

Combined Estimation of State-of-Charge and State-of-Health of Li-ion Battery Cells Using SMO on Electrochemical Model

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Abstract— Advanced battery management systems require accurate information of battery State-of-Charge (SOC) and State-of-Health (SOH) for diagnostics and prognostics as well as for efficient capacity utilization. In this paper, an integrated SOC and SOH estimation scheme is presented that applies sliding modes on an electrochemical model for Li-ion battery cell. The electrochemical model is selected and progressively reduced to sufficiently describe the relevant temporal and spatial evolution of Li-ion concentration in each electrode. The proposed estimation scheme is comprised of three sub-estimators which work jointly: two separate adaptive sliding mode observers (SMO) for estimation of Li-ion concentration and film resistance, and a separate parameter estimator for the solid state diffusion coefficient of negative electrode. Convergence of the observers has been proven using Lyapunov's stability theory. Simulation results are included to demonstrate the effectiveness of the overall scheme.

I. INTRODUCTION

Lithium-ion (Li-ion) batteries have become the dominant energy storage technology option in transportation, electronics and stationary power applications [1], [2]. This is due their several advantages over other battery technologies, including high specific energy and power, very low self-discharge, no memory effect and negligible environmental impact. However, Li-ion battery technology still has the challenges of high cost, reliability and safety issues such as thermal runaway. Therefore, safe, reliable and efficient utilization of Li-ion batteries call for advanced Battery Management Systems (BMS). These BMSs require accurate knowledge of battery State-of-Charge (SOC) and State-of-Health (SOH) of individual cells, to perform its intended functions.

The two problems of SOC and SOH estimation have been explored to various degrees of success. The main technical

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challenge of Li-ion cell SOC estimation arises from the weak observability and the excitation of complex thermo-electrochemical processes in high current applications such as electric vehicles [3]. The fundamental challenge in SOH estimation problems lies in the lack of established and readily computable SOH indicators. Multiple metrics have been proposed in the recent literature (charge capacity [5], internal resistance [7], etc). Moreover, simultaneous estimation of SOC and SOH in real time is particularly very challenging due to limited available measurements (voltage, current and temperature). This work attempts to address the combined estimation of SOC-SOH of individual cells.

Different techniques have been applied for SOC-SOH estimation which can be broadly classified based on the type of model used 1) Data-driven approach [4], [5], 2) Equivalent circuit model (ECM)-based approach [6], [7], [8], and 3) Electrochemical model-based approach. However, data-driven and ECM-based approaches suffer the drawbacks of requiring large amount of data for parameterization, inability to capture complex dynamics and the lack of physical meaning of the identified model parameters.

Electrochemical models are derived from porous electrode and concentrated solution theories and have greater potential to capture complex battery dynamics than data-driven or ECM models [9]. Moreover, the parameters of such models have physical significance and are useful in describing battery dynamics and state of health. The main challenge in the full electrochemical models (known as pseudo two-dimensional (P2D) model [10], [11]) is the complexity as it consists of coupled nonlinear partial differential equations. This necessitates some level of model reduction before suitable estimator designs can be derived. For example, different model reductions have been used for estimator design using linear Kalman filter [15], unscented Kalman filter (UKF) [19], multi-rate particle filtering (PF) [17]. Although UKF and PF generally perform well, the computational complexity can be an issue for real-time implementation. Moreover, the sufficient conditions for convergence of estimation errors are difficult to verify.

A popular reduction of the P2D model is the Single Particle Model (SPM) where the electrodes are approximated as two spherical particles neglecting electrolyte dynamics within the electrodes [12], [13], [14]. In our previous work (Dey, et. al., in [23]), we presented two nonlinear observer designs for SOC estimation based on SPM. In this paper, we use SPM for combined SOC and SOH estimation. Only a few other works use SPM for simultaneous SOC-SOH estimation. In [18], [20] simultaneous state and parameter estimation

problem is addressed using Iterated Extended Kalman Filter (IEKF). However, the computation burden for such a scheme can be high in real-time application and tuning the estimator parameters could be highly non-trivial. An adaptive PDE observer framework is used in [16] where a backstepping PDE observer is applied for SOC estimation in conjunction with parameter estimation schemes. However, stability of the overall scheme is not verified analytically despite the mutual inter-dependence of the state and parameter estimators.

In this paper, we present an adaptive SOC-SOH estimation scheme based on sliding mode theory. The scheme is simple to design and implement and is computationally efficient. We also analyze the stability properties of the estimator based on Lyapunov's stability theory. We use a finite-dimensional approximation of the SPM as the design model where SOC is computed based on Li-ion spatial concentrations and the SOH estimation problem is posed as a physical parameter estimation problem (namely, solid-state diffusion coefficient and the film resistance as they capture the effect of cell aging over time [24]). Essentially, the SOC-SOH estimation scheme consists of three sub-estimators, which work together: two separate sliding mode observers [21] for estimation of SOC and film resistance and a parameter estimator for solid-state diffusion coefficient. The motivation of using sliding mode observer comes from its inherent capability of dealing with uncertainties.

The rest of the paper is organized as follows. Section II describes the Li-Ion battery cell model used in this work, Section III discusses the design of the joint SOC and SOH estimation scheme in detail, and Section IV presents results and discussions. Finally, Section V briefly summarizes the conclusions of this work.

II. LITHIUM-ION CELL MODEL

As discussed before, due to the computational complexity of the P2D model [10], [11], a reduced version called the Single Particle Model (SPM) is used here for designing the estimators [12]. The SPM consists of two linear solid-state diffusion PDEs for the electrode particles (1), and a nonlinear output voltage function derived from Butler-Volmer kinetics (2):

$$\begin{aligned} \frac{\partial c_s^\pm}{\partial t} &= \frac{D_s^\pm}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial c_s^\pm}{\partial r} \right) \\ \frac{\partial c_s^\pm}{\partial r} \Big|_{r=0} &= 0, \quad \frac{\partial c_s^\pm}{\partial r} \Big|_{r=R} = \frac{\pm I}{a_s^\pm F D_s^\pm AL^\pm} \end{aligned} \quad (1)$$

$$\begin{aligned} V &= \frac{\bar{R}T}{\alpha^+ F} \sinh^{-1} \left(\frac{I}{2a_s^+ AL^+ \sqrt{c_e c_{s,e}^+ (c_{s,max}^+ - c_{s,e}^+)}} \right) \\ &- \frac{\bar{R}T}{\alpha^- F} \sinh^{-1} \left(\frac{I}{2a_s^- AL^- \sqrt{c_e c_{s,e}^- (c_{s,max}^- - c_{s,e}^-)}} \right) \\ &+ U^+(c_{s,e}^+) - U^-(c_{s,e}^-) - R_f I \end{aligned} \quad (2)$$

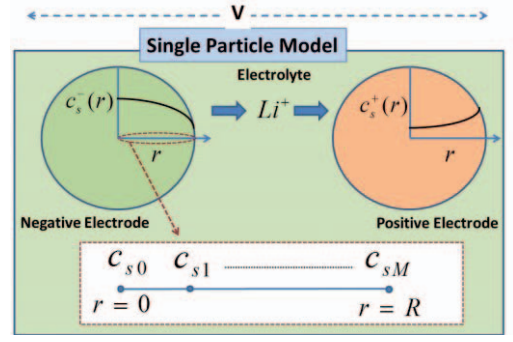


Figure 1. Schematic of Single Particle Model

where c_s^\pm is the Li-ion concentration of the positive and negative electrode, V is the output voltage and I is the input current. The reader may refer to Table I for the rest of the nomenclature. In [13], it is discussed that SPM states in (1) are weakly observable from the output (2). To resolve this observability issue, the positive electrode diffusion dynamics can be ignored as it is much faster than that of negative electrode [14]. Therefore, the model is further reduced to a strongly observable single PDE describing the diffusion of Li-ions in negative electrode with a nonlinear output voltage map. Detail of this model reduction steps can be found in [14].

In order to get a finite-dimensional approximation of the PDE, the method of lines is used where the spatial derivatives are approximated using finite difference methods. The resulting ODEs (containing only time derivatives) form the finite-dimensional state-space model given in (3) below. Here, we use a central difference discretization including imaginary nodes at the end locations. The SPM with this discretization is illustrated in Fig. 1. For a discretization with $(M+1)$ nodes, $[c_{s0}, c_{s1}, \dots, c_{sM}]$ are the Li-ion concentration at the nodes.

$$\begin{aligned} \dot{c}_{s0} &= -3ac_{s0} + 3ac_{s1} \\ \dot{c}_{sm} &= \left(1 - \frac{1}{m}\right) ac_{s(m-1)} - 2ac_{sm} + \left(1 + \frac{1}{m}\right) ac_{s(m+1)} \\ \dot{c}_{sM} &= \left(1 - \frac{1}{M}\right) ac_{s(M-1)} - \left(1 - \frac{1}{M}\right) ac_{sM} - \left(1 + \frac{1}{M}\right) bI \end{aligned} \quad (3)$$

with $m = 1, \dots, (M-1)$, discretization step $\Delta = R/M$, $a = D_s^-/\Delta^2$, $b = 1/a_s^- F \Delta AL^-$. An indication of the bulk SOC of the cell can be given as bulk concentration ($\sum_{i=0}^M c_{si}$) which is related to the energy capacity of the cell. The surface concentration c_{sM} is an indication of the surface SOC (which is related to instantaneous power capacity of the cell).

III. ESTIMATION SCHEME DESIGN

The above reduced model (3) can be re-written in the state-space form:

$$\begin{aligned} \dot{x} &= Ax\theta + Bu \\ y &= h(x_M, u) - R_f u \end{aligned} \quad (4)$$

where states $x = [c_{s1}, \dots, c_{sM}]^T \in R^M$ is the spatially distributed Li-ion concentration in the negative electrode, $x_M = c_{sM}$, is the surface concentration state, $\theta = D_s^- / \Delta^2 \in R$ is scalar parameter related to diffusion coefficient, $u = I \in R$ is the input current, $y = V \in R$ is the output voltage, $R_f \in R$, is film resistance, and the matrices A and B are derived from (3) and the output function h follows from (2). Note that, zero-th node concentration is ignored in (4). This is due to the fact that keeping the zero-th node dynamics leads to unobservability of the model. However, this removal does not cause any information loss as the other states do not depend on the zero-th node and reconstruction of zero-th node concentration is possible using the estimated 1st node concentration.

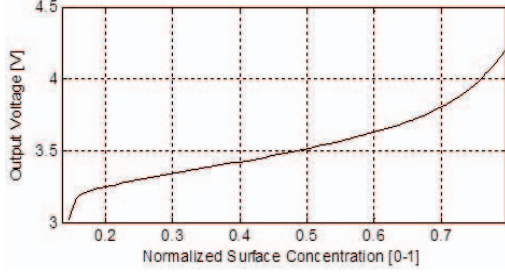


Figure 2. Output Voltage as a function of State

We make one observation about the above model that will be exploited in the estimator design to follow. The output function of the system (shown in Fig. 2) is strictly increasing with respect to state and can be assumed to be continuously differentiable with respect to the state within the operating region.

An illustration of the overall proposed joint SOC and SOH estimation scheme is given in Fig. 3. While designing the various components of this scheme, we have made the following assumptions:

- Li-ion cell SOH can be inferred from diffusion coefficient and film resistance information [24]. There are other physical parameters which also indicate SOH such as reaction rate constant, boundary coefficient [16] etc. However, those will not be considered here.
- The initial value and dynamics (nature of variation) of the diffusion coefficient (D_s^-) are unknown. This is a valid assumption as it is difficult to measure the diffusion coefficient outside of a dedicated laboratory setup. Moreover, the identification of the diffusion coefficient is also difficult as can be seen in (4) where it is multiplied by states that are not measurable.
- The initial value of the film resistance (R_f) is known with certain accuracy. However, film resistance varies with time and its dynamics are uncertain. The identification of film resistance is not as difficult as that of the diffusion coefficient because in the model (4) it is multiplied by the measured input current. Therefore, in case of R_f , we can pose it as a parameter tracking problem. An estimate of R_f of a certain accuracy can be found by monitoring the measured voltage drop ($R_f u$) in the output when the current goes from zero to nonzero value.

- All the other parameters of the model (4) are assumed known with sufficient accuracy.

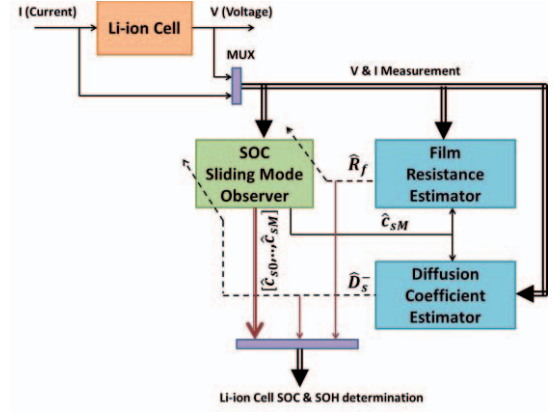


Figure 3. Schematic of Combined SOC and SOH Estimator

The working principle of the scheme is briefly described below:

1. The SOC sliding mode observer estimates surface concentration state x_M in face of unknown D_s^- and known R_f and achieve convergence in finite time.
2. Diffusion coefficient estimator estimates D_s^- by taking converged surface concentration estimate (x_M) and known current input (u), and by using a linear input-output model between surface concentration and current.
3. The diffusion coefficient estimator feeds D_s^- back to SOC sliding mode observer. Now the SOC observer will thereafter use the updated estimate of D_s^- .
4. Meanwhile, the film resistance estimator which is also designed as another sliding mode observer, tracks R_f based on the voltage and current measurements without knowing the exact dynamics of R_f .
5. Finally, the SOC observer uses the updated D_s^- and R_f information and goes on updating the estimates of Li-ion concentration states throughout the domain.

The detailed designs of the three estimators, i.e, the SOC observer, the diffusion coefficient estimator, and the film resistance estimator, are discussed in the following subsections.

A. SOC Observer

We apply sliding mode theory [21] to design this observer. Starting with the system dynamics given by (4), we partition the state vector $x = [\bar{x}_1 \ \bar{x}_2]^T$ where $\bar{x}_2 = x_M$ is the surface concentration state and $\bar{x}_1 = [x_1 \ \dots \ x_{M-1}]^T$ contains all the other states. In the partitioned form, the system dynamics can be written as:

$$\begin{aligned}
\dot{\tilde{x}}_1 &= \theta A_{11}\tilde{x}_1 + \theta A_{12}\tilde{x}_2 \\
\dot{\tilde{x}}_2 &= \theta A_{21}\tilde{x}_1 + \theta A_{22}\tilde{x}_2 + Bu \\
y &= h(\tilde{x}_2, u) - R_f u
\end{aligned} \tag{5}$$

The following observer dynamics is chosen:

$$\begin{aligned}
\dot{\hat{x}}_1 &= \hat{\theta} A_{11}\hat{x}_1 + \hat{\theta} A_{12}\hat{x}_2 - Lv \\
\dot{\hat{x}}_2 &= \hat{\theta} A_{21}\hat{x}_1 + \hat{\theta} A_{22}\hat{x}_2 + Bu + v \\
\hat{y} &= h(\hat{x}_2, u) - \hat{R}_f u
\end{aligned} \tag{6}$$

where $v = M \text{sgn}(\tilde{x}_2 - \hat{x}_2)$ and M is constant gain and L is a constant observer gain vector to be determined. Note that, we do not have the \tilde{x}_2 measurement. However, as discussed earlier we know y is a strictly increasing function of \tilde{x}_2 (refer to Fig. 2), therefore, $\text{sgn}(\tilde{x}_2 - \hat{x}_2) = \text{sgn}(y - \hat{y})$ (provided $(R_f - \hat{R}_f)$ is sufficiently small). It is safe to assume that $(R_f - \hat{R}_f)$ is sufficiently small as the initial value of R_f is known with certain accuracy and in the subsequent time, the film resistance estimator would provide updated estimates of R_f . The state estimation error dynamics can be written as:

$$\begin{aligned}
\dot{\tilde{x}}_1 &= \dot{\hat{x}}_1 - \dot{\tilde{x}}_1 \\
&= \theta A_{11}\tilde{x}_1 + \theta A_{12}\tilde{x}_2 - \hat{\theta} A_{11}\hat{x}_1 - \hat{\theta} A_{12}\hat{x}_2 + Lv \\
\dot{\tilde{x}}_2 &= \dot{\hat{x}}_2 - \dot{\tilde{x}}_2 \\
&= \theta A_{21}\tilde{x}_1 + \theta A_{22}\tilde{x}_2 - \hat{\theta} A_{21}\hat{x}_1 - \hat{\theta} A_{22}\hat{x}_2 - v
\end{aligned} \tag{7}$$

Now, consider the \tilde{x}_2 dynamics. We choose a Lyapunov function candidate $V = \frac{1}{2}\tilde{x}_2^2$ to analyze the stability of this partition.

$$\begin{aligned}
\dot{V} &= \tilde{x}_2 \dot{\tilde{x}}_2 \\
&= \tilde{x}_2 (\theta A_{21}\tilde{x}_1 + \theta A_{22}\tilde{x}_2 - \hat{\theta} A_{21}\hat{x}_1 - \hat{\theta} A_{22}\hat{x}_2) \\
&\quad - M \tilde{x}_2 \text{sgn}(\tilde{x}_2) \\
&\Rightarrow \dot{V} \\
&\leq |\tilde{x}_2| (\theta A_{21}\tilde{x}_1 + \theta A_{22}\tilde{x}_2 - \hat{\theta} A_{21}\hat{x}_1 - \hat{\theta} A_{22}\hat{x}_2) - M |\tilde{x}_2| \\
&\Rightarrow \dot{V} \leq |\tilde{x}_2| (\theta A_{21}\tilde{x}_1 + \theta A_{22}\tilde{x}_2 - \hat{\theta} A_{21}\hat{x}_1 - \hat{\theta} A_{22}\hat{x}_2 - M) \\
&\Rightarrow \dot{V} \leq -\alpha \sqrt{V}, \text{ where } \alpha \text{ some positive number} \\
&\Rightarrow V(t) \leq \left(-\frac{\alpha}{2}t + \sqrt{V(0)}\right)^2
\end{aligned}$$

In practice, \tilde{x}_2 converges to a boundary manifold Δ_x in finite time. Hence, this establishes that the surface concentration error will go to Δ_x in finite time even without the knowledge of the diffusion coefficient (related to θ where $\theta = D_s^-/\Delta^2$). Width of Δ_x depends on M and error in R_f estimation. After the convergence of \tilde{x}_2 and θ estimate, the equivalent output error injection will be $v_{eq} = \theta A_{21}\tilde{x}_1$ (ignoring negligible Δ_x). Therefore, the \tilde{x}_1 dynamics becomes,

$$\dot{\tilde{x}}_1 = \theta(A_{11}\tilde{x}_1 + Lv_{eq}) \Rightarrow \dot{\tilde{x}}_1 = \theta(A_{11} + LA_{21})\tilde{x}_1$$

As $\theta > 0$ from physical properties, and we choose L such that eigenvalues of $(A_{11} + LA_{21})$ are at the desired position, \tilde{x}_1 converges asymptotically.

B. Diffusion Coefficient Estimator

A linear input-output model between the surface concentration (\tilde{x}_2) and input current (u) can be obtained by a reduced order approximation. In this work, this model is obtained by a three node discretization of the PDE using finite difference method and given as:

$$\frac{\bar{X}_2(s)}{I(s)} = \frac{K(s + \theta)}{s(s + P\theta)} \tag{8}$$

where $\theta (= D_s^-/\Delta^2)$ is the unknown parameter to estimate and K and P are known constants. To estimate θ from (8) involves use of derivatives of the signals, which is a drawback of this scheme. To avoid noise amplification due to differentiation, we use filters. From (8),

$$s^2 \bar{X}_2(s) + s \bar{X}_2(s) P\theta = sI(s)K + I(s)\theta K$$

Multiplying both sides by $F(s) = \frac{1}{\beta s^2 + \gamma s + 1}$ which is a second order filter [22],

$$\begin{aligned}
s^2 F(s) \bar{X}_2(s) + s F(s) \bar{X}_2(s) P\theta \\
= s F(s) I(s) K + F(s) I(s) \theta K \\
\Rightarrow z_1(s) + z_2(s) P\theta = z_3(s) K + z_4(s) \theta K
\end{aligned}$$

where $z_1(s) = s^2 F(s) \bar{X}_2(s)$, $z_2(s) = s F(s) \bar{X}_2(s)$, $z_3(s) = s F(s) I(s)$, $z_4(s) = F(s) I(s)$. Therefore, the parameter θ can be estimated via the following expression:

$$\theta = \frac{z_3(s)K - z_1(s)}{z_2(s)P - z_4(s)K}$$

Hence, the diffusion coefficient can be estimated as $D_s^- = \theta \Delta^2$, where Δ is the spatial discretization step.

C. Film Resistance Estimator

Here the problem is to estimate the film resistance R_f with known initial condition and uncertain dynamics (variation in time). This estimator is designed using sliding mode theory [21]. An arbitrary time variation of R_f can be written as:

$$\dot{\hat{R}}_f = f(t) \tag{9}$$

where $f(t)$ is uncertain function. A sliding mode observer is chosen as:

$$\dot{\hat{R}}_f = \hat{f}(t) + M_2 \text{sgn}(\tilde{R}_f) \tag{10}$$

where $\hat{f}(t)$ is nominal dynamics and M_2 is constant gain to be determined and $\tilde{R}_f = R_f - \hat{R}_f$. Now the question is how to get $\text{sgn}(\tilde{R}_f)$ as R_f is not measured. The output function is $y = h(\tilde{x}_2, u) - R_f u$ and estimate of the output function can be constructed as $\hat{y} = h(\tilde{x}_2, u) - \hat{R}_f u$ after the convergence of \tilde{x}_2 . Therefore, $y - \hat{y} = (\hat{R}_f - R_f)u$ from which we can write (using the formula $\text{sgn}(\bar{a}\bar{b}) = \text{sgn}(\bar{a})\text{sgn}(\bar{b})$):

$$\text{sgn}(y - \hat{y}) = -\text{sgn}(\tilde{R}_f)\text{sgn}(u) \quad (11)$$

Using (11), we can find $\text{sgn}(\tilde{R}_f)$ as u and y are measured. However, one downside of this scheme is the requirement of nonzero input as $u = 0$ makes the above relationship undefined. This simply excludes open circuit cases. Now, we choose a Lyapunov function candidate $V = \frac{1}{2}\tilde{R}_f^2$ to analyze the stability.

$$\begin{aligned} \dot{V} &= \tilde{R}_f \dot{\tilde{R}}_f = \tilde{R}_f f(t) - \tilde{R}_f \hat{f}(t) - M_2 \tilde{R}_f \text{sgn}(\tilde{R}_f) \\ \Rightarrow \dot{V} &\leq |\tilde{R}_f| (f(t) - \hat{f}(t) - M_2) \end{aligned}$$

In practice, \tilde{R}_f converges to a boundary layer Δ_R in finite time. Width of Δ_R depends on M_2 and \bar{x}_2 estimation error.

Note that the R_f observer requires estimate of \bar{x}_2 and the SOC observer requires estimate of R_f . There is a coupling between these two observers. However, we are assuming that initial value of R_f is known with sufficient accuracy and there is a large time scale separation between the R_f and \bar{x}_2 dynamics. Therefore, initially, the SOC observer will have sufficiently accurate information of R_f (by assumption). Subsequently, once R_f starts to change significantly from its initial value, updated \bar{x}_2 estimate will be available because of the faster finite time convergence of the SOC observer. This updated \bar{x}_2 estimate will be used to further improve the estimate of R_f . Also note that, width of boundary manifolds Δ_x and Δ_R play an important role in this scheme. Boundary manifold Δ_R should be sufficiently small for the relation $\text{sgn}(\tilde{x}_2) = \text{sgn}(\hat{y})$ to be true. Similarly, Δ_x should be sufficiently small for (11) to be true. Moreover, convergence of \hat{x}_2 should be faster so that when R_f starts deviating significantly, estimate of \hat{x}_2 must be available. Therefore, gains M and M_2 should be selected carefully taking the above issues into consideration.

IV. RESULTS AND DISCUSSIONS

In this section, the performance of the proposed SOC and SOH estimation scheme is demonstrated via simulation studies. The observers are applied on the SPM model of the Li-ion battery cell. Model parameters of the Li-ion cell have been taken from [15]. To simulate realistic scenarios, mV level noise has been added to the measured voltage from the plant. SOC observer has been initialized with 20% different initial condition than the plant model. Diffusion coefficient estimator is initialized with 50% initial parameter error. The uncertain dynamics of film resistance is simulated with a linearly increasing very slow function of time to represent slow ageing [8]. The nominal dynamics in film resistance estimator is initialized with 50% error. The input current profile used for simulation is a charge/discharge square wave of pulse width 50 sec and amplitude ± 5 A. A 4-node discretization has been used in the finite difference approximation of the SPM. The performance of SOC estimation is shown in Fig. 4 and parameter estimators' performance is shown in Fig. 5.

It can be seen from Fig. 4 that the proposed scheme performs satisfactorily in voltage and SOC estimation. Similar performance is found for the parameter estimates given in Fig. 5.

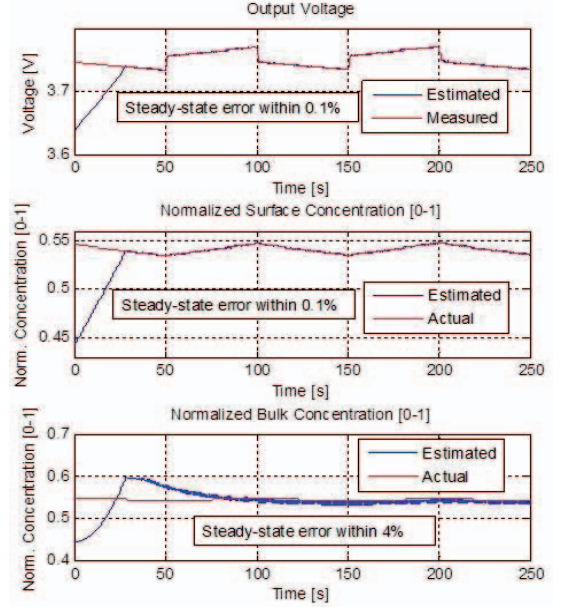


Figure 4. Voltage and SOC estimation Performance of the Adaptive Scheme

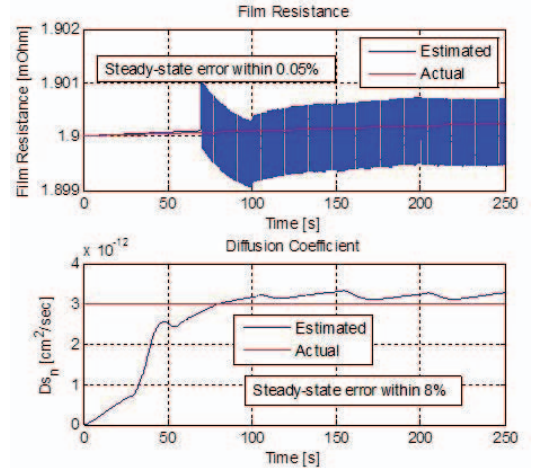


Figure 5. Parameter Estimation Performance of the Adaptive Scheme (Rf estimator is activated at certain time (70 sec) after \tilde{x}_2 convergence)

In estimation results given Fig. 4 and Fig. 5, there are visible boundary layers in the estimated variables. This is due to the noise scenario and imperfect parameter estimation that leads us to the trade-off between the convergence time and magnitude of the boundary layer. Selecting high gains M , L and M_2 will result in faster convergence but at the same time amplify the noise. Therefore, proper tuning of the gains should be done based on the noise scenario and required convergence criterion. The other tuning parameters for the estimation scheme are poles of the filter $F(s)$. The poles should be selected in light of the trade-off between the convergence requirement of the diffusion coefficient and steady-state error in its estimated value.

V. CONCLUSION

In this paper, an estimation scheme is presented for combined SOC and SOH estimation of Li-ion battery cells applying sliding mode theory on electrochemical models. The scheme consists of three estimators: two sliding mode observers for SOC and film resistance estimation and a parameter estimator for the diffusion coefficient estimation. The performance of the overall scheme has been demonstrated via simulations which showed that the proposed scheme is able to track the SOC and SOH parameters with sufficient accuracy. Main tuning parameters in this scheme are the observer gains (M , L and M_2) and filter poles ($F(s)$), which should be selected considering the trade-off between convergence speed and steady-state noise band in estimated variables.

In this work, we ignored the uncertainties in other Li-ion cell physical parameters like reaction rate constant, boundary coefficients etc. We also ignored the thermal dynamics of the cell which can have a large impact in battery SOC and health especially in case of large currents. As future work, we plan to incorporate these parametric uncertainties and thermal dynamics in estimation scheme. Moreover, experimental plan is in progress to evaluate the effectiveness of the scheme via real-time implementation.

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TABLE I: LI-ION BATTERY MODEL NOMENCLATURE

Symbol	Definition and Unit
A	Current collector area (cm ²)
a_s^\pm	Specific surface area (cm ² /cm ³)
c_e	Electrolyte phase Li-ion concentration (mol/cm ³)
c_s^\pm	Solid phase Li-ion concentration (mol/cm ³)
$c_{s,e}^\pm$	Solid phase Li-ion concentration at surface (mol/cm ³)
$c_{s,max}^\pm$	Solid phase Li-ion saturation concentration (mol/cm ³)
D_s^\pm	Effective diffusion coefficient in solid phase (cm ² /s)
F	Faraday's constant (C/mol)
I	Current (A)
L^\pm	Length of the cell (cm)
r	Radial coordinate (cm)
R	Radius of solid active particle (cm)
\bar{R}	Universal Gas Constant (J/mol-K)
R_f	Contact film resistance (Ω)
T	Temperature (K)
U^\pm	Open circuit potential (V)
α^\pm	Charge transfer coefficient
Superscript	
\pm	positive/negative electrode