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Design of a robust unknown input observer for the state of charge estimation for Lithium-ion batteries

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Highlights

- Robustness in battery SoC estimation is a key challenge.
- UIO mitigates disturbances and model uncertainties.
- UIO excels with simplicity and reduced complexity.
- Proven performance makes it ideal for large-scale applications.

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Abstract

The robustness of an observer against model uncertainties is a main challenge during the Lithium-ion battery state of charge (SoC) estimation. Also, for large-scale applications such as electric vehicles, disturbances in measurement may increase the SoC estimation error. To overcome this problem, this paper presents an Unknown Input Observer (UIO) for the battery SoC estimation. This observer can eliminate the effect of the disturbances and model uncertainties. The main superiority of such an observer is the lack of chattering and complexity compared to other robust methods such as sliding mode observers and H∞. The performance of the proposed method for the SoC and terminal voltage estimation has been compared to the Ah-counting method as a commonly used method for different applications through a set of simulations and software in the loop validation. The results confirm the good performance of the proposed method and show that it is a good choice for large-scale applications.

Nomenclature

Parameters		***Variables***	
a_1	*Identification parameter*	$F(X,u)$	*Transient function of the battery model*
a_2	*Identification parameter*	$H(SoC)$	*Non-linear relation between the SoC and Voc.*
b_1	*Identification parameter*	T_{pf}	*Time constant of the RC loop*
b_2	*Identification parameter*	T_{ps}	*Time constant of the RC loop*
		X	*State vector*
		Δf	*Unknown unction of nonlinearity and uncertainties*
		Φ	*Benefit factor*
		Γ	*Coefficient of the function*
		τ	*Process noise*
		ω	*Measurement noise*

1. Introduction

1.1. Motivation and Incitement

Rechargeable battery energy storage technologies are becoming increasingly necessary as renewable energy sources advance. One of the often-used battery types in these systems is the lead-acid battery [1]. Due to their advantages over lead-acid batteries, lithium batteries are now a very viable substitute in energy storage systems [2]. Among these benefits include a longer lifespan, improved depth of discharge, stable output voltage, less weight, and

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reduced volume. Accurately estimating lithium-ion batteries' SoC is one of the biggest issues when dealing with them because the SoC, as the major function, affects many other functions in the battery management systems (BMS). Because of this, research into SoC estimation using various methodologies has become increasingly popular. Any sensor cannot directly measure the battery SoC since it depends on the chemical reactions inside the battery. Appropriate estimators are required for this purpose [3]–[5].

1.2. Literature Review and Research Gaps

The two most popular techniques for SoC estimate are the impedance measuring approach [6] and the ampere-hour counting method [7]. Compared to other approaches, these are incredibly cheap and straightforward. These techniques are substantially less accurate than others and susceptible to environmental changes. The Kalman filter is one of the recursive mathematical techniques for estimating a system's parameters with precise state space dynamics [8]. The capability of this filter to estimate the state in the presence of noise in the system dynamics or measurement is one of its benefits. In other words, this filter can estimate system state variables even in the face of measurement and process noise. One common approach is utilising the Kalman filter to estimate SoC in lithium-ion batteries [9]. The extended Kalman filter (EKF) [10], [11] and the Unscented Kalman filter (UKF) [12], [13] are appropriate alternatives since the battery has nonlinear dynamics. The conventional Kalman filter [14] is a suitable method for estimating the SoC using the linear dynamics of the battery. Due to the linearization in its approach, EKF has a minor mistake in the SoC estimation, whereas UKF has a greater computational burden. The requirement for an accurate dynamic model of the batteries, one of the drawbacks of Kalman filters in SoC estimation, means that the uncertainties resulting from inaccurately identifying the battery model and the variations in the environmental conditions of the laboratory test reduce the estimation's accuracy.

Robust estimators are excellent solutions for the issue of model uncertainty in batteries. The most popular observers for SoC estimations are sliding mode estimators [15] and H observers [16]. One drawback of utilizing H filters is the high level of mathematical formulas and the necessity for extremely strong processors to do complex calculations. Sliding-based filters, on the other hand, exhibit a chattering phenomenon in their operation, which in turn lowers the estimation accuracy. Adaptive forms of sliding mode observers [17] resolve this issue. Fuzzy systems [18] and neural networks [19] are two intersecting methods used to modify the primary filter to lessen chattering. Additionally, these robust filters cannot estimate the battery SoC in the face of measurement disturbances.

Neural networks [20], intelligent systems, and artificial intelligence [21] are additional useful techniques for calculating the SoC of lithium-ion batteries. Additionally, fuzzy systems [22] are employed as a supplementary technique or to estimate the charge level directly. Fuzzy systems have the drawback of not having good accuracy on their own, necessitating optimization to improve accuracy. Some trustworthy and sufficient knowledge is also required to set rules in fuzzy systems. The battery SoC has recently been estimated using data-based techniques [23], like machine learning [24], deep learning [25], and reinforcement learning [26]. However, the fundamental drawback of these approaches and neural networks is the requirement for a complete and trustworthy data set to train these intelligent systems.

1.3. Contributions and Paper Organization

To overcome the problems of the robust estimation methods, such as the chattering of sliding mode observers and the complexity of H_∞, this paper presents an Unknown Input Observer (UIO) for the battery SoC estimation. This observer can eliminate the effect of the disturbances and model uncertainties. The main superiority of such an observer is the lack of chattering and complexity compared to other robust methods such as sliding mode observers and H_∞. The remaining sections of the paper can be categorized as follows.

The modeling of the battery is presented in section 2. The proposed method is formulated in section 3. The results are discussed in section 4, and section 5 concludes the paper.

2. Modeling of the battery

Choosing a precise model for the battery cell is one of the most crucial factors in the battery SoC estimation. The equivalent circuit model (ECM) employed in this study is a widely used option for battery modelling in industrial applications, particularly EV applications.

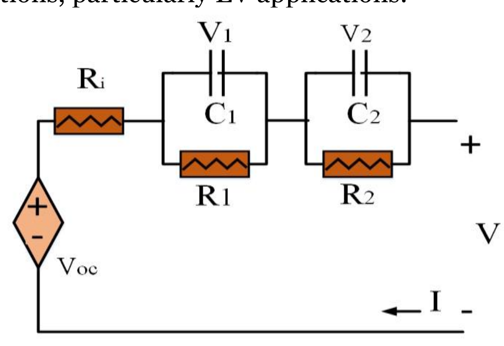

Fig. 1. Battery model

The battery's nominal capacity and total energy stored are shown in Fig. 1. The terminal voltage (Vt) and battery discharge (I) are two different concepts. The VOC-dependent voltage source indicates the battery voltage or estimated battery charge, which ranges from 0 to 100%.

The Coulomb coefficient is chosen to be as much as 1 in Eq. 1. By combining Fig. 1 and the Kirchhoff voltage law, following Equation is gotten:

$$V = V_{oc}(Soc) - V_1 - V_2 - IR_i + \Delta \quad (1)$$

where the electrochemical and concentration polarization voltages across C_1 and C_2, respectively, are denoted by V_1 and V_2. Uncertain, f_2, f_3, and f_4 are model errors that have been incorporated into the circuit specification so that, in the event of an error, the circuit's performance may be tracked. The SoC is derived polarized, and the resulting relationship is obtained.

$$S\dot{o}C = -(\frac{I}{C_{tot}}) + \Delta f_2 \quad (2)$$

$$\dot{V}_1 = -\frac{V_1}{R_1 C_1} + \frac{I}{C_1} + \Delta f_3 \quad (3)$$

$$\dot{V}_2 = -\frac{V_2}{R_2 C_2} + \frac{I}{C_2} + \Delta f_4 \quad (4)$$

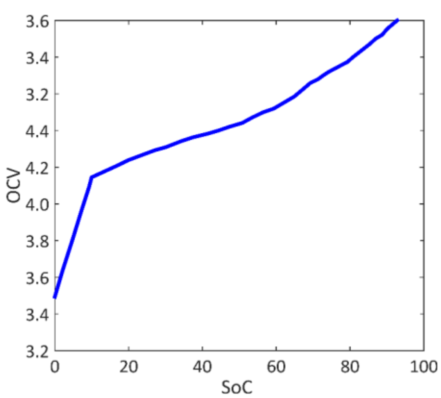

Fig. 2. OCV-SoC curve of Li-Battery

Fig. 2 depicts a nonlinear Voc-SoC curve, but in the locations indicated by the red dots, Voc can be introduced as a linear function of SoC. Following this:

$$V_{oc}(Soc) = nSoc + \varphi \quad (5)$$

where different SoCs have different values for k and v. Now, the equations mentioned above can be simplified as follows if the discharge flow rate is considered to remain constant:

$$\dot{V} = -n(\frac{I}{C}) + \frac{V_1}{R_1 C_1} - \frac{I}{C_1} + \frac{V_2}{R_2 C_2} - \frac{I}{C_2} + \Delta f_1 \quad (6)$$

The battery state space model is obtained by solving Eq. 2 in terms of current (I) and inserting the result into Eq. 3. Then, Eqs. 3 to 6 are recalculated as follows.

$$\begin{aligned} \dot{V} &= -k_1 V + k_1 V_{oc}(SoC) - k_3 V_1 - k_4 V_2 - a_1 I + \Delta \\ \dot{S}oC &= k_2 V - k_2 V_{oc}(SoC) + k_2 V_1 + k_2 V_2 + \Delta f_2 \\ &\dot{V}_1 - k_4 V_1 + a_2 I + \Delta f_3 \\ &\dot{V}_2 - k_3 V_2 + a_3 I + \Delta f_4 \end{aligned} \quad (7)$$

In these equations, the coefficients are described in following Table 1:

Table 1. Coefficients of the battery model

Coefficients	Value
k1	(1/R1C1)+(1/R2C2)
k2	(1/RiC)
(1) k_3	(1/R2C2)
k_4	(1/R1C1)
a_1	(n/C)+(Ri/R1C1)+(1/C1)+(Ri/R2C2) (1/C2);
(1) a_2	(1/C1)
a_3	(1/C2)

Sthe circuit's inputs are u (t), and the outputs are y (t).

$$\dot{x}(t) = Ax(t) + Bu(t) + \Delta f(x, u, t) \quad (8)$$

$$y(t) = Cx(t) \quad (9)$$

The matrices A, B, C, and X values are as follows.

$$A = \begin{bmatrix} -k_1 & k_1 & -k_3 & -k_4 \\ k_2 & -k_2 & k_2 & k_2 \\ 0 & 0 & -k_4 & 0 \\ 0 & 0 & 0 & -k_3 \end{bmatrix} B = \begin{vmatrix} -a_1 \\ 0 \\ a_2 \\ a_3 \end{vmatrix}$$
$$C = [1 \quad 0 \quad 0 \quad 0]$$
$$x(t) = [V \quad V_{oc}(SoC) \quad V_1 \quad V_2]^T$$
$$y(t) = Cx(t) \quad (10)$$

The nonlinear OCV-SOC curve, depicted in Fig. 2, is linearized to create Eq. for modelling the battery, with the ECM parameters being considered constants (10).

It can be assumed that the unknown function f(x,u,t) represents the matched model uncertainties, including the parameter value errors and linearizing errors for Fig. 2.

$$\Delta f(x, u, t) = N\Phi(x, t) \quad (11)$$

Where N is the input matrix of the model uncertainties ,a nd Φ (x,t) is a unknown bounded function.

$$|\Phi(x,t)| \leq \psi \quad \nabla x \in R^4, t \geq 0 \tag{12}$$

So, the state space model of the battery will be:

$$\dot{x}(t) = AX(t) + Bu(t) + N\Phi(x,t) \tag{13}$$

Experimental testing can be used to determine the ECM's parameters. In this context, Fig. 3 depicts the organization of an experimental test setup. The following is a description of each component of this test bench. A 2.4 Ah LFPO4 battery. A programmable resistant load. A DSP for justifying the load value when the battery is discharging. Internal A/D converters for the current and voltage measuring. An RS232 serial port for the connection.

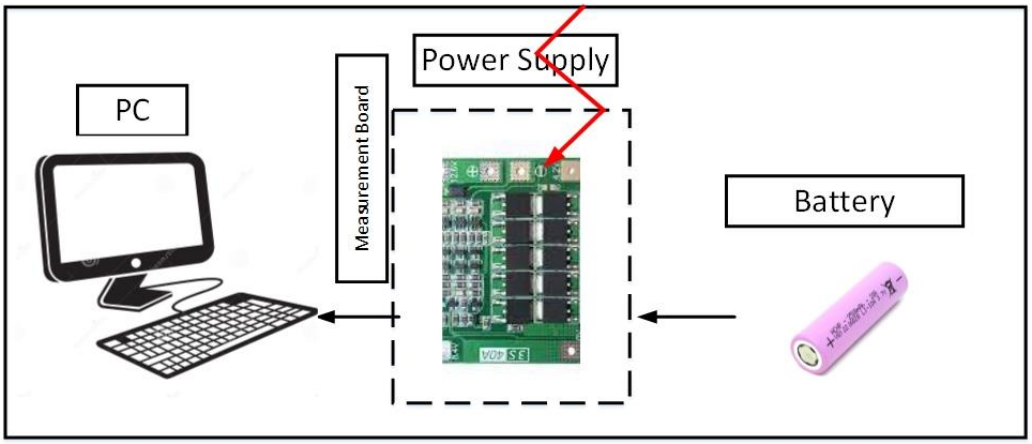

Fig. 3. Test bench

The battery model parameters are extracted using the techniques described in the reference[16]. These parameters and their values are displayed in Table 2.

Table 2. Battery model parameters

Elements	
C_2	1380
C_1	44
C	8635
R_2	39
R_1	2.4
R_i	91

3. Proposed observer formulation

In this paper, the traditional OPF algorithm for

Suppose the dynamic model of the system whose equations are as follows:

$$\begin{aligned} \dot{x} &= Ax + Bu + f(x) + E\varphi(x,w) \\ y &= Cx \end{aligned} \tag{14}$$

where$x \in R^{n_x}$, $u \in R^{n_u}$, and $y \in R^{n_y}$are the system state, the system input, and the system output, respectively.

The model uncertainty, s local Lipschitz function, is presented by the function $f(x)$ in the equations. The bounded disturbance is included in the function $\varphi(x,w) \in R^r$which is considered as unknown input. By considering the Lipschitz property for the function$f(x)$, Equation (15) is obtained as follows:

$$\|f(x) - f(\hat{x})\| \leq \alpha \|F(x - \hat{x})\| \tag{15}$$

Consider the system in (14). To estimate the states, an unknown input observer is proposed as follows:

$$\begin{aligned} \dot{z} &= Sz + UBu + Uf(\hat{x}) + My \\ \hat{x} &= z + Ly \end{aligned} \tag{16}$$

x and state vector estimation where $\hat{x} \in R^{n_x}$ and $z \in R^{n_x}$ denote the estimation of x and state vector of (16), respectively. Also, $S \in R^{n_x \times n_x}$, $M \in R^{n_x \times n_y}$, $L \in R^{n_x \times n_y}$, and $U \in R^{n_x \times n_x}$are the observer gains which must be designed. The estimation error dynamics $e = x - \hat{x}$ can be calculated as follows, with $M = M_1 + M_2$:

$$\begin{aligned} e &= x - \hat{x} = x - z - Ly = (I_n - LC)x - z \\ \dot{e} &= (A - LCA - M_1C)e + (A - LCA - M_1C - S)z + [(A - LCA - M_1C)L - M_2]y \\ &\quad + [(I_n - LC)B - UB]u + (I_n - LC)f(x) - Uf(\hat{x}) + (I_n - LC)E\varphi(x,w) \end{aligned} \tag{17}$$

Now, if the following equations hold:

$$(I_n - LC)E = 0 \tag{18}$$

$$S = A - LCA - M_1C \tag{19}$$

$$U = I_n - LC \tag{20}$$

$$M_2 = SL \tag{21}$$

then (5) is simplified as follows:

$$\dot{e} = Se + (I_n - LC)(f(x) - f(\hat{x})) \tag{22}$$

The influences of state disturbances are completely decoupled in (22). The proposed method aims to design the matrix S so that the $\dot{e}$ is asymptotically stable. The following lemmas help obtain the theorem.

Lemma 1: For real matrices $H,\ G$and$\varepsilon > 0$:

$$H^TG + G^TH \le \varepsilon H^TH + \varepsilon^{-1}G^TG \tag{23}$$

Lemma 2 (Schur complement): The following inequalities are equivalent:

$$\begin{pmatrix} Q & T \\ T^T & N \end{pmatrix} > 0 \equiv \begin{cases} N > 0,\ \ Q - TN^{-1}T^T > 0 \\ Q > 0,\ N - T^TQ^{-1}T > 0 \end{cases} \tag{24}$$

where $Q = Q^T$and $N = N^T$are nonsingular matrices.

Theorem 1: Consider the system (14). A robust observer formed as (16) exists to decouple the influences of state-disturbances in the estimation error of the observer, provided that there exist matrices $P > 0$**,** Y**,** $W$and scaepsilon that the following inequality be feasible:

$$\begin{pmatrix} \begin{matrix} A^TP + PA - PaCA - WbCA - YC - C^TY^T - A^TC^Ta^TP \\ -A^TC^Tb^TW + \varepsilon\alpha^2F^TFI_n \end{matrix} & P - PaC - WaC \\ * & -\varepsilon I \end{pmatrix} < 0 \tag{25}$$

Where $Y = PM_1$, $W = PL_0$, $a = E(CE)^\dagger$, $b = I - (CE)(CE)^\dagger$, $L = a + L_0b$.

Proof. By considering the standard Lyapunov function, there is: $V(e) = e^TPe\,;\ \ P = P^T\ > 0$

The derivative of V is calculated as follows:

$$\begin{aligned} &\dot{V}(e) = \dot{e}^TPe + e^TP\dot{e} \\ &\Rightarrow \dot{V}(e) = e^T(A^TP + PA - PLCA - PM_1C - C^T(PM_1)^T - A^TC^TL^TP)e \\ &+e^TP(I_n - LC)(f(x) - f(\hat{x})) + (f(x) - f(\hat{x}))^T(I_n - LC)^TPe \end{aligned} \tag{26}$$

According to Lemma 1 and (2):

$$\begin{aligned} &e^TP(I_n - HC)(f(x) - f(\hat{x})) + (f(x) - f(\hat{x}))^T(I_n - LC)^TPe \\ &\le \frac{1}{\varepsilon}e^TP(I_n - LC)(I_n - LC)^TP^Te + \varepsilon \parallel f(x) - f(\hat{x}) \parallel^2 \\ &\le \frac{1}{\varepsilon}e^TP(I_n - LC)(I_n - LC)^TP^Te + \varepsilon\alpha^2e^TF^TFe \end{aligned} \tag{27}$$

By applying (27) in (26), the following Equation is obtained have:

$$\begin{aligned} &\dot{V}(e) \le e^T(A^TP + PA - PLCA - PM_1C - C^T(PM_1)^T - A^TC^TL^TP \\ &+\frac{1}{\varepsilon}P(I_n - LC)(I_n - LC)^TP^Te + \varepsilon\alpha^2F^TF)e \end{aligned} \tag{28}$$

Assuming$L = a + L_0b$, $a = E(CE)^\dagger, b = I - (CE)(CE)^\dagger, Y = PM_1$, and $W = PL_0$, (28) can be simplified as follows:

$$\dot{V}(e) \leq e^T(A^TP + PA - PaCA - WbCA - YC - C^TY^T - A^TC^Ta^TP - A^TC^Tb^TW + \frac{1}{\varepsilon}P(I_n - LC)(I_n - LC)^TP^T + \varepsilon\alpha^2F^TF)e \tag{29}$$

The designed observer estimation error will be asymptotically stable; therefore, Equation (30) is obtained:

$$A^TP + PA - PaCA - WbCA - YC - C^TY^T - A^TC^Ta^TP - A^TC^Tb^TW + \frac{1}{\varepsilon}P(I_n - LC)(I_n - LC)^TP^T + \varepsilon\alpha^2F^TF < 0 \tag{30}$$

Using Lemma 2, the inequality (25) is confirmed, and the proof of Theorem 1 is completed.

Lemma 3: The necessary and sufficient conditions for the UIO (16) to exist for the system (1) can be stated as follows:

1) $rank(CE) = rank(E)$
2) $((I - LC)A, C)$is a detectable pair

Proof: See [27].

4. Results and discussion

4.1.Simulation results

A comprehensive set of simulations has been run in the MATLAB version 2020 software to validate the suggested method, and the results are reported in this section. As described in the second section, a non-linear dynamic model has been applied in these simulations. Hardware requirements for the ideal computer system to run these simulations are as follows. 12 GB of RAM with an Intel Core i7-3537U processor operating at 2.00 GHz. These simulations use a pulse current with a 5-amp magnification, 500 seconds, and a 250% bandwidth as the input to the battery current model. In Figure 4, the estimated output voltage of the battery is shown next to its actual value as one of the state variables. This figure shows that the suggested estimator successfully estimated the output voltage with respectable accuracy and a minimum overshoot of 0.35 v. The suggested method also offers a fast-estimating speed, allowing for convergence in less than 7.5 seconds. Additionally, the battery SoC estimation is shown in Figure 5. In a manner, this figure also supports the earlier one. To put it another way, the suggested estimator has been able to estimate the SoC with a respectable accuracy of 0.34% better than the Ah-counting technique. It is also obvious in the second portion of this figure that the proposed approach's SoC estimation error is less than 0.35% of the Ah-counting method. The suggested method for SoC estimate also converges in less than 7.3 seconds at a respectable pace. Instead of an actual battery, a simulated battery model has always been employed in these simulations. Figures 6 and 7 in the battery's circuit model depict the expected voltage for two RC loops. These graphs compare the estimated voltages to their actual values taken from the simulated battery model. The accuracy of the suggested method is very high, as can be seen from this figure, and it has been able to predict these voltages with an overshoot of less than 2.4e-2 volts.

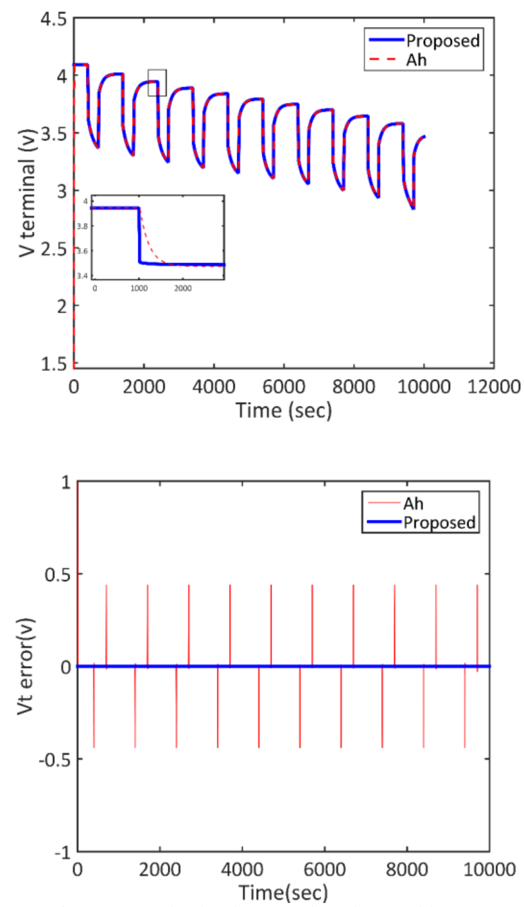

Fig. 4. Terminal voltage estimation and its error

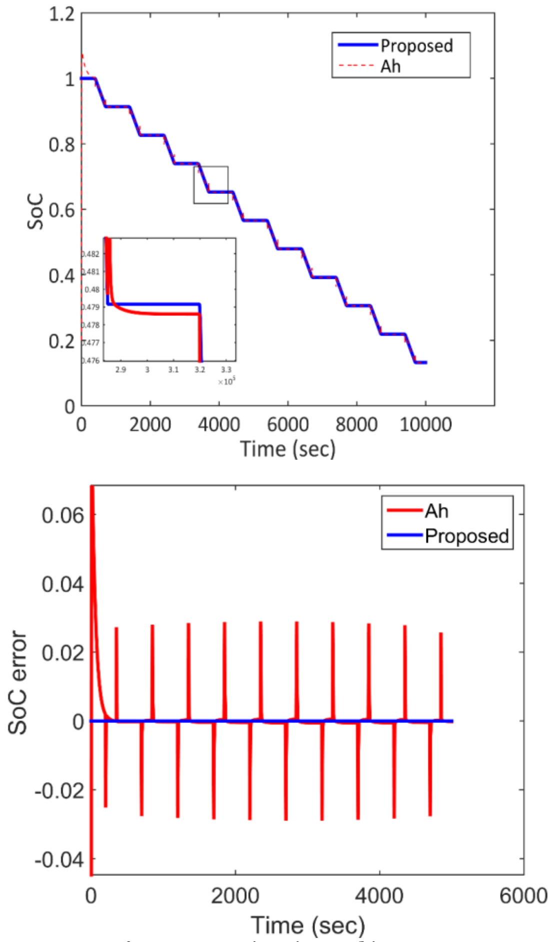

Fig. 5. SoC estimation and its error

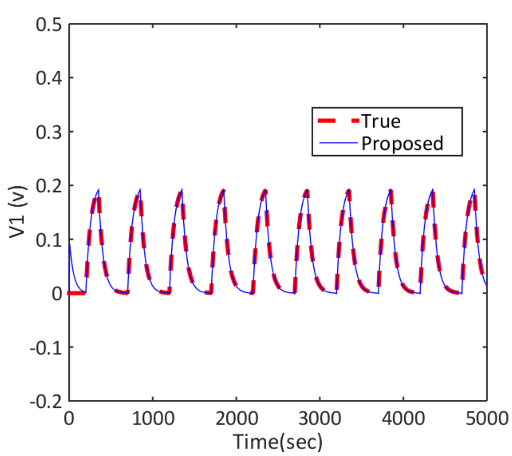

Fig. 6. V1 estimation

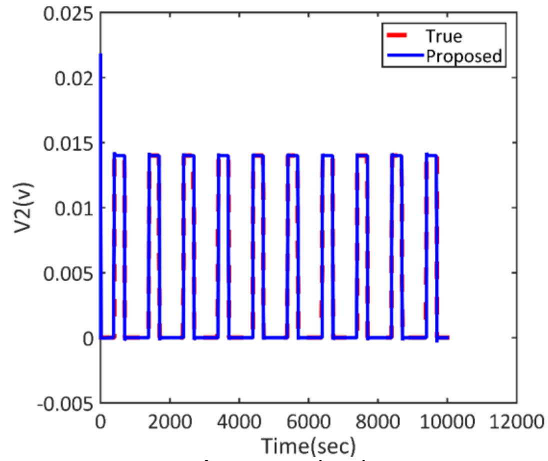

Fig. 7. V2 estimation

4.2. Software-in-the-Loop (SIL)

A series of lab tests have been carried out to evaluate the proposed method's performance using real-world data per Figure 8. This process involved simulating the proposed method using the voltage and current data from practical experiments and extracting the findings. In Figure 9, the performance outcomes of the suggested approach and the Ah-counting method are also contrasted. This statistic makes it evident that, in comparison to the Ah-counting approach, the proposed method has been able to estimate the battery charge level with an accuracy of 0.32%. Conversely, the proposed method's convergence rate is much faster than the Ah-counting method, allowing it to converge in less than 7.4 seconds.

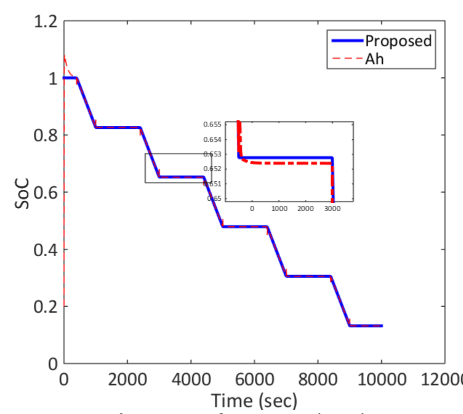

Fig. 8. SIL for SoC estimation

5. Conclusions

This paper tackled the disturbances and uncertainty problem for the SoC estimation in lithium-ion batteries and tried to eliminate the effect of the disturbances and model uncertainties. Also, the main superiority of this observer is the lack of chattering and complexity compared to other robust methods such as sliding mode observers and H∞. The results confirm the good performance of the proposed method and show that it is a good choice for large-scale applications. According to the results, the proposed observer can estimate the SoC more accurately than a commonly used SoC estimation method, Ah-counting, by as much as 0.32%.

The suggested method also offers a fast-estimating speed, allowing for convergence in less than 7.5 seconds. To put it another way, the suggested estimator has been able to estimate the SoC with a respectable accuracy of 0.34% better than the Ah-counting technique. It is also obvious that the proposed approach's SoC estimation error is less than 0.35% of the Ah-counting method. The suggested method for SoC estimate also converges in less than 7.3 seconds at a respectable pace. This method is a very good choice for applications in which the complexity of calculations and robustness against disturbance and model uncertainty are very important. The SoC estimation using a combined method, including machine learning and sliding mode observer, is suggested for future works.

COMPETING OF INTERESTS

The authors declare no competing interests.

AUTHORSHIP CONTRIBUTION STATEMENT

Omid Rezaei: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Mohammadali Faghih: Methodology, Software, Validation.

DATA AVAILABILITY STATEMENT

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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