
- **B =** $\begin{bmatrix} \frac{-1}{(3600*c)} \\ R_1 * \left(1 - e\left(\frac{-\Delta t}{(R_1 * c_1)}\right)\right) \\ 0 \end{bmatrix}$
- **C =** $[0.7160 - 1 \quad - U_{input}]$
- **D = - R0**

III. 3-state Joint Extended Kalman Filter Model (OCV-R-RC) - Results



SOC and Vt comparison with experimental data



R0 Estimation using 3 state Joint extended Kalman filter

RMSE Calculation:

- SOC = 0.0412
- VT = 0.0066
- R0 = 0.02968

Kalman filter Algorithm

III. 5-state Joint Extended Kalman Filter Model (OCV-R-RC)

i. **State – predication Time Update** $\hat{x}_{a,k} = \bar{A}_{a,k-1}\hat{x}^{+}_{a,k-1} + \bar{B}_{a,k-1}u_{k-1}$

ii. **Error- Covariance Time Update** $P_k^{-} = \bar{A}_{a,k-1}P^{+}_{k-1}\bar{A}^{T}_{a,k-1} + \Sigma_{\omega}$

iii. **Output Prediction** $\hat{y}_k = f(\hat{x}_{a,k}, \mu_k)$

iv. **Kalman Gain Computation** $K_k = P_k^{-} {C^{x}_{a,k}}^{T} \left[C^{x}_{a,K} P_k^{-} {C^{x}_{a,k}}^{T} + \Sigma_v\right]^{-1}$

v. **State-estimation Measurement Update** $\hat{x}^{+}_{a,k} = \hat{x}_{a,k} + K_k[y_k - \hat{y}_k]$

vi. **Error-covariance Measurement Update** $P_k^{+} = \left[I - K_k\, C^{x}_{a,k}\right] P_k^{-}$

- **A =** $\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & e^{\left(\frac{-\Delta t}{(R_1 * c_1)}\right)} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

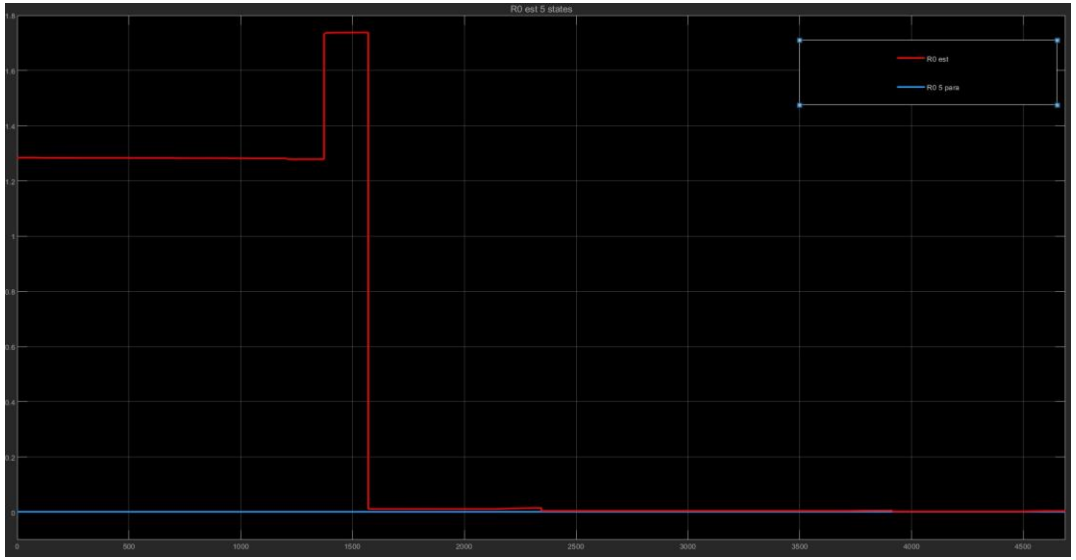
- **B =** $\begin{bmatrix} 1 \\ \frac{-1}{(3600 * c)} \\ R_1 * \left(1 - e^{\left(\frac{-\Delta t}{(R_1 * c_1)}\right)}\right) \\ 0 \\ 0 \\ 0 \end{bmatrix}$

- **C =** $[0.7160 - 1 \quad C\theta]$

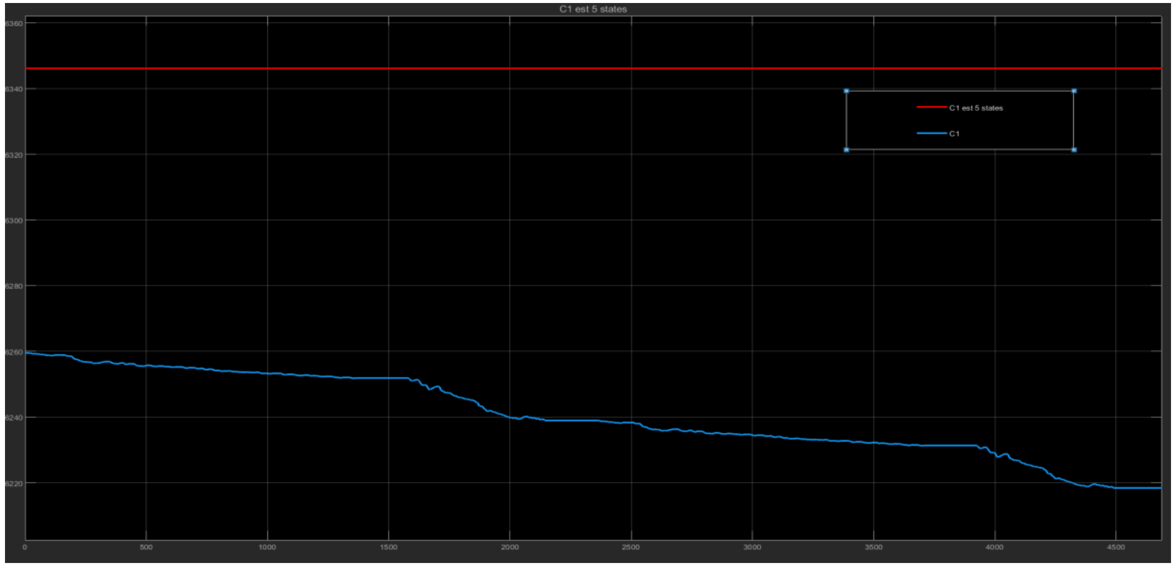
- **Cθ =** $\left.\frac{dy_k}{d\theta}\right|_{x_k=\hat{x}_k^{-},\theta=\hat{\theta}_k^{-}} \Rightarrow \left[-I_{b,k} \quad -e^{\frac{\Delta t}{R_1C_1}}\frac{\Delta t}{R_1^2C_1}V_{1,k-1} - \left(1 - e^{\frac{\Delta t}{R_1C_1}} - R_1e^{\frac{\Delta t}{R_1C_1}}\frac{\Delta t}{R_1^2C_1}\right)I_{b,k-1} \quad -e^{\frac{\Delta t}{R_1C_1}}\frac{\Delta t}{R_1C_1^2}V_{1,k-1} + R_1e^{\frac{\Delta t}{R_1C_1}}\frac{\Delta t}{R_1C_1^2}I_{b,k-1}\right]$

- **D = - R0**

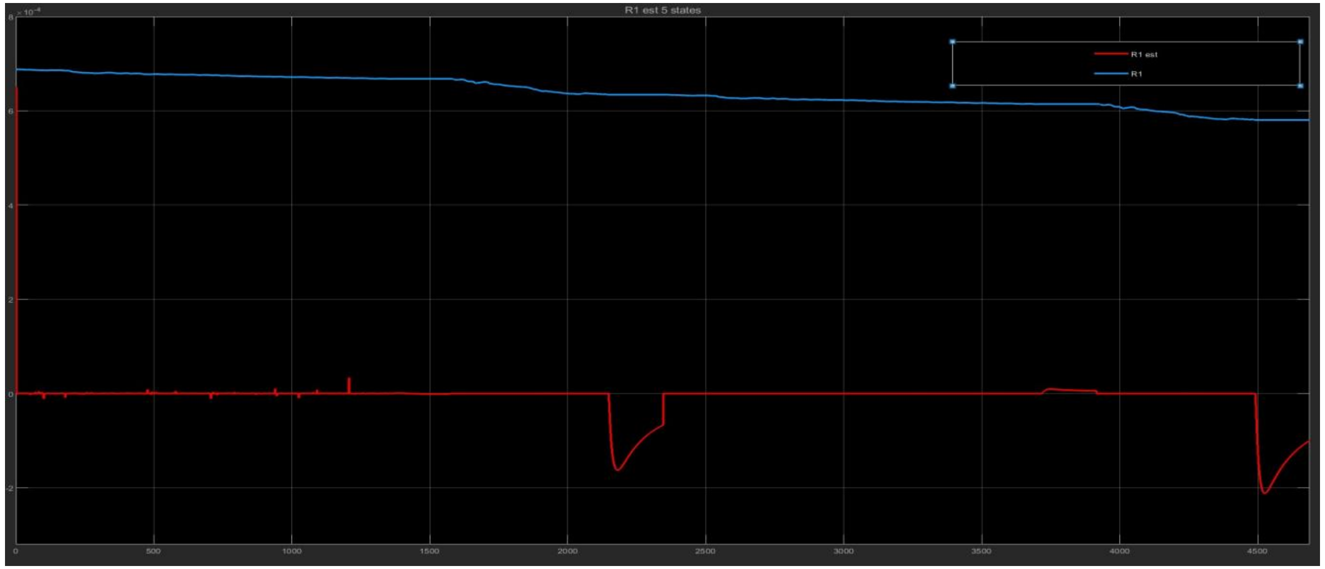
III. 5 state Joint Extended Kalman Filter Model (OCV-R-RC) - Results



R0 Estimation using 5 state Joint extended Kalman filter

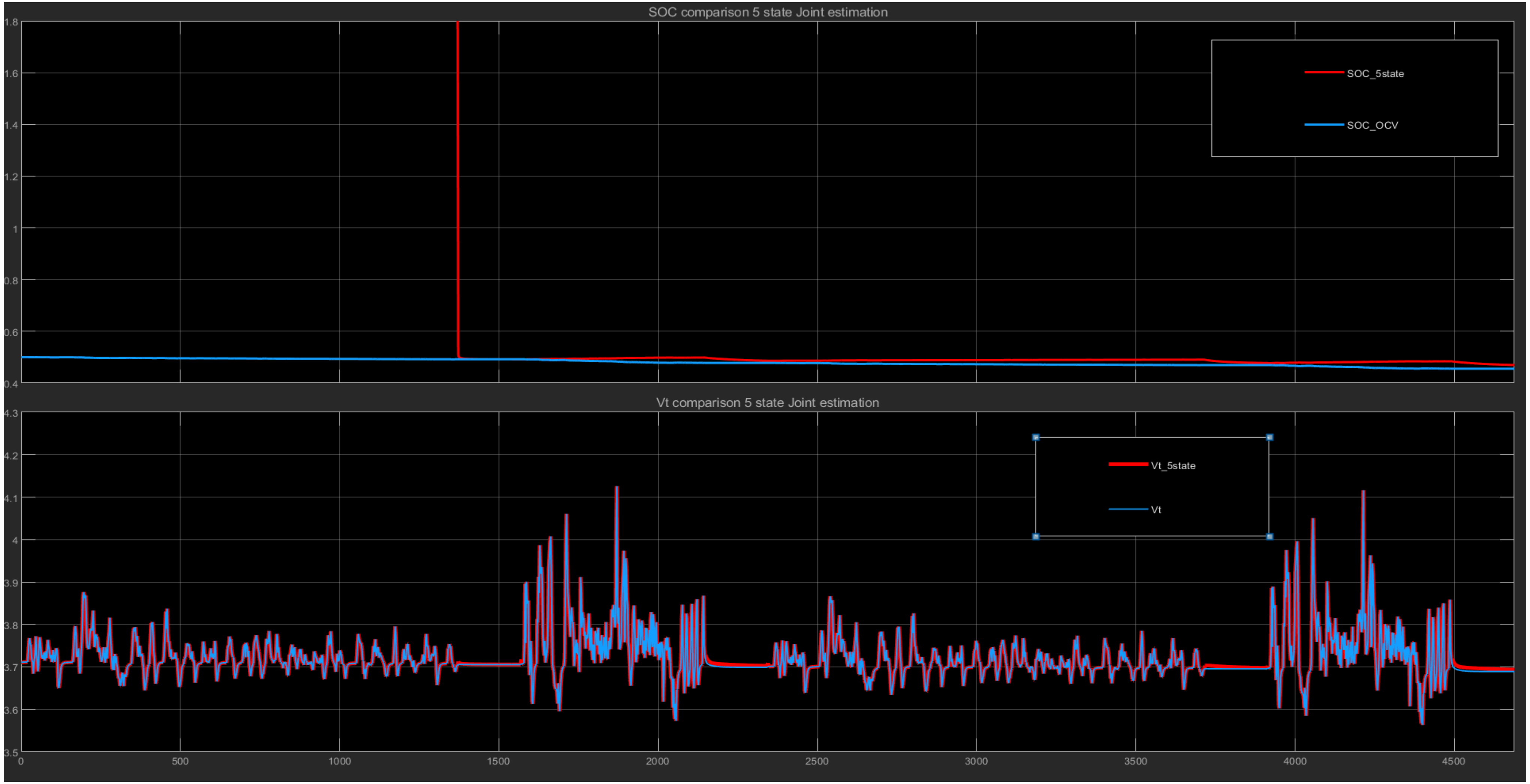


C1 Estimation using 5 state Joint extended Kalman filter



R1 Estimation using 5 state Joint extended Kalman filter

III. 5 state Joint Extended Kalman Filter Model (OCV-R-RC) - Results



SOC and Vt comparison with experimental data

RMSE Calculation:

- SOC = 0.7154
- VT = 0.00215
- R0 = 0.7792
- R1 = 0.00064
- C1 = 106.27

Dual Kalman Filter for parameter estimation

i. **State – predication Time Update**

ii. **Error- Covariance Time Update**

iii. **Output Prediction**

iv. **Kalman Gain Computation**

v. **State-estimation Measurement Update**

vi. **Error-covariance Measurement Update**

$$\hat{\theta} = \hat{\theta}_k^{+} - 1$$

$$\mathrm{S}_\mathrm{k}^{-} = \mathrm{S}_{\mathrm{k}-1}^{+} + \Sigma_r$$

$$\hat{x}_k^{-} = \bar{A}_{k-1}\hat{x}_{k-1} + \bar{B}_k - \mu_{k-1}$$

$$P_1 = \bar{A}_{k-1}P_{k-1}^{+}\bar{A}_{k-1}^{T} + \Sigma_w$$

$$\hat{\mathrm{y}}_\mathrm{k} = \mathrm{f}(\hat{\mathrm{x}}_{\mathrm{a,k}}, \mu_\mathrm{k})$$

$$\mathrm{K}_\mathrm{k} = \mathrm{P}_\mathrm{k}^{-}\mathrm{C}_\mathrm{k}^{\mathrm{x}\,\mathrm{T}}\left[\mathrm{C}_\mathrm{K}^{\mathrm{x}}\mathrm{P}_\mathrm{k}^{-}\mathrm{C}_\mathrm{k}^{\mathrm{x}\,\mathrm{T}} + \Sigma_\mathrm{v}\right]^{-1}$$

$$\hat{\mathrm{x}}_\mathrm{k}^{+} = \hat{\mathrm{x}}_\mathrm{k} + \mathrm{K}_\mathrm{k}[\mathrm{y}_\mathrm{k} - \hat{\mathrm{y}}_\mathrm{k}]$$

$$\mathrm{P}_\mathrm{k}^{+} = [\mathrm{I} - \mathrm{K}_\mathrm{k}\,\mathrm{C}_\mathrm{k}^{\mathrm{x}}]\,\mathrm{P}_\mathrm{k}^{-}$$

$$\mathrm{L}_\mathrm{k} = \mathrm{S}_\mathrm{k}^{-}C_\mathrm{k}^{\theta\,\mathrm{T}}\left[\mathrm{C}_\mathrm{K}^{\theta}\mathrm{S}_\mathrm{k}^{-}\mathrm{C}_\mathrm{k}^{\theta\,\mathrm{T}} + \Sigma_\mathrm{v}\right]^{-1}$$

$$\hat{\theta}_\mathrm{k}^{+} = \hat{\theta}_\mathrm{k} + \mathrm{L}_\mathrm{k}[\mathrm{y}_\mathrm{k} - \hat{\mathrm{y}}_\mathrm{k}]$$

$$\mathrm{S}_\mathrm{k}^{+} = [\mathrm{I} - \mathrm{L}_\mathrm{k}\,\mathrm{C}_\mathrm{k}^{\theta}]\,\mathrm{S}_\mathrm{k}^{-}$$

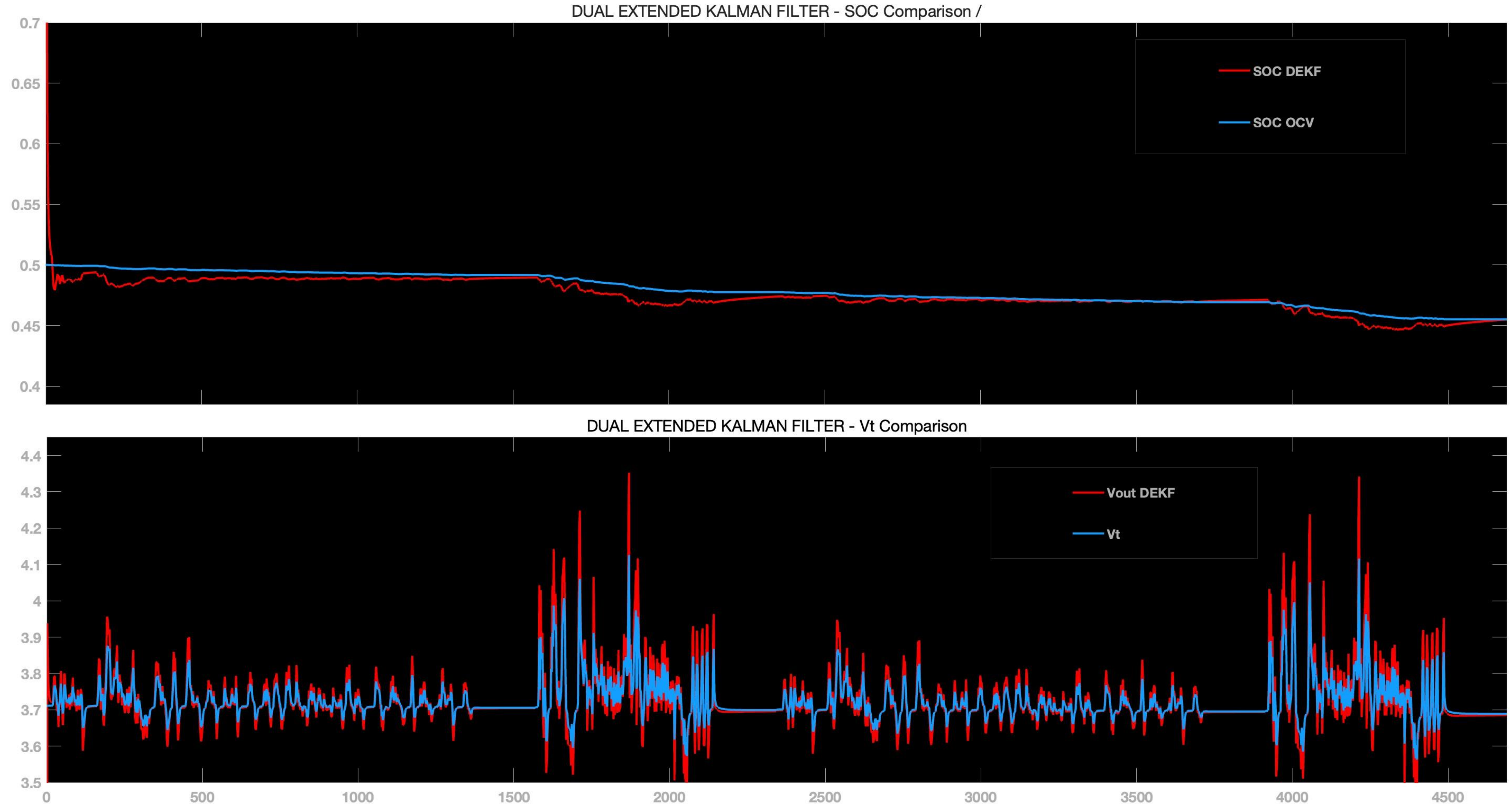
State Matrix

- A = $\begin{bmatrix} 1 & 0 \\ 0 & e^{\frac{-\Delta t}{R_1 * C_1}} \end{bmatrix}$
- B = $\begin{bmatrix} \dfrac{-1}{(3600 * C)} \\ R_1 * \left(1 - e\left(\frac{-\Delta t}{R_1 * C_1}\right)\right) \end{bmatrix}$
- C = $[0.7160 - 1 \quad]$
- D = - R0

Parameter Matrix

- A_para = eye(3)
- C_para = $\left.\dfrac{dy_k}{d\theta}\right|_{x_k=\hat{x}_k^-,\theta=\hat{\theta}_k^-} \Rightarrow \left[-I_{b,k} \quad -e^{\frac{\Delta t}{R_1C_1}}\dfrac{\Delta t}{R_1^2C_1}V_{1,k-1} - \left(1 - e^{\frac{\Delta t}{R_1C_1}} - R_1e^{\frac{\Delta t}{R_1C_1}}\dfrac{\Delta t}{R_1^2C_1}\right)I_{b,k-1} \quad -e^{\frac{\Delta t}{R_1C_1}}\dfrac{\Delta t}{R_1C_1^2}V_{1,k-1} + R_1e^{\frac{\Delta t}{R_1C_1}}\dfrac{\Delta t}{R_1C_1^2}I_{b,k-1} \right]$

Dual Kalman Filter for parameter estimation



SOC and Vt comparison with experimental data

Observations

RMSE :

- ***Joint Estimation – 5 states (Soc, Vt, R0, R1, C1) :***
- Since many unknown states, the result produces more RMSE values.
- C1 estimation didn't converge as expected
- Soc RMSE is high as it took much time to converge at the initialization point.

- ***Joint Estimation – 3 states (Soc, Vt, R0) :*** The results are more accurate with slightly low computational time.
- R0 & Soc results are good as compared to 5 state estimation

- ***Linear and Extended :***
- *Output voltage profiles are more likely same and SOC with good accuracy in Linear than extended.*
- *Soc values are expected to be poor when actual Soc are below 15 percentage and above 85 percentage of charge, as linearization was done.*

RMSE	SOC	VT	R0	R1	C1
JOINT Extended KF 5 – state	***0.715491239***	***0.002156926***	***0.77923902***	***0.000649979***	***106.2741516***
JOINT Extended KF 3 – state	***0.041269839***	***0.006695574***	***0.029687896***		
Extended KF	***0.043527***	***0.029787***			
Linear KF	***0.025347***	***0.030111***			

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Thank you!