Report: Comparative Analysis of State of Charge Estimation Techniques for Lithium-Ion Batteries

1. Executive Summary

This report evaluates methods for estimating the State of Charge (SOC) in Lithium-Ion batteries, a critical component of Electric Vehicle (EV) technology. Because SOC cannot be measured directly by sensors, it must be estimated using mathematical algorithms. This study compares three specific observer techniques: the Luenberger Observer (LO), the Sliding Mode Observer (SMO), and the Super Twisting Observer (STO). Simulation results indicate that while the Luenberger Observer offers theoretical accuracy, the Sliding Mode and Super Twisting Observers provide superior convergence speeds and robustness for real-world applications, with the STO specifically addressing the issue of signal "chattering"[1]

2. Introduction

2.1 Context and Motivation

The global shift toward Electric Vehicles (EVs) is largely driven by international climate agreements, such as the Paris Agreement, which aim to reduce greenhouse gas emissions2. As the automotive industry transitions toward zero-emission sales, the efficiency and safety of the energy storage systems become paramount [10]

Lithium-ion batteries (LIBs) are currently the standard for EVs due to their high energy density and longevity4. However, they are non-linear and complex systems. To manage these batteries safely—preventing dangerous overcharging or deep discharging—a Battery Management System (BMS) is required [9].

2.2 The Problem of SOC Estimation

The State of Charge (SOC) functions similarly to a fuel gauge in a combustion engine vehicle, representing the ratio of remaining energy capacity (E_{cr}) to the actual maximum energy capacity (E_{ca}).

It is expressed as a percentage:

$$SOC(t) = \frac{E_{cr}}{E_{ca}} \times 100$$

A major challenge in BMS design is that SOC cannot be directly measured using physical sensors; it must be inferred from measurable variables such as current and terminal voltage using specific algorithms [1].

3. System Modeling

To estimate the SOC, a mathematical representation of the battery is required. This study utilizes the Electrical Equivalent Circuit Model (EECM), specifically a Resistor-Capacitor (RC) framework. This model is chosen for its balance between computational simplicity and accuracy.

3.1 The RC Model Structure

The battery is modeled using a resistor (R_t) in series with a parallel RC network (R_p and C_p) and a voltage source representing the Open Circuit Voltage (V_{oc})10. The terminal voltage (V_t) is expressed as:$V_t = V_{oc}(Z) + IR_t + V_p$11

The system accounts for non-linear behaviors where the Open Circuit Voltage varies based on the SOC (represented as Z). For the purpose of the state-space model, the relationship is linearized within specific ranges as $V_{oc}(Z) = kZ + d$12 [11].

3.2 State-Space Equations

The dynamic behavior of the battery is described by the following state equations, where modeling errors and uncertainties are treated as external disturbances

$$V_t = -a_1V_t + a_1kZ + b_1I + \Delta f_1$$

$$Z = a_2V_t - a_2kZ - a_2V_p + \Delta f_2$$

$$V_{\dot{p}} = -a_1V_p + {}_2I + \Delta_3 3$$

Here, the parameters a and b are derived from the battery's resistance and capacitance values1

4. Methodology: Observer Design

Three distinct observers were designed and implemented to estimate the internal states of the battery.

4.1 Luenberger Observer (LO)

The Luenberger Observer, also known as a state observer, creates a replica of the battery system and corrects the estimation based on the error between the measured terminal voltage and the estimated voltage. It uses a gain matrix H to drive the error to zero exponentially [12].

- **Mechanism**: It applies linear correction terms proportional to the estimation error

$$(e_1 = V_t - \hat{V}_t)$$

4.2 Sliding Mode Observer (SMO)

The SMO is a non-linear observer known for its robustness against modeling uncertainties and noise.

- **Mechanism:** It utilizes a discontinuous switching function, $sign(y - \hat{y})$, to force the system states onto a sliding surface [1]
- **Pros/Cons:** While it offers finite-time convergence and high robustness, it introduces a high-frequency oscillation known as "chattering".

4.3 Super Twisting Observer (STO)

The STO is a second order sliding mode algorithm designed to mitigate the chattering inherent in standard SMOs while maintaining robustness [14].

- **Mechanism:** It integrates the discontinuous sign function, producing a continuous control signal that effectively smooths out the chattering effect19. The algorithm includes correction terms based on the square root of the error: $h_1|e_1|^{2/3}sign(e_1)$20.

5. Simulation Results and Discussion

The observers were validated using MATLAB/Simulink on a model of a 5Ah Lithium-Polymer (Li-Pb) battery21. Two distinct testing profiles were used.

Results: Battery Model

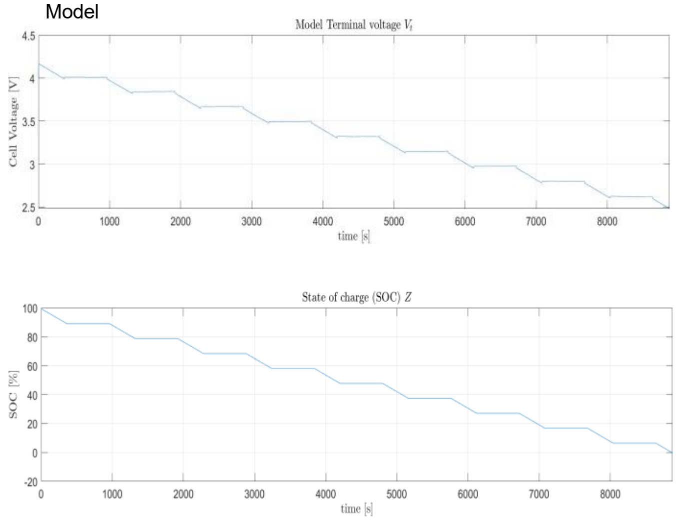

Figure: Vt and Soc plots for the cell model

Result: Luenberger Estimation Under CCD

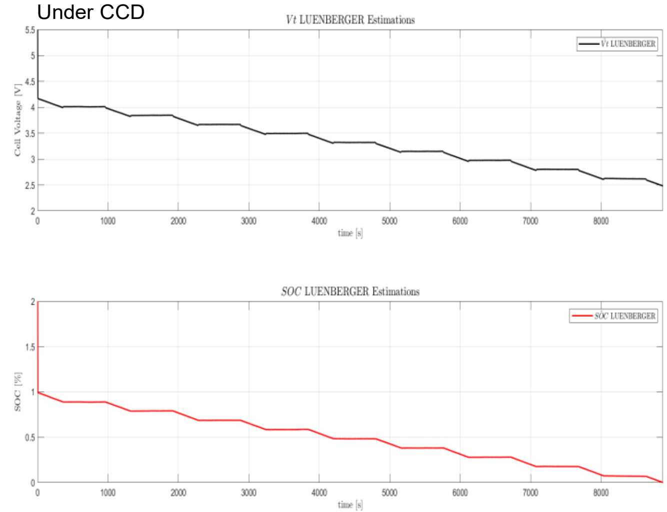

Figure: Vt and Soc Luenberger Estimation Plots

Results: SMO Estimation
Under CCD

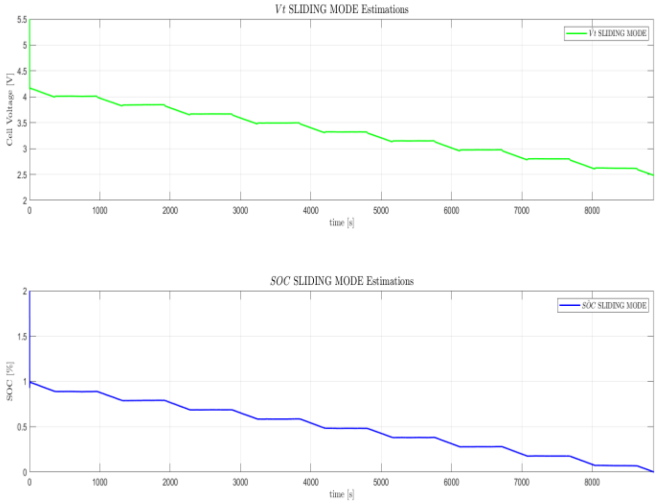

Figure: Vt and Soc SMO Estimation
Plots

Results: STO Estimation
Under CCD

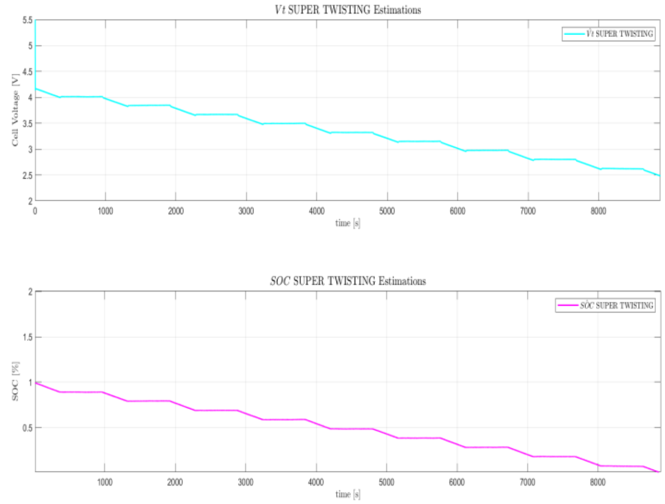

Figure: Vt and Soc STO Estimation
Plots

Results: Luenberger Estimation
Under UDDS

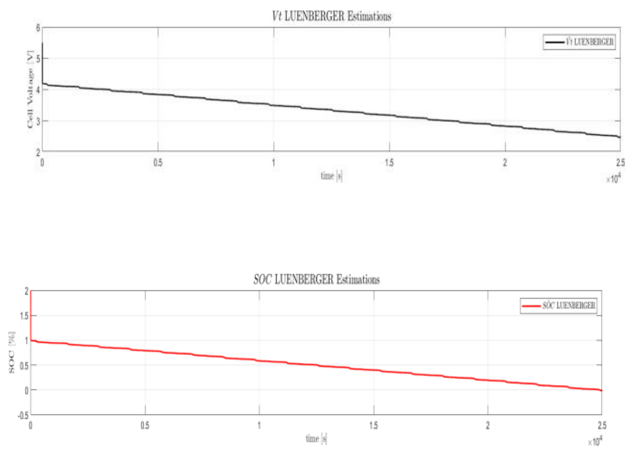

Figure: Vt and Soc Luenberger Estimation
Plots under UDDS Profile

Results: SMO Estimation Under UDDS

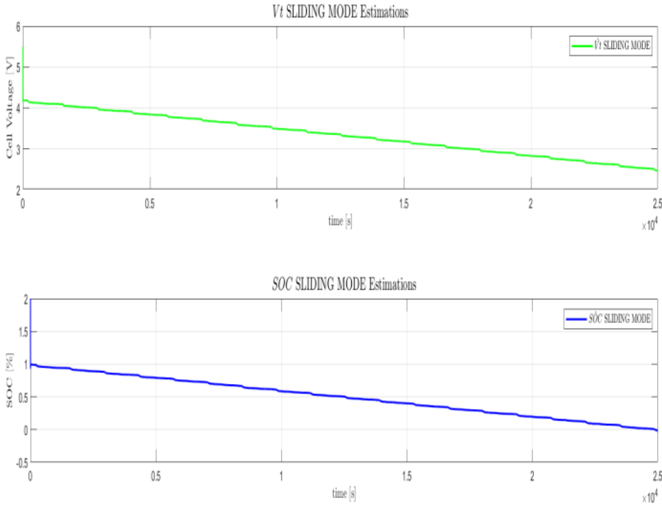

Figure: Vt and Soc SMO Estimation plots under UDDS Profile

Results: STO Estimation Under UDDS

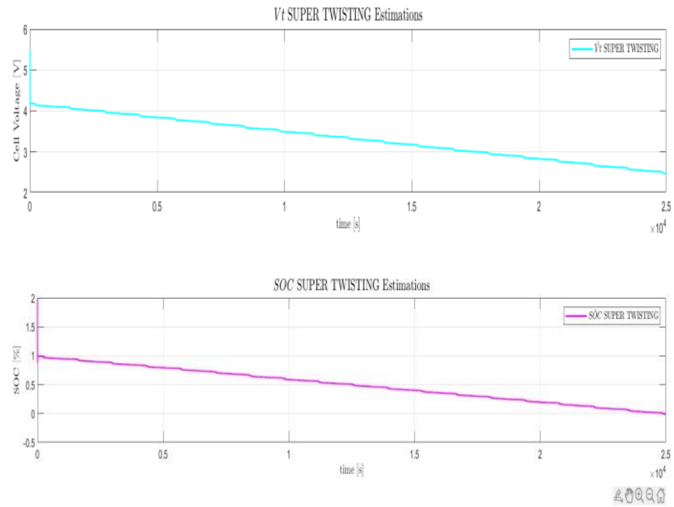

Figure: Vt and Soc STO Estimation plots under UDDS Profile

Results: Convergence of The Three Observers

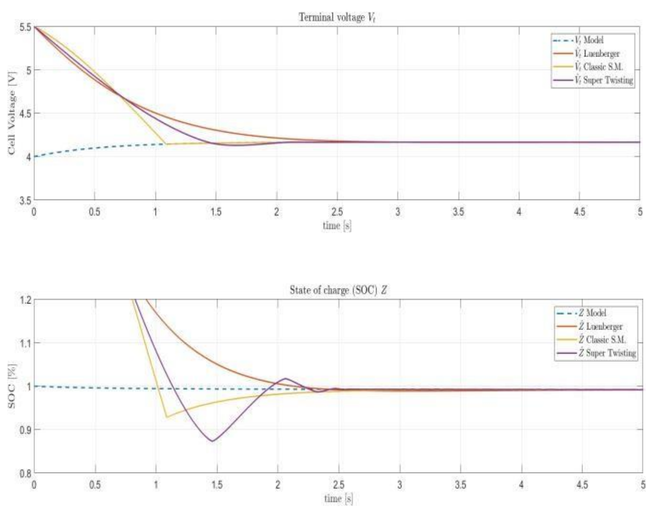

Figure: Luenberger, SMO and STO convergence

Results: Chattering of STO

Figure below presents a close look at the convergence curves of the SOC estimation. In the classic SMO, the curve has a small chattering as expected (simulation sampled time 1 ms), and furthermore, the super twisting observer complies with the proposal to reduce the chattering caused by the sign $(y - \hat{y})$ function.

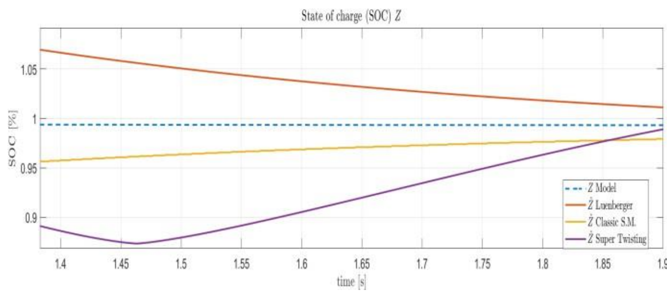

Figure: SMO chattering in SOC estimation.

Results: Estimation Error

Integral Squared Error (ISE)

$$ISE = \int e^2 \, dt. \tag{10}$$

Integral Absolute Error (IAE)

$$IAE = \int |e| \, dt. \tag{11}$$

Results: Estimation Error

State Variable	Metric	Luenberger Observer	Sliding Mode (SMO)	Super Twisting (STO)
Terminal Voltage (Vt)	ISE	0.8438	0.8971	0.8577
	IAE	2.1084	6.8321	1.0472
State of Charge (Z)	ISE	0.3053	0.3362	0.3263
	IAE	1.4025	4.6641	4.0959
Polarization Voltage (Vp)	ISE	0.3023	0.3023	0.3026
	IAE	4.5814	4.5792	5.0604

Table: Estimation Errors Comparison for UDDS current profile

Evaluation Criteria	**Luenberger Baseline**	**Sliding Mode (SMO)**	**Super Twisting (STO)**
Response/Convergence Time	Moderate	High-Speed	Moderate
System Robustness	Limited	Advanced	Advanced
Signal Integrity (Chattering)	High (No Noise)	Low (Significant Noise)	High (Noise Filtered)
Operational Suitability	Ideal/Linear only	Dynamic/Non-linear	Optimal for Real-world

Table: Performance Comparison of Observers

5.1 Constant Current Discharge (CCD)

In this test, a constant discharge current of 5A was applied in pulses.

- **Convergence**: The SMO demonstrated the fastest convergence (stabilizing between 1s and 2s). The Luenberger observer was slower, taking approximately 2.5s to intersect the true state [1]
- **Accuracy**: All three observers successfully tracked the model's behavior. Error analysis using Integral Squared Error (ISE) showed comparable accuracy across all three methods

5.2 Urban Dynamometer Driving Schedule (UDDS)

This profile simulates realistic city driving conditions with frequent stops, starts, and regenerative braking24.

- **Performance**: All observers tracked the voltage and SOC changes effectively under dynamic current loads.
- **Chattering**: As expected, the classic SMO exhibited chattering (oscillations) in its estimation. The STO successfully reduced this phenomenon, providing a smoother estimation curve [1]
- **Error Metrics**: The SMO showed higher Integral Absolute Error (IAE) values compared to the others in this specific test, likely due to the chattering effect reacting to the rapid current changes.

6. Conclusion

This project evaluated the effectiveness of three observer techniques for EV battery management. The key findings are:

- **Robustness**: The Sliding Mode Observer (SMO) and Super Twisting Observer (STO) are superior to the Luenberger Observer for handling modeling errors and uncertainties.
- **Speed**: The SMO offers the fastest convergence speed
- **Real-World Application**: While the Luenberger observer performs well in ideal linear simulations, it is less suitable for the non-linear nature of real batteries. The SMO and STO are the preferred choices for online applications due to their high-frequency action
- **Recommendation:** The Super Twisting Observer is recommended as the optimal solution as it retains the speed and robustness of the SMO while significantly reducing the undesirable chattering effect.

References

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