Novel Battery SOC/SOP/SOH Estimation Algorithms in a Unified Framework

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Abstract

The performance of pure electric and hybrid electric vehicles highly depends on accurate and reliable knowledge of internal battery parameters. Specifically, parameters such as the state-of-charge (SOC), state-of-health (SOH) and state-of-power (SOP) are of particular interest. This paper presents new algorithms for estimating these three key parameters using an OCV-R-RC electrical equivalent circuit model. The proposed SOC, SOH and SOP estimation algorithms are tightly coupled and work cooperatively. In order to estimate the SOC, this paper introduces a combined *Coulomb counting and Regressed Voltage*-based SOC estimation method that combines the traditional Coulomb counting with a regressed open-circuit voltage (OCV)-based SOC estimation technique. As a by-product of the SOC estimation algorithm, the electrical parameters are estimated and used to predict the SOH. For SOP estimation, unlike the traditional HPPC method that uses fixed battery parameters and voltage limits, this papers proposes a dynamic power capability estimation method by taking into account voltage limits, current limits and the estimated electrical parameters. The proposed algorithm is called the *IV-limited SOP estimation* algorithm. Finally, computer simulations are performed to validate the effectiveness of these algorithms.

I. Introduction

The state-of-charge (SOC), state-of-health (SOH) and state-of-power (SOP) are three key variables used in battery control and energy management. The SOC is defined as a ratio of the remaining capacity to the nominal capacity. The performance and safety of hybrid and pure electric vehicles is highly dependent on the accurate and immediate assessment of the amount of charge available for use by the vehicle at any time. The range, fuel economy and other critical, calculated performance criteria rely greatly on the SOC. Consequently, estimating the SOC accurately will ultimately improve both vehicle safety and customer satisfaction.

The SOH is often related to the loss of battery's rated capacity. When the capacity reduces to 80% of the beginning of life capacity, the battery is considered to have reached its end of life. Cycling and calender aging cause the battery to loose its capacity. The capacity fade of a battery can be detected by observing power capability fade or changes in electrical equivalent circuit model parameters such as ohmic resistance and the time constant. Specifically, the capacity fade is caused by the growth of the SEI (Solid-Electrolyte Interface) layer leading to increased resistance. Therefore, the SOH has an inverse correlation with the resistance. In this paper, the SOH is defined in terms of ohmic resistance:

$$SOH \triangleq \frac{R_{o,nom}}{\hat{R}_{o,t}},$$

where $R_{o,nom}$ is the nominal ohmic resistance of a fresh battery and $\hat{R}_{o,t}$ refers to the estimated ohmic resistance at time t measured in hrs/weeks/months. $R_{o,t}$ is readily available as a by-product of the proposed SOC estimation algorithm.

In addition to SOC and SOH, the SOP is of critical importance in the context of hybrid energy storage systems. The SOP refers to the battery's present ability to provide power over the next T_p seconds under voltage and/or current limits. In hybrid vehicles, the battery management system needs to know the battery's present power capability so that it can prepare the other alternative power sources such as internal combustion engines or fuel cells to bridge the gap between demanded power and available power from the battery pack. The SOP depends on SOC, SOH, temperature and time. It has to be accurately predicted in real time such that over- and under-voltage conditions will not occur in the next T_p seconds, assuming a constant current rate.

The main motivation of this paper is to present new algorithms for the purpose of estimating the SOC, SOH and SOP under a unified framework. To this end, we take the following five steps:

- A linear regression model is constructed based on an OCV-R-RC (OCV- Open Circuit Voltage, R- Resistance, C- Capacitance) equivalent circuit model that correlates the behavior of a battery and the values of its circuit elements.
- For online parameter identification, a square-root version of the recursive least-squares (SR-RLS) algorithm with forgetting factor is deployed. The outputs of this algorithm are the battery electrical parameters and the OCV. Subsequently, the SOC is inferred from the estimated OCV using a SOC-OCV map. As mentioned above, the battery's SOH is inferred from the electrical parameters.

- For accurate estimation of the SOC, we go on to propose a so-called combined *Coulomb Counting and Regressed Voltage* based SOC estimation method that fuses the SOC output of the regressed OCV-based SOC estimation method as just mentioned above as well as the idea of Coulomb counting.
- Unlike the traditional 'static' SOP estimation method proposed by the PGNV, we derive a 'dynamic' SOP estimation method based on the OCV-R-RC model by taking into account both the voltage and current limits for more accurate prediction. This method is named the *IV-limited SOP estimation method*.
- Finally, in order to validate the new algorithms, computer experiments are performed based on the UDDS (urban dynamometer driving schedule).

II. SOC/SOH Estimation

The first step in the construction of an optimal battery state estimator is to develop a suitable model of the battery that can describe the salient features of both steady-state and transient responses. It has been found that the OCV-R-RC model is sufficient to meet this requirement. For this reason, we develop our state estimators based on this model in the following sections.

A. Deriving a Linear Regression Model for Parameter Estimation

The governing equations of the circuit depicted in Fig. 1(a) can be expressed as:

$$V_{p,k} = aV_{p,k-1} + bI_{L,k-1} \tag{1}$$

$$V_{t,k} = V_{p,k} + cI_{L,k} + V_{oc} \tag{2}$$

where the parameters $a = e^{-T_s/\tau}, b = R_p(1 - e^{-T_s/\tau})$ and $c = R_o$. Hence, the transfer function from the load current, I_L, to the terminal voltage, V_t, in the Z-domain can be written as

$$\begin{aligned} V_t(z) &= \left(\frac{b}{z-a}\right)I_L(z) + cI_L(z) + V_{oc} \\ \Rightarrow (z-a)V_t(z) &= \Big(b + c(z-a)\Big)I_L(z) + (z-a)V_{oc} \end{aligned} \tag{3}$$

Because the open circuit voltage, V_{oc}, is treated as a constant, taking the inverse z-transform of (3) yields the following difference equation:

$$V_{t,k} = (b - ac)I_{L,k-1} + cI_{L,k} + aV_{t,k-1} + (1-a)V_{oc} \tag{4}$$

The linear regression model (4) can be compactly written as the inner product

$$V_{t,k} = \theta^T \mathbf{\Phi}_k, \tag{5}$$

where θ is the parameter vector and $\mathbf{\Phi}_k$ is a regressor consisting of known signals:

$$\theta = [(b - ac) \;\; c \;\; a \;\; (1-a)V_{oc}]^T \tag{6}$$

$$\mathbf{\Phi}_k = [I_{Lk-1} \;\; I_{L,k} \;\; V_{t,k-1} \;\; 1]^T \tag{7}$$

The most pragmatic solution to estimate θ from the ARX model (5) is to apply the Recursive Least Squares (RLS) algorithm. A square-root version of the RLS method is used in this paper for its computational efficiency and stability. Since the square-root RLS algorithm guarantees a positive-definite and symmetric covariance matrix, it is highly numerically stable and achieves high estimation accuracy and robustness. In order to closely track slowly varying parameters, a forgetting factor is included in the RLS. The battery electrical parameters R_o, R_p, C_p and V_{oc} can be recursively estimated upon estimating θ as follows:

$$\begin{aligned} \hat{R}_o &= \theta(2) \\ \hat{R}_p &= \frac{\theta(1) + \theta(2)\theta(3)}{1 - \theta(3)} \\ \hat{C}_p &= \frac{T_s}{\ln(\theta(3))}\frac{\theta(3) - 1}{\theta(1) + \theta(2)\theta(3)} \\ \hat{V}_{oc} &= \frac{\theta(4)}{1 - \theta(3)} \end{aligned}$$

The battery's SOH is predicted based on $\hat{R}_o$.

B. Combined Coulomb Counting and Regressed-Voltage SOC Estimation Algorithm

This subsection derives the combined Coulomb Counting and Regressed-Voltage SOC estimation algorithm, which we briefly call the *CRV method* in this paper, by incorporating the SOC estimated from two different SOC estimation techniques:

- **The Regressed Voltage Method (*RV Method*)**, in which the open-circuit voltage, V_{oc}, estimated from the RLS algorithm is used to calculate the SOC according to the SOC→OCV map (see Fig. 1(b)) or a look-up table. Due to the fact that the SOC is coupled with a current integration technique and therefore it is a slowly time-varying signal, the noisy (spiky) SOC estimate obtained from the RV method, which we denote $\widehat{SOC}_{nRV}$, is filtered by a exponentially-weighted moving average filter to get a clean and smooth SOC signal:

$$\widehat{SOC}_{RV,k} = (1-\alpha)\widehat{SOC}_{RV,k-1} + \alpha\widehat{SOC}_{nRV,k}, \tag{8}$$

  where α is the filter gain and takes a small positive value, typically in the range of $10^{-4} - 10^{-2}$.
- **The Coulomb Counting Method (*CC Method*)**. Unlike the traditional CC method, the CC method used within the CRV framework gets its initial estimated SOC from the CRV method. For this reason, the CC method is able to correct the initial SOC error.

The CRV method can be mathematically described by the following equation:

$$\widehat{SOC}_{CRV,k} = \begin{cases} \widehat{SOC}_{RV,k}, & s_k = 1 \\ \widehat{SOC}_{CRV,k-1} + \frac{\eta}{Q}\frac{T_s}{3600}\frac{I_{L,k-1}+I_{L,k}}{2}, & s_k = 0 \end{cases} \tag{9}$$

where the parameter η refers to the Columbic efficiency, Q is the battery's nominal capacity in Ah and s_k is a trigger signal with binary states. Initially, the trigger signal s is set to be one so that it takes the regressed voltage-based SOC estimates. For our experiment, a trigger signal with a fixed period of 1000s and a duty ratio of 0.05 has been found to work well.

III. IV-LIMITED SOP ESTIMATION ALGORITHM

The Partnership for a New Generation of Vehicles (PNGV) provided a SOP (also called 'peak-power capability') estimation method based on the HPPC test. However, this method is plagued by two key limitations: (i) The PGNV method assumes a basic OCV-R (ohmic-) battery model. (ii) Battery current limits are not considered in predicting the SOP. Unlike the PNGV method, the proposed IV-limited SOP estimation algorithm calculates the charge-power capability for a duration of T_p s, $P_{chg,max}(T_p)$, from an OCV-R-RC circuit model by taking into account both the current limit, $I_{chg,lim}$, and the voltage limit, $V_{chg,lim}$, during a charging process. The discharge-power capability, $P_{dchg,max}(T_p)$, is calculated similarly. This enables us to ensure that the battery is not abused during its operation.

A. Charge-Power Capability Estimation

Recall the OCV-R-RC equivalent circuit model described by (1)-(2). The terminal voltage at the time instant $t = (k+1)T_s$, $V_{t,k+1}$, is written as

$$\begin{aligned} V_{t,k+1} &= V_{oc,k+1} + V_{p,k+1} + R_{o,k+1}I_{L,k+1} \\ &= V_{oc,k+1} + R_{p,k+1}(1-e^{-T_s/\tau})I_{L,k+1} + e^{-T_s/\tau}V_{p,k} + R_{o,k+1}I_{L,k+1} \end{aligned} \tag{10}$$

Assuming that the battery parameters R_o, R_p and C_p do not change within the the time interval T_s, we rewrite (10) as

$$V_{t,k+1} = V_{oc,k+1} + R_{p,k}(1-e^{-T_s/\tau})I_{L,k+1} + e^{-T_s/\tau}V_{p,k} + R_{o,k}I_{L,k+1} \tag{11}$$

Replacing the time instant $t = (k+1)T_s$ with $t = (kT_s + T_p)$ in (11) yields

$$V_t(kT_s+T_p) = V_{oc}(kT_s+T_p) + R_{p,k}(1-e^{-T_p/\tau})I_L(kT_s+T_p) + e^{-T_p/\tau}V_{p,k} + R_{o,k}I_L(kT_s+T_p) \tag{12}$$

Applying the first-order Taylor series expansion, the open circuit voltage, V_{oc}, can be approximated as

$$\begin{aligned} V_{oc}(kT_s+T_p) &\approx V_{oc}(kT_s) + \Big(\frac{\partial V_{oc}}{\partial SOC}\Big)\frac{\eta}{Q}\frac{T_p}{3600}I_L(kT_s+T_p) \\ &= V_{oc,k} + \mu I_L(kT_s+T_p), \end{aligned} \tag{13}$$

where the SOC-dependant quantity

$$\mu = \Big(\frac{\partial V_{oc}}{\partial SOC}\Big)\frac{\eta}{Q}\frac{T_p}{3600}.$$

Here, μ is calculated at SOC estimated at $t = kT_s$; In theory, $\left(\frac{\partial V_{oc}}{\partial SOC}\right)$ defines the slope of the OCV-SOC map, which can be empirically obtained in advance– A lookup table covering the values of $\left(\frac{\partial V_{oc}}{\partial SOC}\right)$ at various SOCs (and temperatures) can

thus be established. Substituting (13) into (12) yields

$$\begin{aligned} V_t(kT_s+T_p) &= V_{oc,k}+\mu I_L(kT_s+T_p)+R_{p,k}(1-e^{-T_p/\tau})I_L(kT_s+T_p)+e^{-T_p/\tau}V_{p,k}+R_{o,k}I_L(kT_s+T_p) \\ &= V_{oc,k}+\big(R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu\big)I_L(kT_s+T_p)+e^{-T_p/\tau}V_{p,k} \\ &= V_{oc,k}+\big(R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu\big)I_L(kT_s+T_p)+e^{-T_p/\tau}R_{p,k}I_{L,k} \end{aligned} \tag{14}$$

From (14), the charge current

$$I_L(kT_s+T_p) = \frac{V_t(kT_s+T_p)-V_{oc,k}-e^{-T_p/\tau}R_{p,k}I_{L,k}}{R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu} \tag{15}$$

Due to the voltage constraint

$$V_{dchg,lim} \leq V_t \leq V_{chg,lim}$$

the maximum charge current can be derived from (15):

$$\begin{aligned} I_{chg,max}(T_p) &\triangleq \max(I_L(.)) \\ &= \frac{V_{chg,lim}-V_{oc,k}-e^{-T_p/\tau}R_{p,k}I_{L,k}}{R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu} \end{aligned} \tag{16}$$

For (16) to be valid, it is assumed here that $I_{chg,max}(T_p) \leq I_{chg,lim}$.

If $I_{chg,max}(T_p) > I_{chg,lim}$, due to a current clipping, we redo (16) to obtain the corresponding terminal voltage. From (14), we get

$$V_t(kT_s+T_p) = V_{oc,k}+\big(R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu\big)I_L(kT_s+T_p)+e^{-T_p/\tau}R_{p,k}I_{L,k} \tag{17}$$

Due to the current constraint

$$I_{dchg,lim} \leq I_L \leq I_{chg,lim}$$

the maximum charge voltage is expressed as

$$\begin{aligned} V_{chg,max}(T_p) &\triangleq \max(V_t(.) \\ &= V_{oc,k}+\big(R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu\big)I_{chg,lim}+e^{-T_p/\tau}R_{p,k}I_{L,k} \end{aligned} \tag{18}$$

Combining (16) and (18) yields the battery's peak charge power capability for a given time duration T_p:

$$P_{chg,max}(T_p) = \begin{cases} I_{chg,max}(T_p)V_{chg,lim}, & I_{chg,max}(T_p) \leq I_{chg,lim} \\ I_{chg,lim}V_{chg,max}(T_p), & \text{otherwise} \end{cases} \tag{19}$$

B. Discharge-Power Capability Estimation

The derivation of the battery's discharge-power capability requires a procedure similar to the charge-power capability derivation.

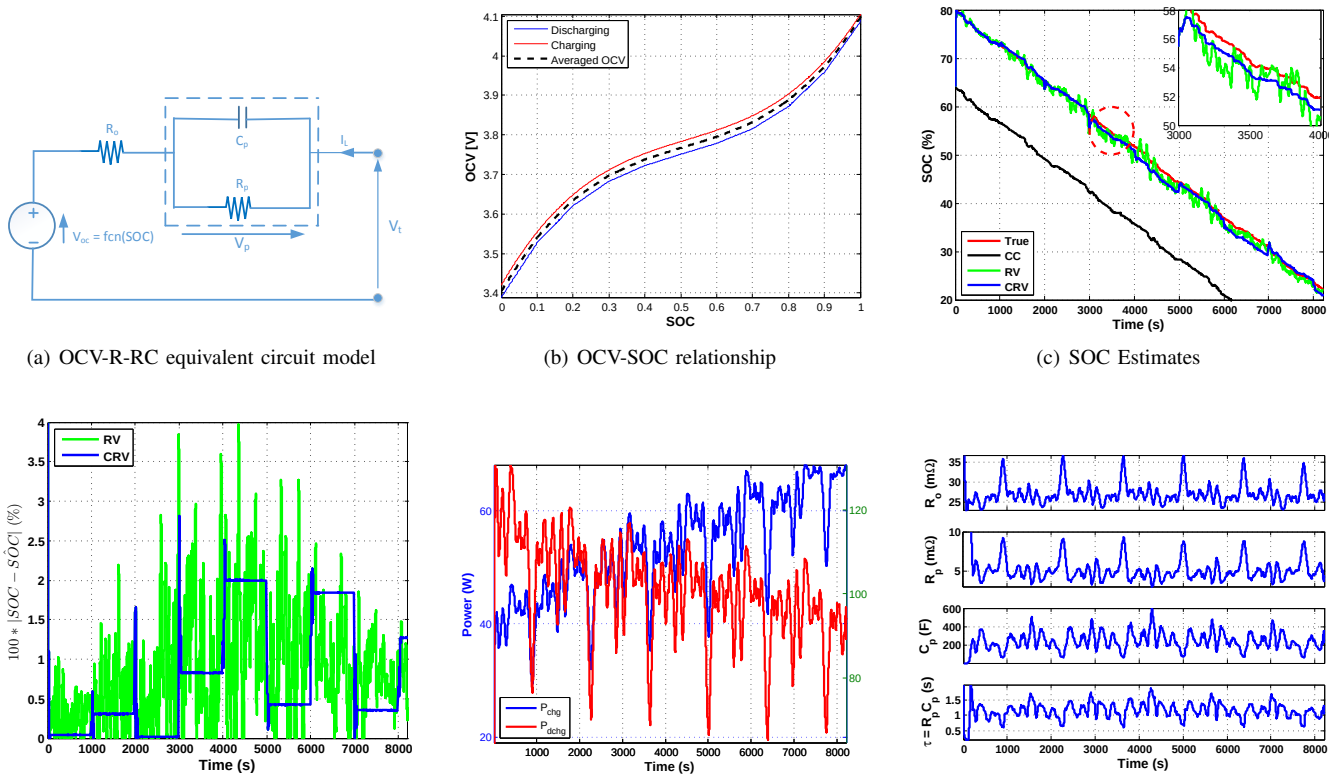
$$P_{dchg,max}(T_p) = \begin{cases} I_{dchg,max}(T_p)V_{dchg,lim}, & I_{dchg,max}(T_p) \leq I_{dchg,lim} \\ I_{dchg,lim}V_{dchg,max}(T_p), & \text{otherwise} \end{cases} \tag{20}$$

where

$$\begin{aligned} I_{dchg,max}(T_p) &= \frac{V_{oc,k}-V_{dchg,lim}-e^{-T_p/\tau}R_{p,k}I_{L,k}}{R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})+\mu} \\ V_{dchg,max}(T_p) &= V_{oc,k}-\big(R_{o,k}+R_{p,k}(1-e^{-T_p/\tau})-\mu\big)I_{dchg,lim}-e^{-T_p/\tau}R_{p,k}I_{L,k}. \end{aligned}$$

IV. Computer Experiments

This section demonstrates the effectiveness of the proposed algorithms in estimating the SOC, SOH and SOP. The current profile used in this study comprises of six UDDS cycle segments joined end-to end with no rest time period between cycles. In order to simulate the practical current and voltage sensors, zero-mean Gaussian noise with varying standard deviations of σ were added to the clean current and voltage signals. The following algorithms were used for SOC estimation: (i) Coulomb Counting (CC) (ii) Regressed Voltage (RV) (iii) Combined Coulomb counting-Regressed Voltage (CRV). The initial SOC estimates of both estimators were set to be 64% whereas the true SOC was set to be 80%. The root-mean square of the



(a) OCV-R-RC equivalent circuit model

(b) OCV-SOC relationship

(c) SOC Estimates

(d) SOC Estimation Error

(e) IV-Limited SOP Estimate

(f) Electrical Parameter Estimates

Fig. 1.

TABLE I

Parameter	True	Noise Free	With Curr. Noise ($\sigma_i = 100mA$)	With Volt. Noise ($\sigma_v = 5mV$)	Both Noisy $\sigma_i = 100mA$ $\sigma_v = 5mV$	Both Noisy $\sigma_i = 100mA$ $\sigma_v = 0.5mV$
R_o $[m\Omega]$	20	24.4	19.26	24.2	23.4	20.2
$\tau = R_p C_p$ $[s]$	3	3.6	2.14	0.97	2.27	2.5
RMSE(V_t) [mV]	-	0.017	0.013	0.03	0.046	0.012

terminal voltage residual (see the third row of Table I) is defined as

$$RMSE(V_t) \quad = \quad \sqrt{\frac{1}{N}\sum_{k=1}^{N}(V_{t,k} - \hat{V}_{t,k})^2},$$

where $V_{t,k}$ is the terminal voltage reading at time instant k and $\hat{V}_{t,k}$ is the filter-predicted terminal voltage. From Table I that shows the parameter estimation results of the RLS algorithm applied to the ARX battery model, the following conclusions can be drawn:

- Presence of a moderate amount of sensor noise is not always bad in the context of parameter estimation. The reason may be attributed to the fact that adding noise causes a rich signal excitation.
- Current sensor noise is less sensitive to parameter estimation than voltage sensor noise. Specifically, the amount of voltage noise can lead to either better or worse parameter estimates.
- The RLS-based parameter estimation method seems to be robust to voltage sensor noise (Compare the standard deviation of the the voltage sensor noise, which is $\sigma_v = 5mV$ with the $RMSE(V_t)$, which is only 0.046mV)

As shown in Fig. 1(c), the CC method does not fix the initial estimation error and it is present throughout the test drive cycle. On the other hand, both the RV and the CRV provide highly accurate SOC estimates. As shown in Fig. 1(d), the absolute SOC

error of the these two methods lies below the standard limit of 5%.. The SOC estimation accuracy of the RV method seems to be highly accurate in the SOC range corresponding to the sloping portion of the OCV-SOC map and degrades in the flat region. When compared to the RV method, the CRV method provides a more smooth SOC estimate (see Figs. 1(c)-1(d)). Fig. 1(e) shows the discharge and charge power estimated by the IV-limited SOP algorithm. As the SOC decreases, the discharge power capability decreases as well, whereas the charge power capability increases.

The accuracy of the CRV method is tightly coupled with the accuracy of the RV method. For optimal performance of the CRV method, unlike the implemented method that uses a trigger signal with the fixed characteristics, it must be a time varying signal. For example, the period and the duty cycle of the trigger signal can be optimally tuned based on the present SOC, the rate of change of the SOC, variations in the current excitation etc. This topic is currently under our investigation.