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# State-of-Charge Estimation of Lithium-Ion Batteries Combining Current and Voltage Based Estimation

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***Abstract*— Battery is the energy source in any Electric Vehicle (EVs) and requires a State of Charge (SOC) estimation to determine its range. Battery State of Charge (SOC) defines the remaining charge as a percentage of the stored charge in a fully charged battery. This paper presents a State of Charge estimation combining current based and voltage based estimation during battery charging/discharging.**

***Index Terms*—Electric vehicle, hybrid electric vehicle, recursive least square, state of charge.**

## I. INTRODUCTION

Today, electric vehicles (EVs) have received much attention as an alternative to traditional vehicles powered by internal combustion engines with the advancement in battery technology and motor efficiency. The secondary batteries are the main energy sources of the EV. Thus, energy management is the most important key factor in EV or HEV design [1]-[2]. Moreover, the electric capacity of the battery will influence the endurance of electric vehicles. Generally, an energy management mechanism is very important for improving system efficiency and extending endurance. Therefore, well design charging strategies incorporating estimation approaches for monitoring battery capacity are key features in energy management of EV or HEV. The knowledge of SOC is critical for PHEV/EV applications. However SOC is not measurable using existing onboard sensing technologies [3]-[6]. Since they do not provide an accurate SOC measurement it results in energy wastage. There are various methods of SOC measurements such as current integration, voltage based SOC estimation etc. The problems associated with these methods cannot be mitigated [7]. Battery Open Circuit Voltage (OCV) can be correlated to SOC, and SOC can be estimated through estimating OCV. But the OCV estimation is dealt with the following: 1)OCV needs to be estimated online during vehicle operation 2)OCV based SOC estimation can recover from a wrong SOC value 3)OCV based SOC estimation is robust to initial values and measurement error, and is adaptive to changes in operation conditions, and battery aging and variation. Thus in this paper we combine the current based SOC and voltage based SOC which provides more robust and accurate SOC estimate. A second order battery model is established based on HPPC data [8] and RLS method [9]-[10] is used to extract battery parameters by matching model input $I$ and output $V$ with measured data. Based on the equivalent RC circuit model, open circuit voltage $Voc$ is inferred from extracted battery parameters from which thermodynamic voltage $Vo$ is determined considering the hysteresis voltage $Vh$..

## II. BATTERY PARAMETER ESTIMATION

### *A. Equivalent Circuit Model*

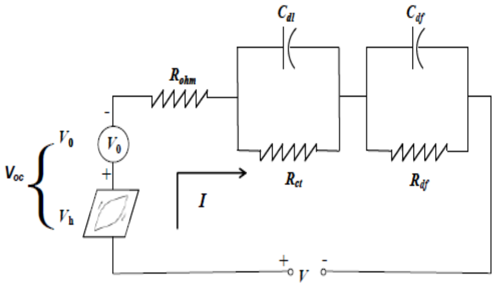


**Fig. 1. A Two-RC-Pair Equivalent Circuit Model Of A Battery.**

Various equivalent circuit models have been proposed to evaluate the state of charge of Lithium- Ion batteries [11]-[12].The RC model was designed by the famous SAFT Battery Company, and has achieved good application via the Advisor software [13]. As shown in Figure 1, it consists of two capacitors ($Cdl$, $Cdf$) and three resistors ($Rohm$, $Rct$, $Rdf$). Resistors $Rohm$, $Rdf$, $Rct$ are named ohmic resistance, charge transfer resistor and diffusion resistance, respectively. The capacitor $Cdl$, is named double layer capacitor and capacitor $Cdf$ is named diffusion capacitance. SOC can be determined by the voltage across the two RC pairs each of which accounts for the dynamic of double layer and diffusion respectively. $Voc$, $Vo$ and $Vh$ are open circuit voltage, thermodynamic voltage and hysteresis voltage, respectively. Voltage equation of two-RC-pair equivalent circuit model is described by

$$V(k) = V_{oc} + I(k)R_{ohm} + V_{dl}(k) + V_{df}(k) \qquad (1)$$

Thus the dynamic behavior of a Li-ion battery can be characterized as a second-order system approximately and to characterize a second-order system, a two-RC-pair equivalent circuit shown in Fig. 1 is widely used.

For some batteries, the relationship between OCV and SOC is history and path dependent. This phenomenon is known as battery hysteresis, resulting in a nonlinear many-to-many mapping between OCV and SOC. It should be noted that battery hysteresis is a static phenomenon which distorts the

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one-to-one OCV-to-SOC static mapping. To compensate for the battery hysteresis, the OCV is further divided into two parts: $Vo$ and $V$h, where $Vo$ is the thermodynamic voltage which has a one-to-one relationship to SOC, and $V$h represents the battery hysteresis voltage. The sum of $Vo$ and $V$h gives $Voc$.

### *B. Transformation to Control Oriented Model*

Consequently battery terminal voltage consists of four parts as given in Equation (1) and is transformed into a standard control oriented second order difference equation.

$$V(k) = (a_1 + a_2)\, V(k-1) - a_1 a_2\, V(k-2) + R_{ohm}(k) + [b_1 - b_2 - R_{ohm}(a_1 + a_2)]\, I(k-1) \quad (2)$$

$$= (a_1 a_2 R_{ohm} - b_1 a_2 - b_2 a_1)\, I(k-2) + (1 - a_1 - a_2 - a_1 a_2)\, V_{oc} \quad (3)$$

$$= [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6]^T\, [V(k-1), V(k-2), I(k), I(k-1), I(k-2), 1] \quad (4)$$

where $_1 = e^{-\Delta t/(R_{ct} C_{dl})}$ $b_1 = R_{ct}(1 - e^{-\Delta t/(R_{ct} C_{dl})})$
$$a_2 = e^{-\Delta t/(R_{df} C_{df})} \quad b_2 = R_{df}(1 - e^{-\Delta t/(R_{df} C_{df})}) \quad (5)$$

In particular, for a first order battery model, $\theta$ is a vector of four parameters as $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$ , and the corresponding vector of signals and known constants is $\varphi(k) = [V(k-1), I(k), I(k-1), 1]^T$ , where $I(k)$ is the measured battery terminal current. Similarly, for a second order battery model, $\theta$ becomes a vector of six parameters as $\theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6]$. The vector of signals and known constants becomes $(k) = [V(k-1), (k-2), (k), I(k-1), I(k-2), 1]^T$.

The parameters to be estimated are

$$\theta_1 = a_1 + a_2$$
$$\theta_2 = -a_1 a_2$$
$$\theta_3 = R_{ohm}$$
$$\theta_4 = b_1 - b_2 - R_{ohm}(a_1 + a_2)$$
$$\theta_5 = a_1 a_2 R_{ohm} - b_1 a_2 - b_2 a_1$$
$$\theta_6 = (1 - (a_1 + a_2) + a_1 a_2) \quad (6)$$

The battery electrical parameters, i.e. $V_{oc}$, $R_{ohm}$, $R_{ct}$, $C_{dl}$, $R_{df}$ and , can be derived from Equation (6) after acquiring $\theta$. In particular, $V_{oc}$ can be calculated by (7).

$$V_{oc} = \theta_6/(1 - \theta_1 - \theta_2). \quad (7)$$

$\theta$ is estimated by minimizing a cost function of the error between the actual $V(k)$ and the predicted value. The cost function often takes a quadratic form

$$J = \sum_{i=1}^{k} w_i (v(i) - \hat{v}(i))^2 \quad (8)$$

## III. SOC ESTIMATION

For the Li-ion battery model described by the difference equation (1), we apply the U-D factorization based RLS estimation method [12]-[13]. When the battery electrical parameters are obtained from the battery parameter estimation algorithm, in particular, the OCV, a voltage-based $SOC_V$ can be inferred. In the presence of battery hysteresis, the relationship between OCV and SOC is not a one-to-one mapping. Such a nonlinear relationship can be generalized as follows:

$$SOC_V = h(Voc, V_h). \quad (9)$$

As discussed in Section II, a switch type of hysteresis model can be used to model the battery hysteresis for iron phosphate Li-ion batteries. The model defines an additional hysteresis voltage $V_h$ in OCV. By taking out the hysteresis voltage from OCV, the remaining voltage $Vo$ can be monotonically mapped
to SOC. The remaining $Vo$, called the thermodynamic voltage,
is defined as the difference between $Voc$ and $V_h$ :

$$Vo(k) = Voc(k) - V_h(k). \quad (10)$$

For the switch type of hysteresis model, $V_h$ is governed by

$$V_h(k) = (k-1) + \theta_7 I(k-1)\, [V_{hmax} - \text{sign}\, I(k-1)\, V_h(k-1)]. \quad (11)$$

where $\theta_7$ is a parameter to determine convergence rate, and $V_{hmax}$ defines the boundaries of battery hysteresis. The values of $\theta_7$ and $V_{hmax}$ can be obtained through experiments and vary with OCV (i.e. SOC). The hysteresis model in (11) describes a type of hysteresis with fast convergence to hysteresis boundaries from any point inside the boundary loop. With such a switch type of hysteresis model, the voltage -based $SOC_V$ is robust to the initial hysteresis voltage, that is, it is not necessary to require accurate knowledge of the initial hysteresis voltage because the hysteresis voltage governed by the model quickly converges to boundaries wherever it starts. The SOC estimation algorithm combines the voltage-based $SOC_V$ and a current-based $SOC_I$ through Coulomb counting. The final SOC estimate is a weighted combination of $SOC_V$ and $SOC_I$ as

$$SOC(k) = w SOC_I(k) + (1 - w)\, SOC_V(k) \quad (12)$$

Where $0 < w < 1$ is the weighting factor. The combined SOC $(k)$ will be used as a new starting point for the next update at the time instant $k+1$. The benefit is to reduce the dependency on the initial SOC and increase algorithm robustness.

The weighting factor $w$ is tuned based on the signal excitation level. For instance, the value of $w$ decreases by 5%when the excitation level is lower than a threshold at the present time instant $k$. On the other hand, the value of (1- $w$) decreases by 5%, when the excitation level is higher than another threshold at the present time instant $k$. The signal excitation level can be evaluated through monitoring the six

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elements in the diagonal matrix $D$ or the determinant of $D$. It should be noted that real Li-ion batteries are not an ideal linear time invariant system. The model given by (12) is a simplified one for the estimation purpose, matching the Li-ion battery dynamics under a specific operation condition. Model uncertainties as well as the shifting of operation conditions, in combination with the use of the forgetting factor λ, will cause the increase of the values in one or several of the six elements in $D$, which should be decreasing in an ideal case of linear time invariant systems.

Following the battery parameter estimation algorithm in Section II, the SOC estimation algorithm is as follows:
Step 1: Starting with initialization, the algorithm sets the initial value of SOC(0) by reading the estimation result of previous operation from ROM.
Step 2: Obtain $Voc$ from the battery parameter estimation algorithm and determine the validity of the estimated $Voc$. If $Voc$ is not valid, set the weighting factor $w$ =0 and go to Step 7.
Step 3: Update $V_h$ using (10).
Step 4: Calculate $Vo$ using (9).
Step 5: Infer $SOC_V(k)$ from $Vo$ at the present time step.
Step 6: Tune the weighting factor $w$ for $SOC_V$ and $SOC_I$ based on the signal excitation level.
Step 7: Read data $(k)$ and calculate the $SOC_I(k)$ via
$SOC_I(k) = SOC_I(k-1) + (k)\Delta t$
where $SOC_I(k-1)$ is from the previous time step, and $I(k)\Delta t$ is the contribution from the Coulomb counting.
Step 8: Calculate the combined $SOC(k)$ using (12)
Step 9: Determine whether it is the end of operation. If yes, save $SOC(k)$ to NVM for next operation and end the algorithm. Otherwise, go back to Step 2 and continue the estimation.

## IV. RESULTS

The developed algorithm is evaluated through laboratory collected data and vehicle data. The evaluation results of manganese-based Li-ion batteries are shown in Fig. 2 and Fig. 3. Fig. 2 shows the trajectories of an offline calculated SOC and the SOC estimate from the algorithm for a charge depletion drive. The calculated SOC is manually derived from the OCV measured before and after the drive, and the measured current during the drive. The battery rests for hours in order to measure OCV. The measured OCV is used to find the reference SOC. The calculated SOC is compared with the SOC estimate. It can be seen from Fig. 2 that the overall estimation error is within 3% in this case. Fig. 3 shows the trajectories of a calculated SOC and the SOC estimate from the algorithm for a charge depletion charge Sustaining -charge increase drive. Note that the battery capacity is different from the case shown in Fig. 2. As shown in Fig. 3, the overall estimation error is within 3% as well.

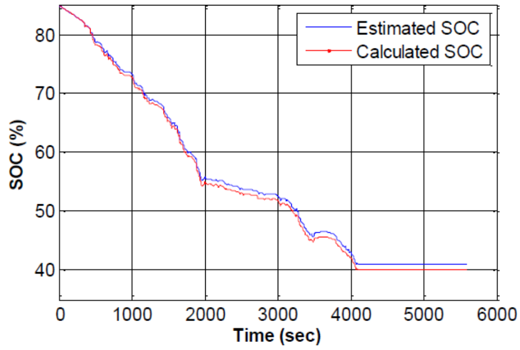


**Fig. 2. Algorithm evaluation on a charge depletion drive for a 30AH manganese-based Li-ion battery pack.**

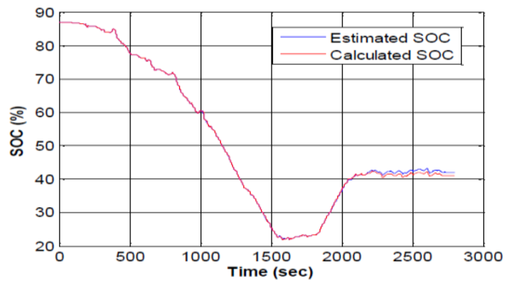


**Fig. 3. Algorithm evaluation on a charge depletion-charge sustaining- charge increase drive for a 45AH manganese-based Li-ion battery pack**

Fig. 4 shows the evaluation result for an iron phosphate Li-ion battery pack, containing trajectories of the three SOC estimates from the algorithm and the calculated SOC for reference. From Fig. 4, it can be seen that $SOC_I$ is unable to recover from a wrong initial point, while $SOC_V$ is robust to initial values. It is also noted that after $SOC_V$ is blended with $SOC_I$, the combined SOC shows improved stability. To evaluate algorithm robustness to sensor noise, a white noise of amplitude 20mV, an even distribution noise of amplitude 5mV, and a sinusoidal noise of amplitude 5mV are added to the measured terminal voltage. Moreover, a white noise of amplitude 1.8A, an even distribution noise of amplitude 0.25A, and a sinusoidal noise of amplitude 0.25A are added to the measured terminal current. Consider that for iron phosphate Li-ion batteries, SOC changes 10% for about 20mV change in OCV. Hence the injected noise is significant. However, it can be seen from Fig. 8 that the injected noise has no significant impact on the SOC estimate. Both trajectories converge to the actual SOC (measured and back calculated offline) within acceptable errors.

## V. CONCLUSION

In the paper, an adaptive battery parameter estimation algorithm is developed for onboard SOC estimation. The developed algorithm has been verified through simulation and in-vehicle testing. The results show effectiveness in SOC estimation and robustness to initial conditions, battery variations, and operation environment. The battery parameters estimated by the developed algorithm can also be used for other applications such as onboard diagnostics and power prediction.

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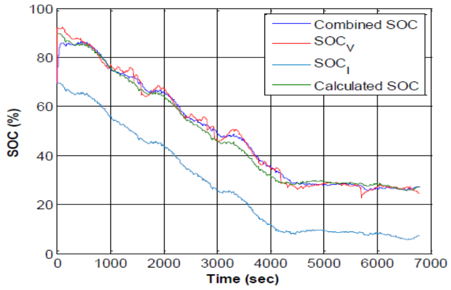


**Fig. 4. Algorithm Evaluation on A Charge Depletion-Charge Sustaining Drive For An Iron Phosphate Li-Ion Battery Pack.**

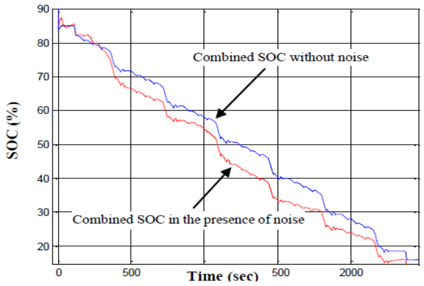


**Fig. 5. Algorithm evaluation in the presence of voltage and current noise.**

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