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Strict Lyapunov super twisting observer design for state of charge prediction of lithium-ion batteries

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Abstract
The effective implementation of battery management system (BMS) in various applications such as electric vehicles (EVs), renewable energy sources (RES) integrated smart-grids and micro-grids, necessitates accurate estimation of the battery parameters and states. This paper primarily focuses on offering an improved solution to the state of charge (SOC) estimation problem of lithium-ion (Li-ion) batteries. After extensive analysis of the current state-of-the-art methods, a new strict Lyapunov super twisting algorithm (SLSTA) based approach is proposed for precise estimation of SOC under a comprehensive range of uncertainties. The error convergence and robustness of the proposed state observer are demonstrated using Lyapunov stability theory. Since the modelling parameters of the battery equivalent circuit utilised in this paper vary with various operational and external factors, a standard online method is employed for their real-time identification. The presented method is executed on a lithium-polymer (LiPo) battery with the help of a dynamic stress test (DST). The experimental results demonstrate that the proposed approach outperforms the well-known approaches in terms of accuracy, computational complexity, and convergence time.

1 INTRODUCTION

Due to the environmental awareness and cost-effectiveness, there is a swift increase in the popularity of electric vehicles (EVs) and use of renewable energy sources (RES) in smart-grids and micro-grids in recent years. The availability of solar and wind energy is intermittent in nature. Hence, an energy storage system such as battery is required to store the energy when available and use it later when needed. Lithium-ion (Li-ion) batteries are widely recognised due to their high density, low self-discharge and low maintenance. In smart-grid, battery can be used for the purpose of peak shaving, voltage regulation and frequency regulation by storing or feeding energy [1]. In micro-grids, intermittent RES are integrated with the battery so that it can store energy in off-peak hours and supply energy in peak hours or during the unavailability of renewable energy [2]. It can also assist in some emergency situations. The electric vehicles use battery as the primary source of energy [3]. Hence, we need a battery management system (BMS) which helps to prevent overcharging and undercharging of battery, increases its capacity utilisation and lifespan, improves reliability, reduces cost, and ensures safety of the battery and its surroundings.

The effective implementation of BMS demands precise estimation of the state of charge (SOC) of the battery for its efficient working [4]. SOC reflects the battery’s unutilised capacity and is defined as the ratio of its residual capacity to its nominal capacity. Such an important parameter is not available for direct measurement by any sensor. The highly nonlinear nature of Li-ion battery has made the accurate estimation of SOC a very challenging task.

In recent years, efforts have been made by many researchers to propose some indirect methods for predicting SOC of a Li-ion battery accurately. The ampere-hour (Ah) method integrates the battery terminal current over a time-period and is used in various applications due to its simple structure [5]. The expression of Ah method to calculate SOC is given as:

$$SOC(t) = SOC(t_0) - \int \frac{\eta i(\tau)}{C_n} d\tau,$$

where $\eta$ is the cell material efficiency, $i(\tau)$ is the battery terminal current, $C_n$ is the nominal capacity of the battery, $SOC(t_0)$ is the initial SOC and $t$ is the time.

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where \( SOC(h_0) \) is the initial value of \( SOC \), \( i(\tau) \) is the instantaneous value of current with \( i(t) > 0 \) for charging and \( i(t) < 0 \) for discharging of the battery, \( C_n \) is the nominal capacitance and \( \eta \) is the coulombic efficiency. It can be observed from (1) that this open-loop method fails to provide an accurate precision of \( SOC \) due to the lack of prior knowledge of initial \( SOC \) and presence of current sensor noise. The open-circuit voltage (OCV) method is employed to predict the battery \( SOC \) utilising the relationship between \( SOC \) and OCV [6]. However, OCV is obtained by disconnection of load followed by a long rest period. Hence, this method is not suitable for online applications. In some approaches [7–10], the battery is assumed as a black box, and intelligent algorithms such as support vector machine and various neural network algorithms are applied to estimate the \( SOC \). The detailed information of the system is not required to implement these algorithms. However, they demand a bulk of training data leading to a high computational burden.

In [11], Kalman filter (KF) is combined with Ah method for \( SOC \) prediction of a battery. KF is generally used only for state estimation of linear models. For nonlinear models, extended Kalman filter (EKF) and adaptive EKF techniques are utilised [3, 12]. They approximate the nonlinear model to the linear one by using Taylor series expansion. This approximation causes error in predicting battery \( SOC \). Iterated EKF (IEKF), sigma point Kalman filter (SPKF), square root central difference Kalman filter (SRCDKF), unscented Kalman filter (UKF) and adaptive UKF (AUKF) overcome this problem and show better performance [13–17]. However, the EKF and UKF based methods need accurate information about the battery model and various statistical properties of the noise, and the recursive computation of various matrices makes these KF based methods computationally complex.

Many observer-based methods such as Luenberger observer, \( H_{\infty} \) observer, proportional-integral (PI) observer, nonlinear observer and sliding mode observer (SMO) have been proposed recently for battery \( SOC \) estimation [18–22]. These methods show better computation complexity compared to that of EKF and UKF [23]. The sliding mode algorithm is one of the most simple and powerful nonlinear observer-based method known for its robustness property against modelling uncertainties, measurement noise, and external disturbance. The superiority of SMO in terms of code complexity, computational time, and memory usage over KF based methods for \( SOC \) estimation purpose is also demonstrated in [24]. In [25], the first order sliding mode is utilised for \( SOC \) estimation, where the gains are obtained offline. The main disadvantage with sliding mode methods is chattering due to the discontinuous control injection and finite frequency, which reduces its accuracy. Moreover, there is a need for low pass filter to extract the estimated signal from these methods, which incurs phase lag and further affects the estimation accuracy. The adaptive gain sliding mode observer (AGSMO), second-order sliding mode observer (SOSMO) and time-varying discrete sliding mode observer (TVDSMO) are employed for \( SOC \) estimation to reduce the chattering [26–29]. They still use the discontinuous control injection and low pass filter for implementation. There are very limited related works that have fully investigated the problem of battery \( SOC \) estimation discussing these issues. So, the challenges to the research community are to improve chattering and eliminate the need of low pass filter, keeping all the other advantages of first order SMO, which motivates this research work.

The super twisting algorithm (STA) is a special kind of second-order sliding mode approach which is well-known for its superiority over other sliding mode methods. It provides continuous control input and demands lesser information and a reduced number of sensors. Recently in [30, 31], conventional STA is utilised for designing the \( SOC \) observer, where the uncertainties considered for designing the robust observer are restricted. This limitation makes the implementation of these approaches infeasible in physical systems where sensor noise and modelling uncertainties can not be ignored. In [31], the STA provides asymptotic stability to only a few error states and exponential stability to the other error states. It creates serious problem if anyone wishes to design a charging controller which uses the estimated states. Moreover, in both [30] and [31], the battery model parameters are assumed to be fixed, which is impractical due to the variation of these parameters with C-rate, \( SOC \), temperature, and ageing. Hence, there is a need for such \( SOC \) estimation method which can provide continuous control input, finite-time convergence, and robustness for a more comprehensive class of uncertainties with real-time identification of the battery model parameters.

In this paper, we propose a new approach for \( SOC \) estimation using strict Lyapunov super twisting algorithm (SLSTA) based observer.1 The main advantages of the proposed observer are: (i) it utilises continuous control injection and reduces chattering significantly, (ii) it deals with a more comprehensive class of uncertainties compared to conventional STA based observer used for battery \( SOC \) estimation, (iii) it eliminates the need of low pass filter to extract the estimated signal which incurs phase lag and affects the estimation accuracy in most of the sliding mode methods, and (iv) it provides finite-time stability of the states rather than asymptotic stability. A standard online approach based on recursive least-square with forgetting (RLSF) is utilised to identify the real-time battery model parameters. Since RLSF approach updates the battery model parameters dynamically as per the current operating condition, the modelling of their slow change due to temperature and ageing can be avoided. The SLSTA based observer, in combination with the RLSF approach, attenuates the influence of the various uncertainties and provides a significant improvement in estimating \( SOC \) compared to the other sliding mode observer based \( SOC \) estimation methods in literature. The proposed technique is implemented on an actual battery set-up by performing a dynamic stress test (DST) on it. The experimental results demonstrate that the proposed approach performs better than the various established approaches in terms of accuracy, computational complexity, and convergence time.

The organisation of the rest of the paper consists of four sections. Section 2 explains the dynamics of the Li-ion battery model and its parameter identification. The design procedure

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1 https://github.com/sethiagautam/Estimation-of-SOC.git
of the proposed state observer is detailed in Section 3. Section 4 demonstrates the experimental results of the proposed technique and compares them with other existing methods for verification of its superiority. Finally, the paper is concluded in Section 5.

2 BATTERY MODELLING

Due to highly nonlinear nature and complex electrochemical phenomena inside a Li-ion battery, it is difficult to derive its equivalent model accurately. Out of the existing battery models, electrochemical and electrical equivalent models are the most popular [32]. For estimation and control, the electrical equivalent models are preferred as they can be analysed mathematically without having knowledge of the electro-chemistry of the battery. Depending upon the application, various electrical equivalent models of Li-ion battery have been proposed in recent years. Among them, RC model, Thevenin model and 2-RC model are the most popular [28, 32–34].

In this work, we utilise RC model [28, 34] to represent the dynamics of the Li-ion battery due to its excellent balance between simplicity and accuracy. It is shown in Figure 1, where \( C_n \) denotes the nominal capacitance which gives information about the charge storage capacity of the battery; \( C_c \) indicates the diffusion capacitance; \( R_e \), \( R_t \) and \( R_i \) represent battery terminal resistance, end resistance and diffusion resistance, respectively. The voltages across \( C_n \) and \( C_c \) are denoted by \( V_{oc}(t) \) (OCV) and \( V_c(t) \), respectively. The terminal voltage \( V(t) \) and the terminal current \( i(t) \) are the only two measurable quantities. The following equations illustrate the behaviour of the battery equivalent circuit model (BECM):

\[
V(t) = i(t)R_e + i_c(t)R_t + V_c(t),
\]

\[
V(t) = i(t)R_e + i_c(t)R_t + V_{oc}(t),
\]

\[
\dot{V}_{oc}(t) = \frac{i(t)}{C_n},
\]

\[
\dot{V}_c(t) = \frac{i(t)}{C_c},
\]

\[
i(t) = i_c(t) + i_i(t).
\]

For simplicity, based on [28, 34], it is assumed that \( R_i \) and \( R_t \) are equivalent. Equating (2) and (3) and then using (4)-(6) yield the following:

\[
\dot{V}_{oc}(t) = \frac{i(t)R_e + V'_c(t) - V_{oc}(t)}{2R_eC_n},
\]

\[
\dot{V}_c(t) = \frac{i(t)R_e - V'_c(t) + V_{oc}(t)}{2R_tC_c},
\]

Adding (2) and (3), we get

\[
V(t) = 0.5V_{oc}(t) + 0.5V_c(t) + (R_e + R_t/2)i(t).
\]

Substituting \( V_c(t) \) from (9) in (7) and (8), we get

\[
\dot{V}_{oc}(t) = \frac{V(t) - V_{oc}(t) - i(t)R_e}{R_eC_n},
\]

\[
\dot{V}_c(t) = \frac{V_c(t) - V(t) + i(t)(R_e + R_t)k}{R_tC_c},
\]

The time derivative of terminal voltage \( V'(t) \) is derived by differentiating both sides in (9) and then substituting (10) and (11) as:

\[
V'(t) = \left( \frac{C_c - C_n}{2R_eC_nC_c} \right) V(t) + \left( \frac{C_n - C_c}{2R_eC_nC_c} \right) V_{oc}(t)
\]

\[
+ \left( \frac{C_nR_t + C_cR_e - C_cR_t}{2R_cC_nC_c} \right) i(t) + (R_e + R_t/2)i(t).
\]

In general, the relationship between OCV and SOC is nonlinear and can be approximated with a very high order polynomial. However, such a relationship will make the SOC observer design very complicated. Hence, in this paper, the SOC–OCV relationship is considered to be piecewise linear because of the approximately linear behaviour of SOC–OCV curve for a small range of SOC [21, 26]. Since the curve is slowly time-varying with various factors such as ageing and temperature, the relationship between OCV and SOC is assumed to be fixed. The SOC–OCV relationship is approximated as:

\[
V_{oc}(t) = p \cdot SOC(t) + q + \Delta f_1,
\]

where \( \Delta f_1 \) is the nonlinearity present in SOC–OCV relationship, \( p \) and \( q \) are distinct constants corresponding to distinct SOC range, which can be determined by fitting of (13) in SOC–OCV curve. For a battery system, it can be inferred from the existing literature that \( p \) and \( q \) are positive [21, 26]. In this paper, the derivation of SOC–OCV curve is explained for the test battery in Section 4.2.

Using (13), (12) can be rewritten as:

\[
\dot{V}'(t) = -a_1 V'(t) + a_2 SOC(t) + q_1 i(t) + q_2 \dot{i}(t) + a_3 q + \Delta f_2,
\]

\[
\dot{V}'(t) = -a_1 V'(t) + a_2 SOC(t) + q_1 i(t) + q_2 \dot{i}(t) + a_3 q + \Delta f_2,
\]
where
\[
a_1 = \frac{C_a - C_i}{2R_cC_i}, \quad q_2 = R_t + R_f/2,
\]
\[
a_2 = a_1 p, \quad q_1 = \frac{C_aR_t + C_iR_t - C_iR_i}{2R_cC_i}.
\]

Using (13) in (10), we get
\[
\dot{SO\tilde{C}}(t) = b_2V(t) - b_1SOC(t) - b_2q + q_1 i(t) + \Delta f_i,
\]
where \( b_1 = 1/R_cC_i, b_2 = b_1/p, q_1 = q_3/p, q_3 = -1/C_a \) and \( \Delta f_i \) is the small error due to the approximation of relationship between \( p \) and \( q \) as given in (13). It can be observed that the parameters \( a_1, a_2, b_1, q_1, q_2 \) are positive and \( q_3 \) is negative.

Considering \( x_1(t) = V(t), \quad x_2(t) = SO\tilde{C}(t), \quad y(t) = V(t), \quad u_1(t) = i(t) \) and \( u_2(t) = i(t) \), (14) and (16) can be rewritten as:
\[
\dot{x}_1(t) = -a_1 x_1(t) + a_1 x_2(t) + q_1 u_1(t) + q_2 u_2(t) + a_1 q + \xi_1,
\]
\[
\dot{x}_2(t) = b_2 x_1(t) - b_1 x_2(t) - b_2 q + q_4 u_1(t) + \xi_2,
\]
\[
y(t) = x_1(t) + \Delta f_i,
\]
where \( \xi_1(t, n) = \Delta f_2 + \Delta f_3, \quad \xi_2(t, n) = \Delta f_3 + \Delta f_6, \quad \Delta f_4, \quad \Delta f_5 \) and \( \Delta f_6 \) are the uncertainties due to measurement noise, modelling accuracy and external disturbances. From the observability test, it is easy to conclude that if \( C_a \neq C_i \), the system considered above is observable. In a practical battery \( C_a \gg C_i \), hence the system is always observable.

The transfer function of the battery model is obtained from (10) and (12) as follows:
\[
Y(s) = \frac{b^2 + \alpha s + d}{s^2 + \alpha s + d},
\]
where
\[
a = \frac{C_a + C_i}{2R_cC_i}, \quad c = \frac{(C_a + C_i)(R_t + R_f)}{2R_cC_i},
\]
\[
b = R_t + R_f/2, \quad d = \frac{1}{2R_cC_i}.
\]

The modelling parameters such as resistance and capacitance change with various factors such as C-rate, SOC, temperature, and ageing. Ordinary recursive least square (ORLS) is being used extensively by many researchers for the purpose of BECM parameter identification [35]. To improve the identification error of ORLS, its variants have been used recently for battery parameter identification such as RLS with forgetting factor (RLSF) [7, 15], weighted RLS [36], recursive extended least square (RELS) [37], moving window RLS [38] etc. All the methods are primarily differentiated by the way they provide weight to the data samples. In this paper, we use standard RLSF approach for identification of the battery model parameters. Unlike the ORLS, in this approach, more weight is assigned to the recent data than the older data. Moreover, the covariance becomes zero with time in ORLS, after which the parameters will not get updated further. Introduction of forgetting factor slows down the fading of the covariance matrix and reduces the identification error.

To implement the RLSF algorithm, the transfer function in (20) is first discretised using the bilinear transformation \( s = \frac{2}{T} \frac{1 - z^{-1}}{1 + z^{-1}} \), and is obtained as follows:
\[
\frac{Y(z^{-1})}{U_1(z^{-1})} = \frac{d_0 + d_1 \xi^{-1} + d_2 \xi^{-2}}{1 + c_1 \xi^{-1} + c_2 \xi^{-2}},
\]
where
\[
c_1 = \frac{-4}{2 + aT}, \quad c_2 = \frac{2 - aT}{2 + aT}, \quad d_1 = \frac{T^2 - 4b}{2 + aT},
\]
\[
d_0 = \frac{4b + 2cT + 2T^2}{2(2 + aT)}, \quad d_2 = \frac{4b - 2cT + 2T^2}{2(2 + aT)}.
\]

‘\( T \)’ is the sampling time and ‘\( \xi^{-1} \)’ is the unit backward shift operator.

The difference equation of the battery model from (22) is obtained as follows:
\[
y(k) = \phi^T (k) \theta(k) + \Delta n,
\]
where \( \Delta n \) is the white noise present in the system, \( \theta(k) \) is the regressor vector and \( \phi(k) \) is the parameter vector. The vectors \( \theta(k) \) and \( \phi(k) \) are given as:
\[
\theta(k) = \begin{bmatrix} y(k-1) & y(k-2) & u_1(k) & u_1(k-1) & u_1(k-2) \end{bmatrix}^T,
\]
\[
\phi(k) = [-c_1 \quad -c_2 \quad d_0 \quad d_1 \quad d_2]^T.
\]

The relationship between \( \phi(k) \) and \( a, b, c, d \) are obtained using (23) and given as:
\[
a = \frac{2(1 - c_1)}{T(1 + c_2)}, \quad b = \frac{d_0 + d_2 - d_1}{2(1 + c_2)},
\]
\[
c = \frac{2(d_0 - d_1)}{T(1 + c_2)}, \quad d = \frac{2(d_0 + d_1 - d_2)}{T^2(1 + c_2)}.
\]

The following set of equations, which govern the RLSF algorithm are used to estimate the parameter vector \( \phi(k) \):
\[
\phi(k) = \phi(k-1) + H(k)[y(k) - \hat{\phi}^T (k) \theta(k)],
\]
\[
H(k) = \frac{G(k-1) \theta(k)}{\lambda + \theta^T (k) G(k-1) \theta(k)},
\]
\[
G(k) = \frac{1}{\lambda} [G(k-1) - H(k) \theta^T (k) G(k-1)],
\]
where $\hat{\phi}(k)$ is the estimated value of $\phi(k)$, $\lambda$ is the forgetting factor which generally lies in the range of $[0.95, 1]$, $H(k)$ is the gain which determines the effect of the current prediction error on the update of the parameter estimate and $G(k)$ is the covariance matrix of the estimated parameters.

From $\hat{\phi}(k)$ and (25), the estimated values of $a, b, c, d$ are obtained. The estimated resistances and capacitances in the battery model are derived using (21) as follows:

$$R_r = 2b - \tilde{c} - \frac{\tilde{c}}{a}, \quad R_i = R_r = 2\left(\frac{\tilde{c}}{a} - b\right),$$

$$\zeta_n = \frac{1}{2} \left[ \frac{\hat{\lambda}}{a} + \left( \frac{\hat{\lambda}^2}{a^2} - \frac{\hat{\lambda}}{(\tilde{c} - \hat{a}b)d} \right)^{1/2} \right],$$

$$\zeta_i = \frac{1}{2} \left[ \frac{\hat{\lambda}}{a} - \left( \frac{\hat{\lambda}^2}{a^2} - \frac{\hat{\lambda}}{(\tilde{c} - \hat{a}b)d} \right)^{1/2} \right],$$

where ‘$\hat{\phi}$’ denotes the estimated value of ‘$\phi$’. Finally, the estimated values of parameters $a_1, b_1, q_1$ and $q_3$ defined in (13) and (16) are calculated using (27).

### 3 DESIGN OF STATE OBSERVER USING STRICT LYAPUNOV BASED SUPER TWISTING ALGORITHM

In this section, a novel SLSTA based observer design procedure for estimation of battery states is presented. The proposed observer provides a continuous control input to propel the sliding variable and its derivative to zero in finite time. It also shows robustness against a more comprehensive class of uncertainties compared to the conventional STA [39]. Conventional STA does not explain how the convergence is affected if both $\xi_1$ and $\xi_2$ in (17) and (18) are non-zero together. The proposed observer overcomes this limitation.

In order to design the observer, we assume that the rate of change of terminal current is negligible. This assumption is valid since the current is almost constant between two sampling instants. The proposed observer designed to estimate the battery states is as follows:

$$\dot{\hat{x}}_1(t) = -\hat{a}_1y(t) + \hat{a}_2\hat{x}_2(t) + \hat{q}_1u_1(t) + \hat{a}_1q + \gamma |\tilde{x}_1|^{1/2} \text{sgn}(\tilde{x}_1)$$

$$\dot{\hat{x}}_2(t) = \hat{b}_2y(t) - \hat{b}_1\hat{x}_2(t) - \hat{b}_2q + \hat{q}_1u_1(t) + \hat{b}_2q + \gamma |\tilde{x}_1|^{1/2} \text{sgn}(\tilde{x}_1),$$

where ‘$\hat{x}$’ denotes the estimated value of ‘$x$’, $\gamma = \gamma_1 \sqrt{\hat{a}_2}, \tilde{x}_1 = x_1 - \hat{x}_1$ and

$$\text{sgn}(\tilde{x}) = \begin{cases} 1, & \text{if } \tilde{x} > 0 \\ -1, & \text{if } \tilde{x} < 0 \\ \in [-1, 1], & \text{if } \tilde{x} = 0 \end{cases}$$

Consider, the error in estimating battery model parameters as:

$$\Delta a_1 = a_1 - \hat{a}_1, \quad \Delta b_1 = b_1 - \hat{b}_1,$$

$$\Delta q_1 = q_1 - \hat{q}_1, \quad \Delta q_3 = q_3 - \hat{q}_3.$$  \hspace{1cm} (29)

The error dynamics using (17)–(19) and (28) and (29) is as follows:

$$\dot{\tilde{x}}_1 = \tilde{a}_2\tilde{x}_2 - y|\tilde{x}_1|^{1/2} \text{sgn}(\tilde{x}_1) + F_1(x_1, \xi, t, u),$$

$$\dot{\tilde{x}}_2 = -\tilde{b}_2 \text{sgn}(\tilde{x}_1) + F_2(x_1, \xi, t, u),$$

where $\tilde{x}_2 = x_2 - \hat{x}_2$.

$$F_2(x_1, \xi, t, u) = -\hat{b}_2\Delta f_4 + \Delta b_2y - b_1\hat{x}_2 - \Delta b_1\hat{x}_2 - \Delta b_2q - \Delta q_4u_1 + \xi_2(x_1, t, u),$$

$$F_1(x_1, \xi, t, u) = a_1\Delta f_4 - \Delta a_1y + \Delta a_2\hat{x}_2 + \Delta q_3u_1 + \Delta a_1q + \xi'_1(x_1, t, u).$$  \hspace{1cm} (31)

Since the battery is a physical system, its terminal voltage, SOC, input current and their derivatives are bounded. The value of SOC also lies in $[0, 1]$. The control input injection of the observer is continuous which makes the derivative of the estimated terminal voltage bounded as well. Considering the uncertainties $\xi_1, \xi_2$ and $\Delta f_4$ bounded, the following inequalities are satisfied:

$$|F_2(x_1, \xi, t, u)| \leq f^+, \quad |F_1(x_1, \xi, t, u)| \leq \varphi_1 + \varphi_2(|\tilde{x}_1| + \hat{a}_2\tilde{x}_2^2)^{1/2},$$  \hspace{1cm} (32)

where $f^+, \varphi_1$ and $\varphi_2$ are positive constants.

**Theorem 1.** Suppose the perturbations to the system (30) is bounded by (32). Then, the following choice of $\tilde{\beta}$ and $\gamma_1$ guarantee the finite-time convergence or global ultimate boundedness of the states:

$$\gamma_1 = \Psi \sqrt{\frac{2k_2f^+}{(1 - k_1)\sigma}},$$

$$\tilde{\beta} = \frac{(1 + k_1)f^+}{(1 - k_1)},$$

provided the following inequality is satisfied

$$\Psi - \frac{2}{k_2} > \sigma^2 - k_1(1 + \Psi)\sigma + \frac{1}{4}(1 + \Psi)^2,$$  \hspace{1cm} (35)

where $0 < k_1 < 1$, $k_2 > 1$, $\Psi$ and $\sigma$ are positive constants. Convergence or ultimate boundedness depends on the value of $\varphi_1$ and $\varphi_2$. When $\varphi_1 = 0$
where $\dot{\Phi} = \Phi^T P \Phi$, where $\Phi = [\Phi_1, \Phi_2] = [e_1, e_2]$ and $P = [p_{ij}]$ is a constant symmetric positive definite matrix. It can be observed that, $\Phi = 0$ ensures $e_1 = e_2 = 0$. It is well known from geometric/Lyapunov methods that if $\gamma > 0$ and $\beta_1 > 0$, then the trajectories will converge to the equilibrium point $e_1 = e_2 = 0$ for $F_1 = F_3 = 0$.

The derivative of $\Phi$ can be written as:

$$\dot{\Phi} = \frac{1}{|\Phi_1|} A_1 \Phi,$$

where

$$A_1 = \begin{bmatrix} -0.5\gamma & 0.5 \\ -\beta_1 & 0 \end{bmatrix},$$

is Hurwitz. Hence, there always exists a symmetric positive matrix $Q_1 = [q_{ij}]$ such that the following Algebraic Riccati equation (ARE) is satisfied:

$$A_1^T P + PA_1 = -Q_1.$$  \hspace{1cm} (40)

The derivative of $\dot{\nu}(\tilde{x})$ using (38) and (39) is obtained as:

$$\dot{\nu}(\tilde{x}) = \frac{1}{|e_1|^2} \Phi^T Q_1 \Phi + \frac{2}{|e_1|^2} \left[ F_1 q_{12} \right] \Phi.$$

(41)

Using (32) and (37), $\dot{\nu}(\tilde{x})$ is rewritten as:

$$\dot{\nu}(\tilde{x}) = |e_1|^{-\frac{1}{2}} \left\{ \Phi^T \left[ A_2^T (t, \nu) P + P A_2 (t, \nu) \right] \Phi + [F_1, 0] \Phi \right\}.$$

(42)

where

$$A_2 (t, \nu) = \begin{bmatrix} -\frac{1}{2} \gamma & -\frac{1}{2} \\ F_3 q_{12} (\nu) - \beta_1 & 0 \end{bmatrix}.$$  \hspace{1cm} (43)

From (38) and (42), it can be seen that $\nu(\tilde{x})$ is positive definite and $A_2^T (t, \nu) P + P A_2 (t, \nu)$ is negative definite if the following inequalities are satisfied:

$$p_{22} > p_{12}^2, \quad p_{12} < 0,$$

$$\gamma p_{12} + 0.25(1 - \gamma p_{12})^2 + 2p_{12}^2 (\beta_1 - F_3 q_{12}(\nu_1))$$

$$-(1 - \gamma p_{12} p_{22}) (\beta_1 - F_3 q_{12}(\nu_1)) + (\beta_1 - F_3 q_{12}(\nu_1))^2 p_{22} < 0.$$  \hspace{1cm} (44)

Using this fact, it follows that (43) will be satisfied if (35) is true, where

$$\Psi = -\gamma p_{12}, \quad k_2 = \frac{p_{22}}{p_{12}}, \quad \sigma = p_{22}(\beta_1 + f_1^+), \quad k_1 \equiv \frac{\beta_1 - f_1^+}{\beta_1 + f_1^+},$$

(45)

Using the fact

$$\lambda_{\text{max}}(Q_2) \| \Phi \|_2 \leq \Phi^T Q_2 \Phi \leq \lambda_{\text{max}}(Q_2) \| \Phi \|_2^2,$$

we obtain

$$\psi(\tilde{x}) \leq -|e_1|^{-\frac{1}{2}} \left[ \lambda_{\text{max}}(Q_2) \| \Phi \|_2^2 - (\phi_1 + \phi_2) \| \Phi \|_2 \| \Phi \|_2 \right],$$

$$\leq -\left[ \lambda_{\text{min}}(Q_2) - \phi_2 \varepsilon \right] \| \Phi \|_2 + \phi_1 \varepsilon,$$

where $\varepsilon = (1 + p_{12})^{1/2}$. When $\phi_2$ is small (i.e. $\phi_2 < \lambda_{\text{max}}(Q_2)/\varepsilon$), the following holds for every $\phi_1$:

$$\psi(\tilde{x}) \leq -\left[ \lambda_{\text{max}}(Q_2) - \phi_2 \varepsilon \right] \| \Phi \|_2 + (1 - d) \| \Phi \|_2 \| \Phi \|_2 + \phi_1 \varepsilon.$$
\[
\leq -\frac{d[\lambda_{\text{min}}(Q_2) - \varphi_2\varepsilon]}{\lambda_{\text{max}}^1(P_1)}\nu^{1/2}(\varepsilon), \quad \forall \|\Phi\|_2 \geq \mu, \tag{47}
\]

where \(0 < d < 1\) is a constant and
\[
\mu = \varphi_1\varepsilon \frac{1}{(1 - d)[\lambda_{\text{min}}(Q_2) - \varphi_2\varepsilon]}.
\]

Since
\[
\lambda_{\text{min}}(P)\|\Phi\|_2^2 \leq \nu(\varepsilon) \leq \lambda_{\text{max}}(P)\|\Phi\|_2^2, \tag{48}
\]

we can write
\[
\|\Phi\| \leq \frac{\nu^{1/2}(\varepsilon)}{\lambda_{\text{min}}^1(P_1)}. \tag{49}
\]

Therefore, the trajectory which enters
\[
\Gamma = \{\varepsilon \in \mathbb{R}^2 | \nu(\varepsilon) \leq \lambda_{\text{max}}(P)\mu^2\}, \tag{50}
\]
in finite time, stays there for all future time such that
\[
\|\Phi\| \leq \lambda_{\text{max}}^1(P)\mu \frac{1}{\lambda_{\text{min}}^1(P)} \tag{51}
\]

Equation (51) guarantees that after convergence, the error trajectories will always remain bounded by a small region around equilibrium even in the presence of various uncertainties. It can be seen that if \(\varphi_1 = 0\), the error dynamics converge to the origin. This completes the proof of robust stability of the observer.

The quadratic strict Lyapunov function used in (38) is not unique, and the convergence is proven for a family of quadratic strict Lyapunov functions. For each \(P\) matrix satisfying (46) and (35), we get a unique Lyapunov function member of the family. Inequality (35) represents the interior of an ellipse in the plane \((\Psi, \sigma)\) parameterised by any arbitrary \((k_1, k_2)\) satisfying \(0 < k_1 < 1, k_2 > 1\). Hence, any point inside this ellipse can be chosen to design the \(P\) matrix. The freedom in selecting the Lyapunov function can be used for different applications. The \(P\) matrix can be chosen from the experience of the system to get the best results for different applications. One such application is given in [41], where a selection method of Lyapunov function is suggested to optimise the value of maximum possible reaching time.

4 | EXPERIMENTAL RESULTS

In this section, the experimental results of the proposed approach for SOC estimation are demonstrated in four separate subsections. Section 4.1 presents the set-up used to perform all the required tests. In Section 4.2, the relationship between SOC and OCV for the test battery is established. Section 4.3 illustrates the identification of BECM parameters and designs the proposed SOC observer. Finally, Section 4.4 shows the results of the proposed method and compares them with a few well-established methods in various aspects such as accuracy, computational time, convergence time, and chattering width. Figure 2 shows the structure of the proposed approach.

4.1 | Experimental set-up

To evaluate the performance and efficiency of the proposed approach, a LiPo battery (BDE6S73104P) of nominal capacity 5000 mAh is considered as shown in Figure 3(a). The dimension of the battery is 90 mm × 60 mm × 5 mm and, it weighs 110 g. The full charge, nominal, and cut off voltages are 4.2 V, 3.7 V, and 3.25 V, respectively. The experiments are performed using a battery testing equipment (BioLogic VMP3), having 16 independent channels. It has a voltage range of ±20 V and the current range of 10 μA–400 mA. The maximum current is enhanced to 10 A using an external booster VMP3B-10 along with BioLogic VMP3 for making it ideal for the experiments. The accuracy of the voltage and the current sensors are very high with resolutions of 5 μV and 760 pA, respectively. The battery testing equipment, as well as the external booster, is shown in Figure 3b. The set-up provides the necessary current and voltage to control the charging and the discharging process through a software known as EC-Lab.
4.2 Relationship between OCV and SOC

In this paper, the relationship between OCV and SOC is obtained by first discharging the LiPo battery from its fully charged state to the fully discharged state and then charging it back to the initial state. Instead of a unidirectional current test, both charge and discharge tests are performed to consider the effect of hysteresis phenomena taking place inside the battery [33]. Before starting the discharge test, the battery is ensured to be fully charged, that is, 4.2 V. A constant discharge current with C/40 rate is then applied to the battery until the battery voltage becomes equal to the cut-off voltage, that is, 3.25 V. This sufficiently small C-rate makes battery terminal voltage and OCV almost equal. After that, a constant voltage discharging is done until the current becomes very small (C/80). Similarly, the cell is again charged with C/40 rate up to the peak voltage, followed by a constant voltage charging until the current reduced to C/80. The terminal voltage versus time data is recorded in the host computer during the process. The SOC is also counted at each sampling instant using coulomb counting method. Figure 4 shows the SOC versus OCV characteristics for the concerned LiPo battery for both charging and discharging process. Finally, the average of both curves is considered as the true OCV. Since the OCV-SOC curve is almost linear for a small SOC range, the values of $p$ and $q$ in (13) for a few SOC range are approximated and shown in Table 1.

4.3 Battery model parameter identification and design of proposed observer

To identify the battery model parameters, a dynamic stress test (DST) is performed in which a few cycles of dynamic stress current profile (DSCP), as shown in Figure 5, is loaded into the LiPo battery. This current profile reflects the fluctuations in battery terminal current while an electric vehicle runs in the city traffic condition. The battery terminal voltage is recorded at every sampling instant and is shown in Figure 6 as ‘Actual’. The present and the previous terminal voltages and current data are utilised to identify $\phi(k)$ at every sampling instant using (26), as explained in Section 2. The sampling time $1\text{ s}$ and forgetting factor $0.95$ are used for this purpose. Then, the relationship, as given in (25), is used to obtain the unknown transfer function parameters $a, b, c$ and $d$, whose values are updated recursively. These values are further utilised to obtain the time-variant battery model resistances and capacitances using (27). The variation of parameters can be seen in Figure 7. Since RLSF approach updates these parameters dynamically as per the current operating condition, the modelling of their changes due to temperature and ageing can be avoided. Finally, the SLSTA based observer parameters are updated using (15) and (16).

Keeping the inequality (33) in mind, we consider $k_{1} = 7.83 \times 10^{-1}$, $k_{2} = 12.83$, $\psi = 10,007 \times 10^{-1}$ and $\sigma = 3.599 \times 10^{-4}$. Using (31) and (32), the observer gains are obtained as $\beta = 4.68 \times 10^{-4}$ and $\gamma_{1} = 5.6$. The same DST current profile is loaded to the designed observer. The actual and the estimated terminal voltage from the proposed observer are compared and is shown in Figure 6. It is observed from the figure that the...
maximum error (after convergence) between them is within 0.2 V, which ensures efficient performance of the proposed method.

### 4.4 Estimated SOC from the proposed approach and its comparison with existing methods

In literature, the efficacy of AGSMO is verified compared to SMO for battery SOC estimation [26, 27]. The effectiveness of PI observer to estimate SOC is also shown in [21]. Hence, in this paper, to demonstrate the superiority in terms of accuracy, computational time, convergence time, and robustness, the proposed approach is compared with AGSMO and PI observer designed for SOC estimation. For each method, efforts have been made to tune the parameters such that the best results are obtained. The initial SOC condition with a 60% error is considered for each experiment. The battery tester BioLogic VMP3 has an inbuilt ampere-hour counter from which the reference SOC is obtained.

The estimated SOC for various methods are presented without adding any external noise in Figure 8, and the % error between them and the actual SOC are shown in Figure 9. The uncertainties considered in this case are due to the internal system noise and modelling errors. Since the battery testing equipment used in laboratory is very accurate, the measurement noise in current and voltage are negligible. It is inferred from Figure 9 that the chattering is reduced in SLSTA based observer compared to AGSMO. Between 3500 and 4000 s, the chattering width for AGSMO and SLSTA are 0.53% and 0.22%, respectively. The maximum error (ME) and root-mean-square error (RMSE) for each method are given in Table 2, which establishes the supremacy of the proposed method over others.

The ME also demonstrates the region of convergence (ROC) of the SOC estimation error. From the table, it is seen that AGSMO converges to its ROC faster than SLSTA. However, the ROC is much greater for AGSMO. The computational time is also found for each method. The computational time of SLSTA is higher than the PI observer, but the difference between them is very small. Since the proposed approach performs better than PI observer on all the other aspects, this difference can be ignored.

To verify the robustness of the proposed method against the external disturbances such as current and voltage measurement noise, a high amount of white noise with standard deviation of 0.08 and 0.04 are added to the current and voltage channels, respectively. Under such condition, the SOC is estimated for each method, as shown in Figure 10. Figure 11 shows the errors in SOC estimation for each method. The chattering

| Method  | ME (%) | RMSE (%) | Computational time (s) | Convergence time (s) |
|---------|--------|----------|------------------------|---------------------|
| SLSTA   | 1.38   | 0.70     | 2.52                   | 589                 |
| AGSMO   | 2.05   | 0.88     | 24.45                  | 429                 |
| PI      | 2.58   | 1.06     | 2.01                   | 713                 |
width for AGSMO and SLSTA for 3500–4000 s are found to be 1.90% and 1.17%, respectively. It shows that under noisy condition, SLSTA deviates lesser compared to AGSMO and provides better results. The ME/ROC, RMSE, computational time and convergence time for each method are shown in Table 3.

It is observed that the estimated SOC in AGSMO and SLSTA deviate less than PI observer when the noise is added due to the the robust nature of sliding mode based methods. Tables 2 and 3 also show that there is least increment in ROC, RMSE and convergence time for SLSTA than the other two methods. Hence, the proposed approach is more robust and performs better under noisy environment compared to the other methods.

The proposed approach is also robust against the parameter identification errors. To verify it, 10% error is added to all the resistances and capacitances of battery model. To show the effect of ageing, we increase the resistances and reduce the capacitances by 10%. Figures 12 and 13 show the SOC estimated from each method and their corresponding errors. It is seen from Figure 13 that the SOC estimated by the proposed approach is more accurate than others, even after adding the model identification errors. For SLSTA, AGSMO and PI, the MEs are 2.23%, 3.58% and 3.87%, and the RMSEs are 1.15%, 1.47% and 1.81%, respectively. The important conclusion from these experiments is that even if the RLSF approach does not provide a good parameter estimation due to ageing and other external factors, the proposed observer can still provide satisfactory results.

Another situation is analysed where both identification errors and noises are considered together. The estimated SOC for each method are shown in Figure 14 and their corresponding errors are demonstrated in Figure 15. The MEs for SLSTA, AGSMO and PI are obtained as 3.14%, 5.01%, 6.24%, and the RMSEs are 1.21%, 1.60% and 2.36%, respectively. Hence, in the presence of modelling uncertainties and various noises, the proposed approach outperforms the existing approaches in terms of accuracy, robustness against noise and sensitivity to the identification errors.

It can be inferred from the above results that the proposed method estimates SOC efficiently for unknown initial conditions due to the robust convergence of the observer. Due
to continuous control injection, the chattering is significantly improved compared to AGSMO. The convergence time of the proposed observer is higher than that of AGSMO but lower than the PI observer. However, there is least increment in convergence time for SLSTA compared to the other methods, which makes it faster under higher noisy conditions. The computational time is slightly greater than PI observer but much lower than AGSMO. Hence, the proposed observer provides a balance between convergence time and computational time. The experimental results indicate that the accuracy and robustness of the proposed observer are higher than the other methods under both normal and noisy conditions, due to various advantages offered by SLSTA. The effect of model identification error and noises together, the proposed approach also efficiently deals with identification errors enabling it to provide satisfactory results under the impact of external factors such as ageing, which may influence the identification parameters. In the future work, we will consider the adaptive version of the proposed observer and a few recent adaptive state estimation techniques [42, 43] to check their effectiveness for estimating battery SOC.

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