

Online State and Parameter Estimation of Battery-Double Layer Capacitor Hybrid Energy Storage System

Satadru Dey, Sara Mohon, Pierluigi Pisu, Beshah Ayalew, Simona Onori

Abstract— Hybrid Energy Storage Systems (HESS) are gaining popularity due to their ability to compensate for the deficiencies of the conventional single energy storage solution. Battery-Double Layer Capacitor (DLC) is one of such HESS that is being adopted for different applications such as vehicle propulsion, auxiliary power unit and renewable energy storage. Real-time estimation of the states and parameters of such HESS is crucial for safe, efficient and optimal operation. In this paper, an online state-parameter estimation scheme is presented based on the electrical and thermal dynamics of the battery and DLC. The estimation scheme consists of two separate state-parameter estimators for battery and DLC each of which exploits a cascaded observer-based structure. The observers are designed based on sliding mode methodology. Theoretical verification of the overall state-parameter estimation is provided using Lyapunov's argument. Effectiveness of the scheme is verified via simulation studies.

I. INTRODUCTION

Hybrid Energy Storage Systems (HESS) are being adopted to compensate for shortcomings of conventional single energy storage systems. Battery-Double Layer Capacitor (DLC) is one of the promising candidates for HESS which are gaining popularity in many different applications. Batteries, which have long been used as an auxiliary power unit in automotive and renewable stationary energy storage applications, suffer from low power densities [1]. On the other hand, DLCs have high power densities and long cycle lives and can assist batteries in peak power situations [2]. In this paper we concentrate on some of the applications that require high power for a short duration such as: 1) Cold cranking of an engine, 2) start and stop ability of the vehicle, and 3) HEV charge sustaining operation. We will refer to these applications as *Hybrid Applications* for the rest of the paper. The use of a battery-DLC in these procedures has obvious advantages to reduce battery aging. In this paper, a real-time/online state and parameter estimation scheme is proposed for battery-DLC HESS.

Estimation of battery states and parameters are important for optimizing performance and life of the battery while maintaining safe operation. Important battery states and parameters include State-of-Charge (SOC), internal resistance, capacity, etc. In particular, internal resistance and capacity can be used as indicators of battery State-of-Health (SOH) and ageing. Different approaches have been presented

in literature for online state and parameter estimation of batteries. Some of them include electrochemical model-based approaches [3]. However, due to the complexity of electrochemical models, we focus on the Equivalent Circuit Model (ECM) of the battery due to its computational simplicity and simple model structure. The most popular ECM based estimation includes Kalman filter based approaches [4],[5]. However, the Kalman filter-based approaches such as linear Kalman filter (KF), extended Kalman filter (EKF), adaptive extended Kalman filter (AEKF) suffer from following issues: 1) it is very difficult to theoretically verify the conditions for error convergence as well as higher initial error may lead to divergence of the estimation error, 2) tuning of noise covariance matrices can be nontrivial. Other ECM-based battery estimation techniques include for instance nonlinear observers [6], sliding mode observers [8],[9], Linear Parameter Varying Technique [7]. However, most of the existing approaches suffer from one or more of the following issues: 1) no theoretical verification of the overall state and parameter error convergence 2) no consideration of thermal dynamics. In this paper, we propose a sliding mode observer based approach using ECM with theoretical verification of the overall state and parameter error convergence. In particular, our scheme is different from most of the existing approaches including the sliding mode-based ones, in two aspects: 1) we include thermal dynamics along with the electrical dynamics of the battery for observer design, and 2) we present a new cascaded observer-based structure that consists of three observers which are based on thermal, electrical and SOC dynamics respectively. This structure essentially enables decomposing the overall estimation problem and significantly simplifies the design task.

Although the cycle life of DLCs is longer than that of the batteries, DLCs are still sensitive to ageing processes if certain operating conditions are not maintained [10]. Moreover, DLC aging information is necessary for state estimation as well as energy management algorithms in battery-DLC HESS. Therefore, it is necessary to monitor states and parameters of DLC to allow for correct operating conditions and optimal management [2],[11]. The common modeling approach for DLCs is also based on ECM. In DLC, the resistance and capacitances of ECM represents the internal impedance and charge capacity respectively and are useful as the SOH indicators [12]. However, unlike batteries, the real-time combined state and parameter estimation problem is relatively less explored for DLCs in the existing literature. In [2],[13] estimators were designed using EKF for state estimation of DLC. Similarly, in [14], a least square technique was used for parameter estimation. A dual Kalman filter based approach is used for combined state and

Research supported by U.S. Department of Energy GATE program under Grant no DE-EE0005571.

S. Dey*, S. Mohon, P. Pisu, B. Ayalew, and S. Onori are with Clemson University International Center for Automotive Research, Greenville, SC 29607 USA (*Corresponding author: phone: 864-908-4336; fax: 864-283-7208; e-mails: {[@clemson.edu](mailto:satadrd,smohon,pisup,beshah,sonori)}).

parameter estimation in [11]. In this paper, we propose a sliding mode observer based combined state-parameter estimation scheme that theoretically verifies the convergence of the overall estimation. Similar to the battery estimation scheme, DLC estimation scheme also exploits the cascaded observer structure in order to simplify the design by decomposing the estimation problem.

The rest of the paper is organized as follows. Section II briefs the modeling of the HESS elements. Section III describes the proposed estimation scheme. Section IV discusses a simulation case study on a passive battery-DLC HESS and Section V summarizes the conclusions of the work.

II. MODELING OF THE HYBRID ENERGY STORAGE SYSTEM

The HESS under consideration consists of two energy sources, namely battery and DLC. In this section, the modeling of these two sources is discussed.

A. Battery Model

In this study, a first order electrical circuit model [1] (Fig. 1) and a lumped thermal dynamics are adopted for the battery.

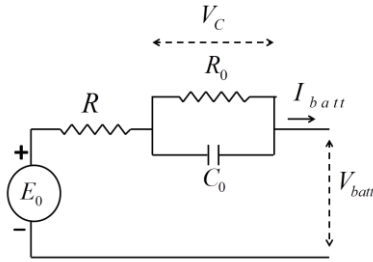


Figure 1. Electrical equivalent circuit model of battery
The electrical dynamics of the battery can be written using Kirchhoff's law, and with a usual definition of SOC:

$$\dot{V}_c = -\frac{V_c}{R_0 C_0} + \frac{I_{batt}}{C_0} \quad (1)$$

$$\dot{SOC} = -\frac{I_{batt}}{Q} \quad (2)$$

$$V_{batt} = E_0 - I_{batt}R - V_c \quad (3)$$

where V_{batt} is the terminal voltage, I_{batt} is the input current, R , R_0 and C_0 are the resistors and capacitors of the electrical circuit, V_c is the voltage across the capacitor C_0 , E_0 is the open-circuit potential (OCP), Q is the capacity of the battery cell. The lumped thermal model of the battery is given by:

$$mc_{batt}\dot{T}_{batt} = I_{batt}^2(R + R_0) - hA_{batt}(T_{batt} - T_{amb}) \quad (4)$$

where T_{batt} is the battery temperature, mc_{batt} is the mass times the specific heat capacity of the battery cell, hA_{batt} is the effective heat transfer coefficient and T_{amb} is the ambient temperature. The OCP is still a function of SOC and temperature and can be written as:

$$E_0 = f(SOC, T_{batt}) \quad (5)$$

B. DLC Model

Similar to the battery, an electrical circuit model (Fig. 2) is adopted for DLC with two series resistance-capacitance pairs ($R_d - C_d$ and $R_f - C_f$) where R_f and R_d are the resistances and C_f and C_d are the capacitances. Moreover, a lumped thermal dynamics is adopted [1].

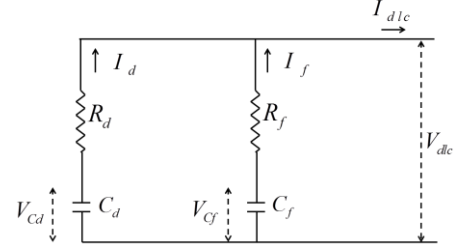


Figure 2: Electrical equivalent circuit model of DLC

The voltage dynamics across the capacitors C_d and C_f can be written as:

$$\dot{V}_{cf} = \frac{I_f}{C_f} \quad (6)$$

$$\dot{V}_{cd} = \frac{I_d}{C_d} \quad (7)$$

where V_{cf} is the voltage across the capacitor C_f , V_{cd} is the voltage across the capacitor C_d , I_d is the current flowing through the $R_d - C_d$ branch, I_f is the current flowing through the $R_f - C_f$ branch. The total current I_{dlc} entering the DLC can be given by Kirchoff's current law:

$$I_{dlc} = I_f + I_d \quad (8)$$

and the voltage V_{dlc} across the DLC is:

$$V_{dlc} = I_f R_f + V_{cf} = I_d R_d + V_{cd} \quad (9)$$

The lumped thermal dynamics of the DLC is given by:

$$mc_{dlc}\dot{T}_{dlc} = I_{dlc}^2 R_f - hA_{dlc}(T_{dlc} - T_{amb}) \quad (10)$$

where T_{dlc} is the DLC temperature, mc_{dlc} is the mass times the specific heat capacity of the DLC, hA_{dlc} is the effective heat transfer coefficient.

III. OBSERVER-BASED ONLINE STATE-PARAMETER ESTIMATION SCHEME

In this section, the online estimation scheme for the HESS is described. Real-time measurements from the HESS are: I_{batt} , T_{batt} , V_{batt} from the battery and I_{dlc} , T_{dlc} and V_{dlc} from the DLC.

A. Battery State and Parameter Estimation

In this section, we detail the design of online estimation of battery state and parameters. Note that, we are interested in SOC , R and Q . Therefore, we focus on estimating those important quantities assuming the other parameters are known. The schematic of the online estimation scheme is shown in Fig. 3. While designing the estimation scheme, we take the following assumptions.

Assumption 1: The parameters R , R_0 and C_0 are constant in the range $SOC \in [SOC_{min}, SOC_{max}]$ considered for the hybrid application. The electrical parameters R_0 and C_0 as well as the thermal parameters mc_{batt} and hA_{batt} are known with sufficient accuracy.

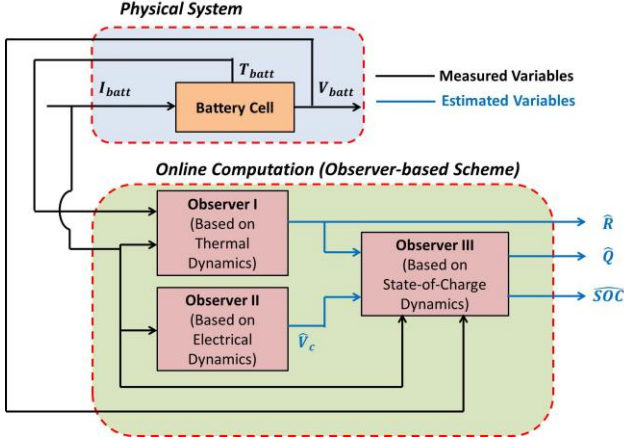


Figure 3: Online battery state-parameter estimation scheme

Assumption 2: The OCP E_0 is a monotonically increasing function of SOC in the range $SOC \in [SOC_{min}, SOC_{max}]$ for any given temperature.

Lemma 1: From *Assumption 2*, for a given $T_{batt} = T_{batt}^*$ and any two points $SOC^{(1)}$ and $SOC^{(2)}$ in the SOC-space within the range $SOC \in [SOC_{min}, SOC_{max}]$ with corresponding two points $E_0^{(1)} = f(SOC^{(1)}, T_{batt}^*)$ and $E_0^{(2)} = f(SOC^{(2)}, T_{batt}^*)$ in E_0 -space and, the following is always true:

$$\text{sgn}(E_0^{(1)} - E_0^{(2)}) = \text{sgn}(SOC^{(1)} - SOC^{(2)}) \quad (11)$$

This can be easily verified by graphically using the battery OCP-SOC curve.

Now, the *Observer I*, *II* and *III* for the battery state and parameter estimation is given as follows.

Observer I:

$$mc_{batt}\dot{\hat{T}}_{batt} = I_{batt}^2 R_0 - hA_{batt}(\hat{T}_{batt} - T_{amb}) + L_T \text{sgn}(\tilde{T}_{batt}) \quad (12)$$

$$\hat{R} = v_T / I_{batt}^2 \quad (13)$$

where v_T is *equivalent output error injection* which is a continuous approximation or filtered version of $L_T \text{sgn}(\tilde{T}_{batt})$.

Observer II:

$$\dot{\hat{V}}_c = -\frac{\hat{V}_c}{R_0 C_0} + \frac{I_{batt}}{C_0} \quad (14)$$

Observer III:

$$\dot{\hat{SOC}} = L_{SOC} \text{sgn}(\tilde{E}_0) \quad (15)$$

$$\hat{Q} = I_{batt} / v_{SOC} \quad (16)$$

where v_{SOC} is *equivalent output error injection* which is a continuous approximation or filtered version of $L_{SOC} \text{sgn}(\tilde{E}_0)$, \hat{T}_{batt} , \hat{R} , \hat{V}_c , \hat{SOC} and \hat{Q} denotes the estimates

of the corresponding states and parameters; $\tilde{T}_{batt} = T_{batt} - \hat{T}_{batt}$, $L_T > 0$ is arbitrarily high constant observer gain; $\tilde{E}_0 = V_{batt} + I_{batt}\hat{R} + \hat{V}_c - \tilde{E}_0$, $\hat{E}_0 = f(\hat{SOC}, T_{batt})$, $L_{SOC} > 0$ is arbitrarily high constant observer gain. Further, other estimation errors are defined as: $\tilde{SOC} = SOC - \hat{SOC}$, $\tilde{V}_c = V_c - \hat{V}_c$, $\tilde{R} = R - \hat{R}$, $\tilde{Q} = Q - \hat{Q}$.

Theorem 1: Consider the system dynamics given in (1)-(4) and the observer structure (12)-(16), if *Assumptions 1-2* and *Lemma 1* hold true then the estimation error \tilde{R} converges to zero in finite time; \tilde{V}_c converges to zero exponentially and \tilde{SOC} and \tilde{Q} converges to zero asymptotically as $t \rightarrow \infty$.

Proof: Subtracting (12) from (4), the error dynamics of the *Observer I* can be written as:

$$mc_{batt}\dot{\tilde{T}}_{batt} = I_{batt}^2 R - hA_{batt}\tilde{T}_{batt} - L_T \text{sgn}(\tilde{T}_{batt}) \quad (17)$$

Note that, the sliding manifold in this case is $s_T = \tilde{T}_{batt}$ as \tilde{T}_{batt} is inside the sign term. The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_T = 0.5mc_{batt}\tilde{T}_{batt}^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_T &= mc_{batt}\tilde{T}_{batt}\dot{\tilde{T}}_{batt} \\ &= \tilde{T}_{batt}\{I_{batt}^2 R - hA_{batt}\tilde{T}_{batt} - L_T \text{sgn}(\tilde{T}_{batt})\} \\ &\Rightarrow \dot{V}_T \leq |\tilde{T}_{batt}|\{|I_{batt}^2 R| - L_T\}, \text{ as } hA_{batt} > 0 \\ &\Rightarrow \dot{V}_T \leq -\alpha\sqrt{V_T} \text{ where } \alpha = -\frac{(|I_{batt}^2 R|_{max} - L_T)}{\sqrt{0.5mc_{batt}}} > 0 \\ &\Rightarrow V_T(t) \leq \left\{-\frac{\alpha}{2}t + \sqrt{V_T(t_0)}\right\}^2 \end{aligned}$$

It can be concluded from the above analysis that the sliding manifold $s_T = \tilde{T}_{batt} = 0$ can be attained in finite time given the observer gain L_T is sufficiently higher and greater than $|I_{batt}^2 R|_{max}$. At the sliding manifold, we have $s_T = \tilde{T}_{batt} = 0$ and $\dot{s}_T = \dot{\tilde{T}}_{batt} = 0$ [15] and (17) can be written as:

$$0 = I_{batt}^2 R - v_T \quad (18)$$

where v_T is the *equivalent output error injection* signal required to maintain the sliding motion. Further, from (18) and (13), it can be concluded that \tilde{R} also goes to zero in finite time.

Now, subtracting (14) from (1), the estimation error for *Observer II* can be written as:

$$\dot{\tilde{V}}_c = -\frac{\tilde{V}_c}{R_0 C_0} \quad (19)$$

The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_{LC} = 0.5\tilde{V}_c^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_{LC} &= \tilde{V}_c\dot{\tilde{V}}_c = \tilde{V}_c\left\{-\frac{\tilde{V}_c}{R_0 C_0}\right\} \\ &\Rightarrow V_{LC} \leq V_{LC}(t_0)\exp\left(-\frac{2t}{R_0 C_0}\right) \end{aligned}$$

It can be concluded from the above analysis that the estimation error goes exponentially to zero as $t \rightarrow \infty$ with a convergence rate determined by $R_0 C_0$. Now, as the estimation error \tilde{R} goes to zero in finite time and \tilde{V}_c goes to zero exponentially, it can be concluded that as $t \rightarrow \infty$, $\hat{R} = R$ and $\hat{V}_c \rightarrow V_c$. Consequently,

$$V_{batt} + I_{batt} \hat{R} + \hat{V}_c \rightarrow V_{batt} + I_{batt} R + V_c = E_0 \quad (20)$$

Under this condition, the following is analyzed after sufficient time such that \tilde{V}_c is sufficiently small. The signal \tilde{E}_0 which is defined after (16) can be written as $\tilde{E}_0 = E_0 - \hat{E}_0$ and further, using Lemma 1, the following can be written:

$$\text{sgn}(\tilde{E}_0) = \text{sgn}(\tilde{SOC}) \quad (21)$$

Now, subtracting (15) from (2), the estimation error dynamics for *Observer III* can be written as:

$$\begin{aligned} \dot{\tilde{SOC}} &= -\frac{I}{Q} - L_{SOC} \text{sgn}(\tilde{E}_0) \\ &= -\frac{I}{Q} - L_{SOC} \text{sgn}(\tilde{SOC}) \end{aligned} \quad (22)$$

Note that, the sliding manifold in this case is $s_{SOC} = \tilde{SOC}$ as \tilde{SOC} is inside the sign term. The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_{SOC} = 0.5 \tilde{SOC}^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_{SOC} &= \tilde{SOC} \dot{\tilde{SOC}} = \tilde{SOC} \left\{ -\frac{I}{Q} - L_{SOC} \text{sgn}(\tilde{SOC}) \right\} \\ \Rightarrow \dot{V}_{SOC} &\leq |\tilde{SOC}| \left\{ \left| \frac{I}{Q} \right| - L_{SOC} \right\} \\ \Rightarrow \dot{V}_{SOC} &\leq -\beta \sqrt{V_{SOC}}, \beta = -\sqrt{2} \left(\left| \frac{I}{Q} \right|_{\max} - L_{SOC} \right) > 0 \\ \Rightarrow V_{SOC}(t) &\leq \left\{ -\frac{\beta}{2} t + \sqrt{V_{SOC}(t_0)} \right\}^2 \end{aligned}$$

It can be concluded from the above analysis that the sliding manifold $s_{SOC} = \tilde{SOC} = 0$ can be attained asymptotically as $t \rightarrow \infty$, given the observer gain L_{SOC} is sufficiently higher than $|I/Q|_{\max}$. At the sliding manifold, we have $s_{SOC} = \tilde{SOC} = 0$ and $\dot{s}_{SOC} = \dot{\tilde{SOC}} = 0$ [15] and (22) can be written as:

$$0 = -\frac{I}{Q} - v_{SOC} \quad (23)$$

where v_{SOC} is the *equivalent output error injection* signal required to maintain the sliding motion. Further, from (23) and (16), it can be concluded that \tilde{Q} also goes to zero asymptotically as $t \rightarrow \infty$. □

B. DLC State and Parameter Estimation

In this section, we discuss the design of online estimation of DLC state and parameters. As discussed before, V_{cd} and V_{cf} represents the slow and fast dynamics of the DLC respectively. In the estimation scheme, we concentrate on the V_{cf} dynamics and estimate the variables associated with $R_f - C_f$ branch of the DLC, namely the state V_{cf} and

parameters R_f and C_f . The schematic of the DLC online estimation scheme is shown in Fig. 4. The estimation scheme consists of three observers: *Observer IV* (based on the thermal dynamics of the DLC), *Observer V* (based on the $R_d - C_d$ dynamics), *Observer VI* (based on the $R_f - C_f$ dynamics).

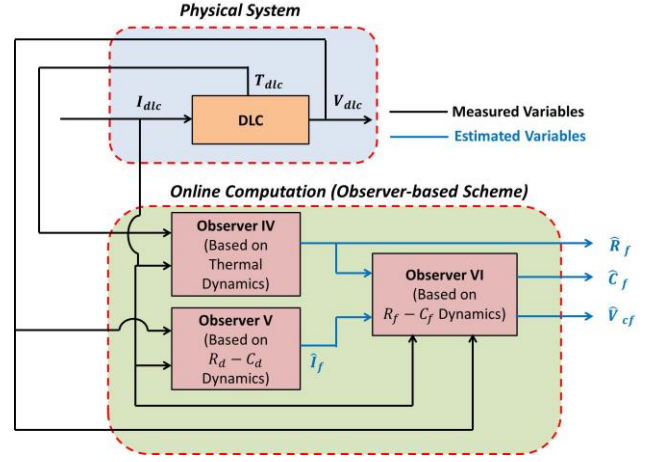


Figure 4: Online DLC state-parameter estimation scheme While designing the estimation scheme, we take the following assumptions.

Assumption 3: The parameters R_f , R_d , C_f and C_d are constants and R_d and C_d , along with the thermal parameters mC_{dlc} and hA_{dlc} are known with sufficient accuracy.

Now, the observer structure for the DLC state and parameter estimation is given as follows.

Observer IV:

$$mC_{dlc} \dot{\hat{T}}_{dlc} = -hA_{dlc} (\hat{T}_{dlc} - T_{amb}) + L_{T2} \text{sgn}(\tilde{T}_{dlc}) \quad (24)$$

$$\hat{R}_f = v_{T2} / I_{dlc}^2 \quad (25)$$

where v_{T2} is the *equivalent output error injection* which is a continuous approximation or filtered version of $L_{T2} \text{sgn}(\tilde{T}_{dlc})$.

Observer V:

$$\dot{\hat{V}}_{cd} = \left(\frac{V_{dlc} - \hat{V}_{cd}}{R_d} \right) \frac{1}{C_d} \quad (26)$$

$$\hat{I}_f = I_{dlc} - \frac{V_{dlc} - \hat{V}_{cd}}{R_d} \quad (27)$$

Observer VI:

$$\dot{\hat{V}}_{cf} = L_V \text{sgn}(\tilde{V}_{cf}) \quad (28)$$

$$\hat{C}_f = \hat{I}_f / v_V \quad (29)$$

where v_V is *equivalent output error injection* which is a continuous approximation or filtered version of $L_V \text{sgn}(\tilde{V}_{cf})$, \hat{T}_{dlc} , \hat{R}_f , \hat{R}_d , \hat{V}_{cf} , \hat{V}_{cd} , \hat{I}_d and \hat{C}_f denotes the estimates of the corresponding states and parameters; $\tilde{T}_{dlc} = T_{dlc} - \hat{T}_{dlc}$, $L_{T2} > 0$ is constant observer gain; $\tilde{V}_{cf} = V_{dlc} - \hat{I}_f \hat{R}_f - \hat{V}_{cf}$,

and $L_V > 0$ is constant observer gain. Further, other estimation errors are defined as: $\tilde{R}_f = R_f - \hat{R}_f$, $\tilde{V}_{cd} = V_{cd} - \hat{V}_{cd}$ and $\tilde{C}_d = C_d - \hat{C}_d$.

Theorem 2: Consider the DLC system dynamics given in (6)-(10) and the observer structure (24)-(29), if the *Assumption 3* holds true then the estimation error \tilde{R}_f converges to zero in finite time; \tilde{I}_f converges to zero exponentially; \tilde{V}_{cf} and \tilde{C}_f converges to zero asymptotically as $t \rightarrow \infty$.

Proof: Subtracting (24) from (10), the error dynamics for *Observer IV* can be written as:

$$mC_{dlc}\dot{\tilde{T}}_{dlc} = I_{dlc}^2 R_f - hA_{dlc}\tilde{T}_{dlc} - L_{T2} \text{sgn}(\tilde{T}_{dlc}) \quad (30)$$

Note that, the sliding manifold in this case is $s_{T2} = \tilde{T}_{dlc}$ as \tilde{T}_{dlc} is inside the sign term. The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_{T2} = 0.5mC_{dlc}\tilde{T}_{dlc}^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_{T2} &= \tilde{T}_{dlc} \{ I_{dlc}^2 R_f - hA_{dlc}\tilde{T}_{dlc} - L_{T2} \text{sgn}(\tilde{T}_{dlc}) \} \\ \Rightarrow \dot{V}_{T2} &\leq |\tilde{T}_{dlc}| \{ |I_{dlc}^2 R_f| - L_{T2} \} \\ \Rightarrow \dot{V}_{T2} &\leq -\gamma\sqrt{V_{T2}} \text{ where } \gamma = -\frac{(|I_{dlc}^2 R_f|_{\max} - L_{T2})}{\sqrt{0.5mC_{dlc}}} > 0 \end{aligned}$$

$$\Rightarrow V_{T2}(t) \leq \left\{ -\frac{\gamma}{2}t + \sqrt{V_{T2}(t_0)} \right\}^2$$

It can be concluded from the above analysis that the sliding manifold $s_{T2} = \tilde{T}_{dlc} = 0$ can be attained in finite time given the observer gain L_{T2} is sufficiently higher than $|I_{dlc}^2 R_f|_{\max}$. At the sliding manifold, we have $s_{T2} = \tilde{T}_{dlc} = 0$ and $\dot{s}_{T2} = \dot{\tilde{T}}_{dlc} = 0$ [15] and (30) can be written as:

$$0 = I_{dlc}^2 R_f - v_{T2} \quad (31)$$

where v_{T2} is the *equivalent output error injection* signal required to maintain the sliding motion and essentially a continuous approximation (filtered version) of the switching term $L_{T2} \text{sgn}(\tilde{T}_{dlc})$. Further considering (31) and (25), the parameter error \tilde{R}_f converges to zero in finite time. Now, considering (7) along with (9) as plant dynamics and *Observer V* given in (26) and (27), the estimation error for *Observer V* can be written as:

$$\dot{\tilde{V}}_{cd} = -\frac{\tilde{V}_{cd}}{R_d C_d} \quad (32)$$

The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_{LD} = 0.5\tilde{V}_{cd}^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_{LD} &= \tilde{V}_{cd} \dot{\tilde{V}}_{cd} = \tilde{V}_{cd} \left\{ -\frac{\tilde{V}_{cd}}{R_d C_d} \right\} \\ \Rightarrow V_{LD}(t) &\leq V_{LD}(t_0) \exp\left(-\frac{2t}{R_d C_d}\right) \end{aligned} \quad (33)$$

It can be concluded from the above analysis that the estimation error goes to zero exponentially as $t \rightarrow \infty$. The convergence rate is determined by $R_d C_d$. Moreover, $\tilde{V}_{cd} \rightarrow V_{cd}$ as $t \rightarrow \infty$, leads to $\hat{I}_f \rightarrow I_f$ using (27).

Under this condition, the following is analyzed after sufficient time such that \tilde{I}_f is sufficiently small. Now, using (9), measured V_{dlc} and known R_f from *Observer IV*, V_{cf} can be reconstructed as $V_{cf} = V_{dlc} - I_f R_f$. This reconstructed signal V_{cf} will be used as pseudo-measurement for *Observer VI*. Subtracting (28) from (6), the error dynamics for *Observer VI* can be written as:

$$\dot{\tilde{V}}_{cf} = \frac{I_f}{C_f} - L_V \text{sgn}(\tilde{V}_{cf}) \quad (34)$$

where the actual V_{cf} and I_f are reconstructed as discussed above. The error dynamics can be analyzed by choosing the positive definite Lyapunov function candidate $V_V = 0.5\tilde{V}_{cf}^2$. The derivative of the Luapunov function candidate can be written as:

$$\begin{aligned} \dot{V}_V &= \tilde{V}_{cf} \dot{\tilde{V}}_{cf} = \tilde{V}_{cf} \left\{ \frac{I_f}{C_f} - L_V \text{sgn}(\tilde{V}_{cf}) \right\} \\ \Rightarrow \dot{V}_V &\leq |\tilde{V}_{cf}| \left\{ \left| \frac{I_f}{C_f} \right| - L_V \right\} \\ \Rightarrow \dot{V}_V &\leq -\zeta\sqrt{V_V} \text{ where } \zeta = -\sqrt{2} \left(|I_f/C_f|_{\max} - L_V \right) > 0 \\ \Rightarrow V_V &\leq \left\{ -\frac{\zeta}{2}t + \sqrt{V_V(t_0)} \right\}^2 \end{aligned}$$

It can be concluded from the above analysis that the sliding manifold $s_V = \tilde{V}_{cf} = 0$ can be achieved asymptotically given the observer gain L_V is sufficiently higher than $|I_f/C_f|_{\max}$. At the sliding manifold, we have $s_V = \tilde{V}_{cf} = 0$ and $\dot{s}_V = \dot{\tilde{V}}_{cf} = 0$ [15] and (34) can be written as:

$$0 = \frac{I_f}{C_f} - v_V \quad (35)$$

where v_V is the *equivalent output error injection* required to maintain the sliding motion. Further, considering (29) and (35), it can be concluded that the parameter error \tilde{C}_f converges to zero asymptotically. \square

IV. CASE STUDY

In this section, we test the effectiveness of the proposed scheme by conducting a case study on a passive battery-DLC HESS. The battery used in this case study is a sealed 12 V lead-acid battery with nominal capacity 90 Ah. The DLC has the following characteristics: total capacitance 1500 F, rated voltage of 2.7 V. The HESS simulator is implemented in MATLAB-Simulink platform and simulation studies are conducted to validate the proposed scheme. The HESS is subjected to a dynamic current profile. The total current and individual currents of the battery and DLC are shown in Fig. 5. To emulate a realistic scenario, noise components have been added to the measured voltages, currents and temperatures. Estimation performance has been shown in Fig. 6 for battery variables and Fig. 7 for DLC variables. It can be seen that the observers perform reasonably and provide sufficiently close estimate of the states and parameters.

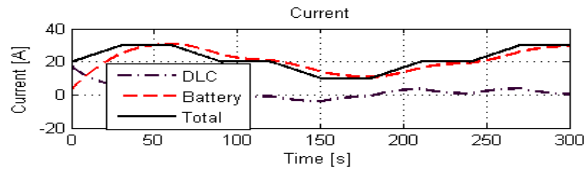


Figure 5: Current components of HESS

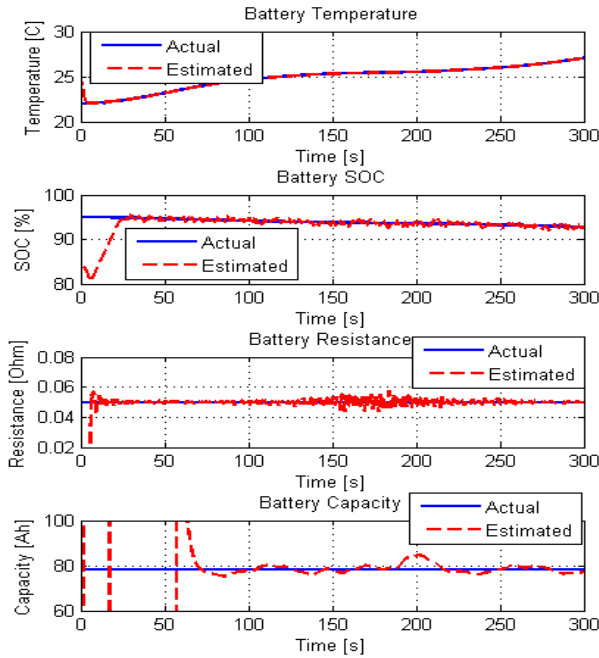


Figure 6: Battery estimation performance

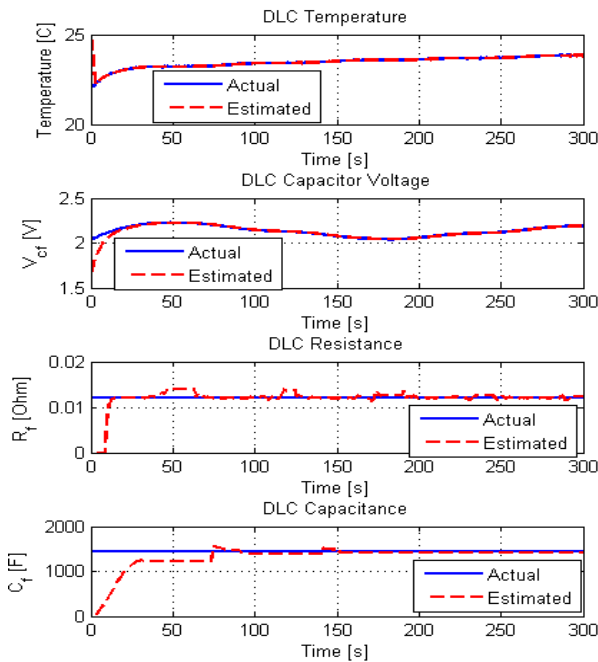


Figure 7: DLC estimation performance

V. CONCLUSION

In this paper, an observer-based scheme is presented for state and parameter estimation for battery-DLC HESS. The

scheme consists of two separate battery and DLC state-parameter estimators based on the sliding mode methods. Each estimator consists of cascaded observers designed with the electrical and thermal dynamics of battery and DLC. Theoretical verification of the overall estimation convergence is provided using Lyapunov's argument. The effectiveness of the scheme is tested via simulation studies which show reasonable performance. As future work, the scheme should be validated with battery experiments. Moreover, the estimation problem here is treated separately for two power sources. Possibly an exploration of the overall coupled system could be used to further enhance the estimation scheme.

REFERENCES

- [1] S. Fiorenti, J. Guanetti, Y. Guezennec, and S. Onori, "Modeling and experimental validation of a Hybridized Energy Storage System for automotive applications," in *Journal of Power Sources*, pp. 112-120, 2013.
- [2] C. Chiang, J. Yang, and W. Cheng, "EKF-based estimation of SOC and temperature in ultracapacitors," in *IEEE International Conference on Control and Automation*, pp. 274-279, 2013.
- [3] S. Dey, B. Ayalew, and P. Pisu, "Adaptive Observer Design for a Li-Ion Cell Based on Coupled Electrochemical-Thermal Model." In *ASME 2014 Dynamic Systems and Control Conference*, 2014.
- [4] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation," in *Journal of Power Sources*, pp. 277-292, 2004.
- [5] M. Rubagotti, S. Onori, and G. Rizzoni, "Automotive battery prognostics using dual Extended Kalman Filter," in *Proceedings of the ASME 2009 Dynamic Systems and Control Conference*, pp. 257-263, 2009.
- [6] B. S. Bhanu, et al., "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," in *IEEE Transactions on Vehicular Technology*, pp. 783-794, 2007.
- [7] Y. Hu., and S. Yurkovich, "Battery cell state-of-charge estimation using linear parameter varying system techniques," in *Journal of Power Sources*, Vol. 198, pp. 338-350, 2003.
- [8] I. Kim, "A technique for estimating the state of health of lithium batteries through a dual-sliding-mode observer," in *IEEE Power Electronics*, Vol 25, pp. 1013-1022, 2010.
- [9] C. Unterrieder, R. Priewasser, S. Marsili, & M. Huemer, "Battery state estimation using mixed Kalman/H ∞ , adaptive Luenberger and sliding mode observer," in *Proc. IEEE Vehicular Power and Propulsion Conference (VPPC)*, pp. 71-76, 2013.
- [10] O. Bohlen, J. Kowal, and D. U. Sauer, "Ageing behaviour of electrochemical double layer capacitors: Part II. Lifetime simulation model for dynamic applications," in *Journal of Power Sources*, Vol. 173, pp. 626-632, 2007.
- [11] D. Pavkovic, V. Smetko, M. Hrgetic, and A. Komljenovic, "Dual Kalman filter-based SoC/SoH estimator for an ultracapacitor module," in *IEEE Control Applications*, pp. 1783-1788, 2014.
- [12] A. Hammar, P. Venet, R. Lallemand, G. Coquery, and G. Rojat, "Study of accelerated aging of supercapacitors for transport applications," in *IEEE Transactions on Industrial Electronics*, Vol. 57, No. 12, pp. 3972-3979, 2010.
- [13] A. Nadeau, G. Sharma, and T. Soyata, "State-of-charge estimation for supercapacitors: a kalman filtering formulation," in *IEEE International Conference on Acoustic, Speech and Signal Processing*, 2014.
- [14] M. Pucci, G. Vitale, G. Cirrincione, and M. Cirrincione, "Parameter identification of a Double-Layer-Capacitor 2-branch model by a least-squares method," in *IEEE IECON 2013*, pp. 6770-6776, 2013.
- [15] V. Utkin, J. Guldner, and J. Shi, *Sliding mode control in electromechanical systems*. CRC press, 1999.