

Real-Time Sliding Mode Observer Estimator Integration in Hybrid Electric Vehicles Battery Management Systems

Nicolae Tudoroiu, Liana Elefterie, Elena-Roxana Tudoroiu,
Wilhelm Kec, Maria Dobritoiu and Nicolae Ilias

Abstract In this paper we develop and implement a real-time sliding mode observer estimator (SMOE) for state-of-charge (SOC) and for current fault in Li-Ion batteries packs integrated in the battery management systems (BMS) structure of hybrid electric vehicles (HEVs). The estimation of SOC is critical in automotive industry for successful marketing of both electric vehicles (EVs) and hybrid electric vehicles (HEVs). Gradual capacity reduction and performance decay can be evaluated rigorously based on the current knowledge of rechargeable battery technology, and consequently is required a rigorous monitoring and a tight control of the SOC level, necessary for increasing the operating batteries lifetime. The novelty of this paper is that the proposed estimator structure can be also tailored to estimate the SOC and the possible faults that could occur inside of the batteries of different chemistry by augmenting the dimension of the model states, according to the number of estimated battery faults. The preliminary results obtained in this research are encouraging and reveal the effectiveness of the real-time implementation of the proposed estimator in a MATLAB/SIMULINK programming simulation environment.

N. Tudoroiu (✉)

Engineering Technologies, John Abbott College, Sainte-Anne-de-Bellevue, Quebec, Canada
e-mail: nicolae.tudoroiu@johnabbott.qc.ca

L. Elefterie

Spiru Haret University, Faculty of Economic Sciences, Constanta, Romania
e-mail: elefterie.liana@spiruharet.ro

E.-R. Tudoroiu · W. Kec · M. Dobritoiu

Faculty of Sciences, University of Petrosani, Petrosani, Romania
e-mail: tudelena@mail.com

W. Kec

e-mail: wwkecs@yahoo.com

M. Dobritoiu

e-mail: mariadobritoiu@yahoo.com

N. Ilias

Mechanical and Electrical Engineering, University of Petrosani, Petrosani, Romania
e-mail: iliasnic@yahoo.com

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1 Introduction

The state-of-charge (SOC) of a battery is defined as its available capacity expressed as a percentage of its rated capacity. More specifically the SOC is the remaining capacity of the battery affected by its load current and temperature [1]. The battery SOC estimation is essential in automotive industry for both electric vehicles (EVs) and hybrid electric vehicles (HEVs). Furthermore the SOC of a battery, representing a critical condition parameter for battery management system (BMS) [1–3]. Also an accurate estimate of the battery SOC is the main issue for its healthy and safe operation no matter its chemistry. Today the most advanced and promising technology in batteries field is the production of nickel-metal hydride (Ni-MH) and lithium-ion (Li-Ion) batteries [1–3, 4]. The both batteries are rechargeable, and consequently they are of a great prospective for automotive industry to be used on a large scale to plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and battery electric vehicles (BEVs). By now it was proved that the Ni-MH batteries lead the competition for a lot of automotive industry applications in electric and hybrid electric vehicles since they are quite inexpensive and have a high specific energy, high specific power, long cycle life, and also no poisonous heavy metals [1–3]. The main disadvantage of these batteries is that they have to be often completely discharged in order to avoid the “memory” effect that reduces the battery’s life [1–3]. They also produce more heat during the charging cycles, and specially in operating conditions at heavy loads the heat increases drastically and thus can reduce significantly the battery’s life. In contrast, Li-Ion batteries are more expensive, but lighter in weight and they have a small size, thus easy to be incorporated inside the vehicle structure. It is worth to mention that they are not affected by a “memory” effect so they should not be completely discharged in order to keep up the battery for a long time; therefore they do not require any maintenance [1–3]. Moreover Li-Ion batteries can be stored for a long time by keeping intact their charge. By reason of their great potential to store higher specific energy and energy density, the implementation of Li-Ion batteries is expected to grow very fast in EVs, mainly in PHEVs and BEVs [1–3, 4]. They perform better if they never are fully charged or discharged, therefore an accurate on-board SOC estimate has to be strictly controlled or a protection switch has to be installed; therefore the equipment complexity and its cost increase. Also at extreme temperatures Li-Ion batteries do not perform well, so a cooling and heating system is required to be installed in order to increase their life’s time [1–3, 4]. The Li-Ion batteries are capable to provide enough power to boost up the acceleration and to increase the energy efficiency through on-board battery energy storage [1–3, 4]. The gradual capacity attenuation and performance degradation of the Li-Ion battery during its time operation can be evaluated strictly based on the current knowledge of rechargeable battery technology, and consequently an

accurate estimate and a tight control of the SOC level in order to increase the operating battery's lifetime are required [1–3]. In this paper we investigate new directions in order to develop the most accurate SOC estimator combined with the most suitable fault detection, isolation and reconstruction (FDIR) technique. In second section we choose the most suitable Li-Ion battery model required to develop in third section a robust sliding mode observer estimator (SMOE) able to estimate with accuracy the SOC of a high power Li-Ion battery SOC for a suburban small HEVs. Therefore the purpose of this paper is to built a robust, accurate SOC estimator, easy to be implemented in real-time, as a viable alternative to Kalman filter estimation techniques [3, 5, 6] developed until now in the literature. The proposed SOC estimator is based on a simple generic battery model described in a state-space representation by two differential first-order state equations. For simulation purpose, in order to show its effectiveness the generic battery model is tailored on a particular Li-Ion battery chemistry.

2 The Li-Ion Battery Model

Until now in the literature are reported three developed fundamental types of battery models, particularly the experimental, electrochemical and electric circuit-based [1–3, 5, 4]. The first two models seems to be inappropriate to represent the cell dynamics of battery packs from state-of-charge (SOC) estimation viewpoint, compared to the electric circuit-based models that are very useful to represent the electrical characteristics of the batteries [2, 3, 4]. The simplest electric model, known as the Thevenin model, consists of an ideal voltage source in series with an internal battery cell resistance [4]. A battery cell is the smallest unit connected in parallel or in series to form one module. A module is then connected in a parallel or series configuration to form one battery pack, as is integrated in the vehicle [1–3, 4]. The voltage measured between the battery pack terminals when a load is applied is called terminal voltage or the measured output of the battery model, and the voltage measured between the battery pack or cell terminals when no load is applied is called open-circuit voltage (OCV) [1–3, 4]. The input of the model is the charging or discharging current. Battery charge rate, denoted by C-rate, describes the rate at which the battery is charged or discharged relative to its maximum capacity [1–3, 4]. A 1C rate means that the applied discharge current will discharge a fully charged battery in 1 h. For example a battery with a capacity of 6 Ah, this equals to a 6 A discharge current. A 5C rate for this battery would be $6 \times 5 = 30$ A, and a C/4 rate would be $6/4 = 1.5$ A. The identification of the electric circuit parameters (the values of the resistances and capacitors) for the model is based on a quite complex technique called impedance spectroscopy [1–3, 4]. Shepherd developed a model described by a first order differential equation that capture the electrochemical behavior of a battery in terms of the measured terminal voltage and discharge current, OCV, internal resistance, and SOC [2, 3, 4]; it is suitable for discharge as well as for charge, and also for SOC estimation. Compared to other models, the

Shepherd model is much more interesting but causes algebraic loop instability in the closed-loop simulation of modular models [2, 3, 4]. Generic battery models that are described by a nonlinear first-order differential state equation with only SOC as a state variable are discussed in [2, 3, 5, 4]. These models are very similar to Shepherd's but don't generate algebraic loop instability in closed-loop simulations [1–3, 4]. This simple model using only SOC as a state variable is capable to reproduce precisely the manufacturer's OCV characteristic curves of the battery under investigation versus its state of charge (SOC). Typically, the values of the battery model parameters are obtained by using a nonlinear least squares curve fitting method based on the nonlinear battery discharging characteristic curves OCV versus SOC for a particular battery chemistry, as is shown in [1–3, 5, 4]. For simulation purpose, as case study we choose a Li-Ion battery model, such as the one developed in [3, 5, 4] that is a simple electric circuit, known as the 1st order RC model consisting of an open circuit voltage (OCV) in series with an internal resistance R_i and one parallel RC circuit [4]. In Figs. 1 and 2 we show the schematic diagrams of the electrical circuit battery model built in a National Instruments MULTISIM

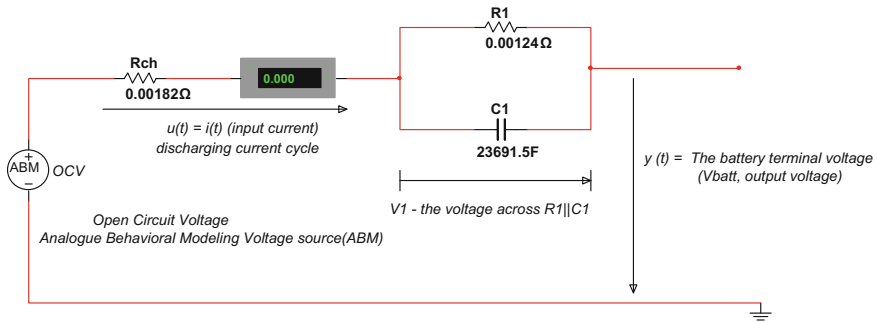


Fig. 1 Schematic diagram of the RC 1st order battery model for charging cycle (in MULTISIM 11 editor)

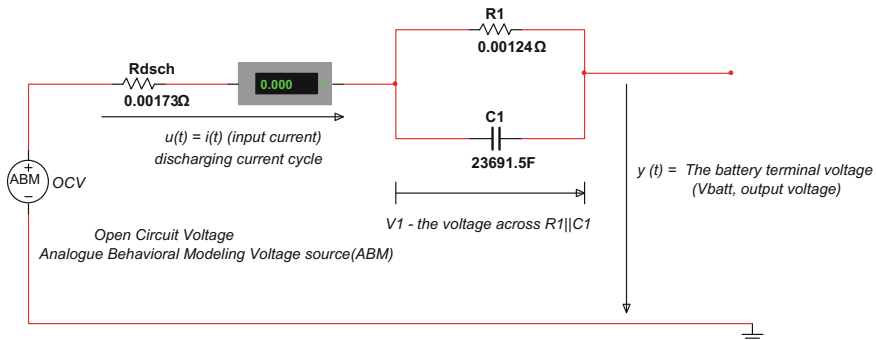


Fig. 2 Schematic diagram of the RC 1st order battery model for discharging cycle (in MULTISIM 11 editor)

11 editor that captures accurately the electrochemical behavior of a battery in terms of the measured battery terminal voltage $y(t)$, charge or discharge current $u(t)$, OCV, battery internal resistance (R_{ch} , R_{dsch}), and SOC. Also this model is suitable for implementation in real-time the SOC sliding mode estimator. The both diagrams are the same, only the values of the battery internal resistance are different, according to charging (R_{ch}) or discharging cycle (R_{dsch}). The overall battery model can be described in discrete time by two states, first one is the voltage across the parallel group (R_1 , C_1) of the components, and the second one is the battery SOC. The third equation is the output equation that relates the terminal battery voltage to the both states, and the input charging or discharging current.

The state and the input-state-output equations can be written as follows:

$$x_{1,k+1} = \left(1 - \frac{T_s}{R_1 C_1}\right) x_{1,k} + \frac{T_s}{C_1} u_k \quad (1)$$

$$x_{2,k+1} = x_{2,k} - \left(\frac{\eta_i}{Q_{nom}} T_s\right) u_k \quad (2)$$

$$y_k = OCV(x_{2,k}) - x_{1,k} - R_i u_k \quad (3)$$

where

- T_s is the sampling time in seconds
- η_i is the columbic efficiency for charging and discharging cycle, $\eta_i = 0.98$ for charging cycle, and $\eta_i = 1$ for a discharging cycle
- Q_{nom} is the nominal capacity of the battery
- $x_{1,k} = V_1(k)$, $x_{2,k} = SOC(k)$
- k is the discrete time, e.g. $t_k = k \times T_s$
- $u_k = i(k)$ is the input current, if $i(k) < 0$ is a charging cycle, and if $i(k) > 0$ is a discharging cycle.
- R_i is the battery internal resistance, for a charging cycle $R_i = R_{ch}$, and for a discharging cycle $R_i = R_{dsch}$
- $R_1 C_1$ is the polarization time constant of the parallel circuit (R_1, C_1)
- y_k is the battery terminal output voltage

The battery terminal voltage y_k may be predicted based on the battery SOC; the most accurate formulation is using a combination of three models Shepherd, Unnewehr universal, and Nernst models, as in [3, 5, 4] for $OCV(x_{2,k})$:

$$OCV(x_{2,k}) = K_0 - \frac{K_1}{x_{2,k}} - K_2 x_{2,k} + K_3 \ln(x_{2,k}) + K_4 \ln(|1 - x_{2,k}|) \quad (4)$$

The model parameters (K_0, K_1, K_2, K_3, K_4) are chosen to fit the model to the manufacture's data by using a least squares curve fitting identification method $OCV = f(SOC)$, as shown in [2, 3, 5, 4], where the OCV curve is assumed to be the average of the charge and discharge curves taken at low currents rates from fully

charged to fully discharged battery. Using low charging and discharging currents can be minimized the cell dynamics. A simple offline (batch) processing method for parameters calculation can be carried out as in [3, 5, 4]. For a high power Li-Ion battery of 6 Ah and nominal voltage 3.6 V olts the rated capacity Q is Amps hours (1C) and its nominal capacity is defined as $Q_{nom} = 0.8 \times Q = 4.8$ Ah. The OCV charging and discharging curves related to the SOC are shown in Figs. 3 and 4, respectively. The values of the parameters that fit the model can be found in [4]. Based on these settings of the model parameters we will build in the next section the sliding mode observer estimator (SMOE) in order to estimate accurately the Li-Ion battery SOC, and extensive simulations will be carried out in a MATLAB/SIMULINK programming environment:

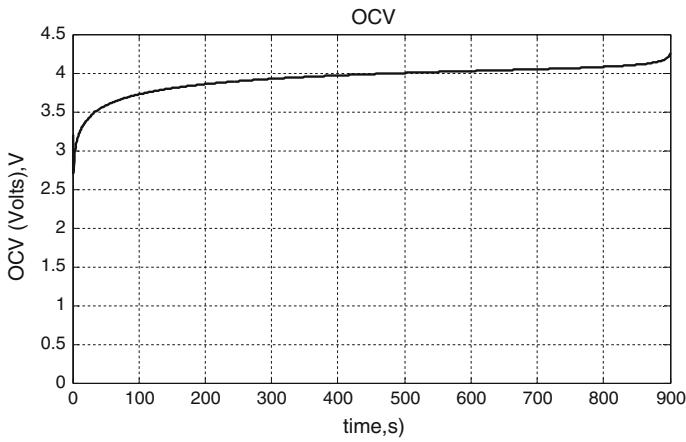


Fig. 3 The OCV charging curve at 5C rate (30 A constant current)

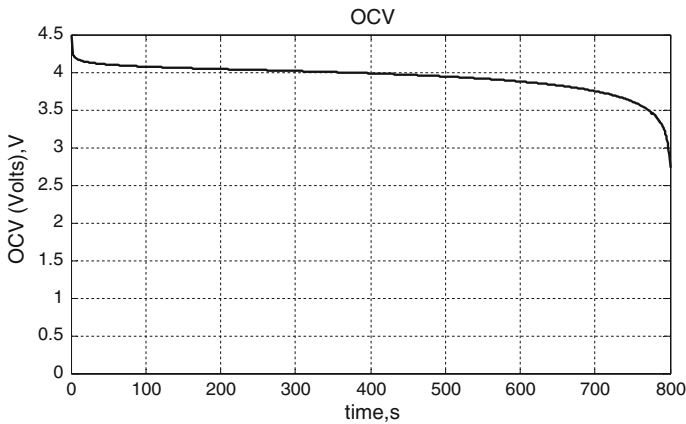


Fig. 4 The OCV discharging curve at 5C rate (30 A constant current)

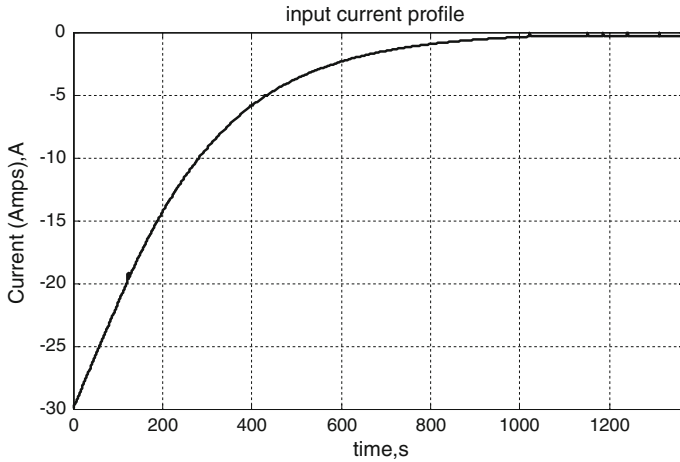


Fig. 5 Advisor EPA UDDS driving cycle current profile (Advisor-2 software package free download open-source)

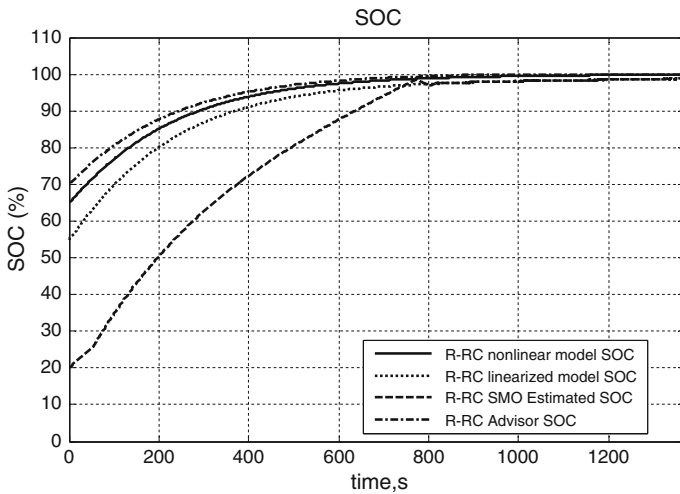


Fig. 6 Li-Ion 6Ah SAFT Battery—SOC curves for R-RC model (nonlinear, linearized, SMO estimator, and ADVISOR-2) for $L = 1$, $M = 0.0001$

$K_0 = 4.23$, $K_1 = 3.8e - 5$, $K_2 = 0.24$, $K_3 = 0.22$, $K_4 = -0.04$, $R_{ch} = 0.00182 \Omega$, $R_{dsch} = 0.00173 \Omega$, $C_1 = 23691.5 \text{ F}$, $R_1 = 0.00124 \Omega$.

Also in our simulations we set the sampling time T_s to be 1 s.

In order to analyze the behavior of the our Li-Ion battery model selection for different driving conditions such as urban, suburban and highway, some different

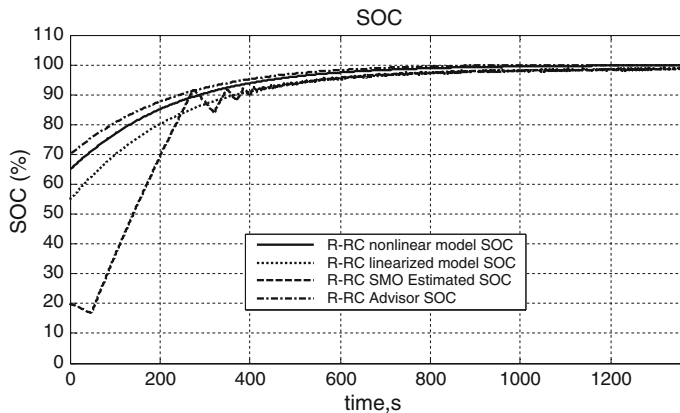


Fig. 7 Li-Ion 6Ah SAFT Battery—SOC curves for R-RC model (nonlinear, linearized, SMO estimator, and ADVISOR-2) for $L = 5$, $M = 0.0001$

current profile tests are used. Also for comparison purpose we use the results of the tests on a suburban small RWD' hybrid electric vehicle under standard initial conditions in an Advanced Vehicle Simulator (ADVISOR) environment, developed by US National Renewable Energy Laboratory (NREL), as in [1–3, 5, 4]. Among different driving cycle current profiles provided by the ADVISOR US Environmental Protection Agency we choose for our case study an Urban Dynamometer Driving Schedule (UDDS) current profile as is shown in Fig. 5. The corresponding SOC curves to this current profile are shown in Fig. 6 with some

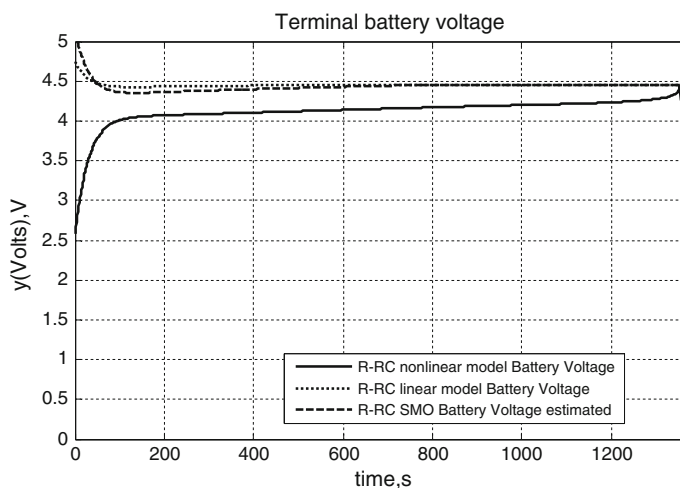


Fig. 8 The battery terminal voltage for UDDS current profile for $L = 5$, $M = 0.0001$

details given in the next section. Also the corresponding terminal voltages of the chosen Li-Ion battery that uses a charging UDDS current profile can be seen in the Figs. 7 and 8.

3 The Sliding Mode Observer Estimator

A combination of sliding mode methods and an observer provide the ability to generate a sliding motion on the error between the measured plant output and the observer output in order to ensure that a sliding mode observer (SMO) produces a set of state estimates precisely matching with the actual output of the plant [7]. Also the analysis of the average value of the applied observer injected signal, known as equivalent injection signal, contains valuable information about the disparity between the observer model and the actual plant [7]. In order to design a SMO estimator (SMOE) of Li-Ion SOC battery we follow the same design procedure used in [7]. The corresponding continuous dynamic description to the discrete time battery model given by (1)–(4) can be arranged in the following matrix state space representation:

$$\frac{dx}{dt} = A_{n \times n}x + B_{n \times m}u \quad (5)$$

$$y = C_{p \times n}x + D_{p \times m}u \quad (6)$$

where $n = 2$ represents the number of states, $m = 2$ is the number of inputs, and $p = 1$ is the number of outputs.

The state vector $x(t)$ is designated by $x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}$, the input vector is $u(t) = \begin{bmatrix} i(t) \\ 1(t) \end{bmatrix}$ ($i(t)$ — input battery current profile, $1(t)$ — step input signal), and the battery output voltage $y(t)$ is related to SOC and OCV by a linear matrix equation. The matrices $C_{p \times n}$, $D_{p \times m}$ are obtained by linearizing the Eq. (4) around an operating point, assuming in our case study $SOC_0 = 0.6$. Following the procedure described in [7], the matrices triplet (A, B, C) is converted into canonical form (A_c, B_c, C_c) , by using a nonsingular state transformation matrix

$$z = T_c x = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}, z_1 \in R^{n-p}, z_2 \in R^p, T_c = \begin{bmatrix} N_c^T \\ C \end{bmatrix}, N_c \in R^{n \times (n-p)} \quad (7)$$

where the column of the matrix N_c spans the null space of C [7], such that

$$A_c = T_c A T_c^{-1}, B_c = T_c B, C_c = C T_c^{-1} = [0 C_2] \quad (8)$$

A robust observer exists for the canonical battery model if $A_{c,11} < 0$ [7], so if it is stable. The sliding mode observer dynamics is attached to this canonical form and can be described by the following two equations [7]:

$$\frac{d\hat{z}_1}{dt} = A_{c,11}\hat{z}_1(t) + A_{c,12}\hat{z}_2(t) + B_{c,1}u(t) + L\vartheta \quad (9)$$

$$\frac{d\hat{z}_2}{dt} = A_{c,21}\hat{z}_1(t) + A_{c,22}\hat{z}_2(t) + B_{c,2}u(t) - \vartheta \quad (10)$$

where $\hat{z}_1(t)$, $\hat{z}_2(t)$ represent the estimates of the battery model states in the canonical form, and L is the linear observer matrix gain. The value of L is given by imposing the spectrum of the matrix $A_{c,11} + LA_{c,21}$ to lie in C_- [7], i.e.

$$A_{c,11} + LA_{c,21} < 0 \quad (11)$$

The vector ϑ can be seen as a nonlinear observer vector switching gain given by:

$$\vartheta_i = M \operatorname{sgn}(\hat{z}_{2,i} - z_{2,i}), M \in R_+, i = 1, \dots, p \quad (12)$$

where the gain coefficient M is a very useful sliding mode observer tuning parameter needed to increase the battery SOC estimate accuracy. Similar, the linear gain L , is a second tuning SMOE parameter that offers a new freedom degree for SMOE to increase the estimate accuracy and to decrease drastically the detection time of possible faults that could occur inside the battery cells. Extensive MATLAB simulations will be done in the next two subsections with the aim to prove the effectiveness of the proposed sliding mode observer estimator in real-time implementation of Li-Ion battery SOC estimation and fault detection.

3.1 Sliding Mode Observer Estimator—SOC Estimation Simulation Results

In this case study we present the simulation results for a high power Li-Ion cell battery 6Ah and 3.6 V nominal voltage developed by SAFT America for small suburban HEVs. This company is part of the U.S. Advanced Battery Consortium, as U.S. Partnership for New Generation of Vehicles programs [2]. Based on the experimental test data, the National Renewable Energy Laboratory (NREL) developed a MATLAB resistive equivalent circuit battery model in order to be compared to a SAFT 2-capacitance battery [2]. For purpose comparison of the sliding mode predictions was used the ADVISOR simulator for different operating conditions provided by two driving cycles tests, US06 and EPA UDDS [2]. Inspired by the usefulness of the ADVISOR simulator and the results obtained in this area we prove the effectiveness of our proposed estimator design strategy using an

EPA UDDS driving cycle current profile integrated in Advisor 2 software package (open-source free download since 2014). This driving cycle current profile is used as a charging current test for the chosen R-RC first order battery model. Then the performance of the battery model and sliding mode observer estimator can be compared to those obtained by the ADVISOR simulator for different Li-Ion HEVs batteries with similar characteristics. The ADVISOR EPA UDDS driving cycle current profile is shown in Fig. 5 and it seems to be a smooth exponential charging current cycle. The continuous battery model dynamics is described in a state-space representation by the matrices quadruplet (A, B, C, D) that appear in the state Eqs. (5)–(6) given by:

$$A = \begin{bmatrix} -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{C_1} & 0 \\ -\eta/Q_{nom} & 0 \end{bmatrix}, C = \begin{bmatrix} -1 \\ C_2 \end{bmatrix}, D = [-R; K_0] \quad (13)$$

$$T_c = \begin{bmatrix} C_2 & 0 \\ 1 & 1 \end{bmatrix}, C_2 = K_1/x_0^2 - K_2 + K_3/x_0 - K_4/(1 - x_0), x_0 = 0.6 \quad (14)$$

$$K_0 = 4.23, K_1 = 3.8e - 5, K_2 = 0.24, K_3 = 0.22, K_4 = -0.04 \quad (15)$$

$$R_{ch} = 0.00182 \Omega, R_{dsch} = 0.00173 \Omega, C_1 = 23691.5 \text{ F}, R_1 = 0.00124 \Omega \quad (16)$$

The Li-Ion battery SOC evolution curves during the charging cycle are shown in Fig. 6, for first order R-RC nonlinear model, for its linearized dynamics and SMO estimator with the gains settings $L = 1$, $M = 0.0001$; also for comparison purpose is shown on the same graph the SOC obtained by the ADVISOR simulator for the same driving current profile. In Fig. 7 we represent the same curves for observer gains tuned to $L = 5$, $M = 0.0001$ that reveal a fast estimation with some small

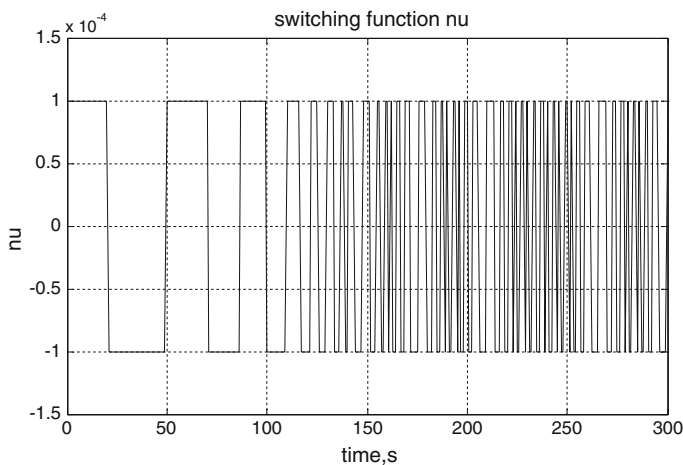


Fig. 9 Switching nonlinear observer gain for $L = 1$, $M = 0.0001$

oscillations around the SOC steady-state value, and sliding mode observer robustness to a big change in the initial SOC value as a first guess starting point value ($SOC_0 = 0.2$ instead to $SOC_0 = 0.7$ as is used in ADVISOR). In Fig. 8 is shown the terminal battery voltages for nonlinear battery model, for its linearized model, and for SMO estimator, when the observer gains are set to $L = 5$, $M = 0.0001$. Again we can see an accurate estimation of the terminal battery voltage when SMO estimator is used. The evolution of switching nonlinear observer gain is shown in Fig. 9.

3.2 Sliding Mode Observer Estimator—Battery Cell Current Fault Detection Simulation Results

The sliding mode observer estimator developed in this research can be also used for fault detection purpose. To prove its effectiveness in fault detection we consider the particular case of an intermittent fault injection in the battery cells current profile, as is shown in Fig. 10. A zero faulty current that simulates an open cell circuit in a battery pack is injected after 100 s and it will be removed after 100 samples. So the window length of the persistent injected fault is only 100 s.

The sliding mode observer estimator reacts very fast to this current. The current fault is detected in some few seconds, as is shown in Fig. 11. In this figure is shown the terminal battery voltage residual generated by the SMOE.

In the future work we will develop some applications of the proposed SMOE to detect and estimate the severity of the faults, by augmenting the model dynamics state-space with a new dimension given by the following fault parameter equation [5]:

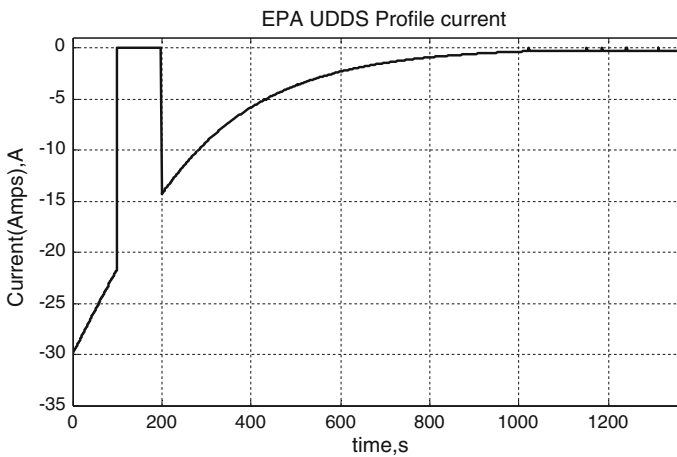


Fig. 10 Intermittent current fault in SAFT battery cell injected between iterations 100 and 200

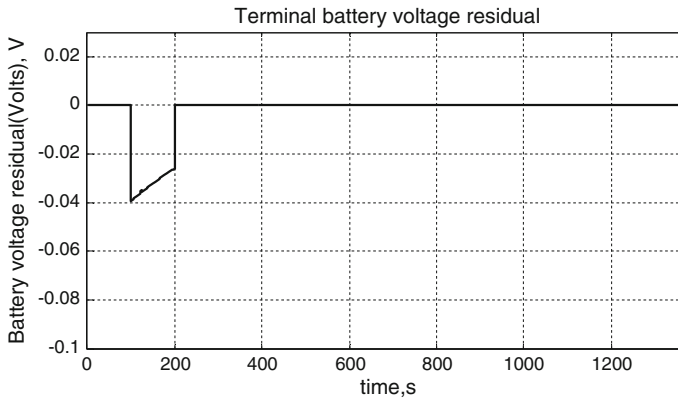


Fig. 11 SMO Fault detection (SAFT battery cell voltage residual)

$$\Theta_{k+1} = \Theta_k + v_k \quad (17)$$

where Θ_k represent discrete time fault parameter description, and v_k is a small level noise. Now the SMO estimator has three states and the procedure to estimate the states will be the same to those used for two states, as in [7]. The big challenge in this development is the capability of the augmented estimator to estimate the severity of the faults.

4 Conclusion

The novelty of this paper is the implementation in real time of a robust Sliding Mode Observer estimator capable to estimate with high accuracy the Li-Ion battery SOC based on a linearised model without disturbance uncertainties, and also to detect the faults inside the battery cells. The proposed SMO estimation strategy seems to be simple, easy to be implemented in real-time, and of lower computations complexity, compared to Kalman filter estimation techniques. The proposed SMO estimator will be very useful in our research to solve problems of fault detection and isolation (FDI) that could appear in the BMS of HEVs and EVs.

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