BMS in the Bayesian Paradigm: Part I: SOC Estimation

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Introduction

- Battery innovation occurs in 3 major areas:
  - Battery chemistry
  - Thermal management
  - Battery control

Figure 1 :

- The State-of-Charge (SOC) is defined as the ratio of remaining charge capacity to nominal capacity

- OEMs target: SOC error $\leq 3\%$ throughout the service life

- Why more precise SOC estimation?
  - To Improve usable energy/fuel economy
  - To prolong battery life

State Estimation (Cont'd)

- 3 major battery modeling techniques
  - Black box/ model free (Coulomb counting, OCV)
  - Grey box (Equivalent circuit models)
  - White box (Electrochemical models)
- Coulomb counting (CC) is the traditional method to estimate the SOC:

$$SOC[t] = SOC[0] + \frac{\eta}{Q}\int_0^t I(t)dt \quad (1)$$

where Q is the nominal capacity, η is the Coulombic efficiency, and I is current

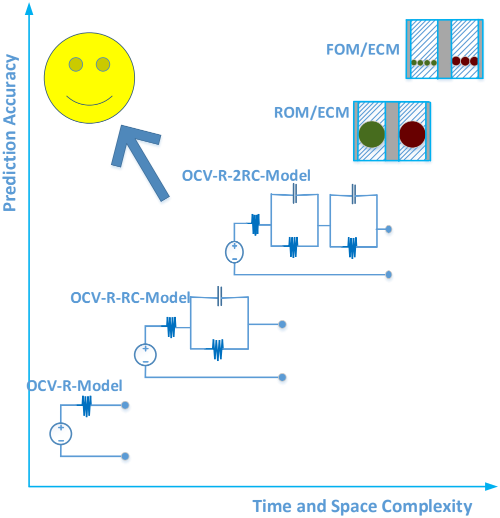
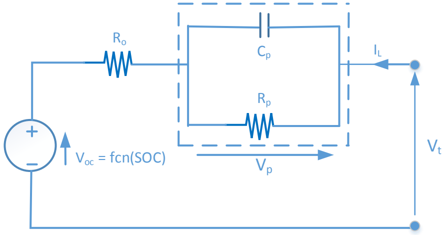
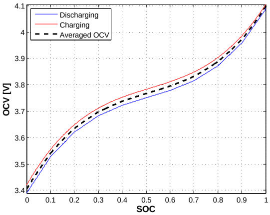

Prediction Accuracy
FOM/ECM
ROM/ECM
OCV-R-2RC-Model
OCV-R-RC-Model
OCV-R-Model
Time and Space Complexity

Figure 2 :

Equivalent Electrical Circuit Modeling



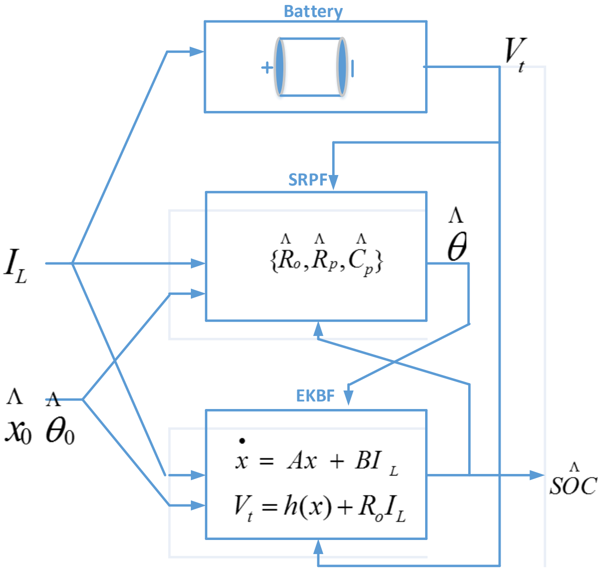
(a) OCV-R-RC equivalent circuit model



(b) OCV-SOC relationship

Figure 3 :

Figure 4 : Dual Bayesian Estimation



- Governing equations:

$$\begin{aligned} \dot{V}_p &= -\frac{1}{\tau} V_p + \frac{1}{C_p} I_L \\ \Rightarrow V_{p,k+1} &= e^{-T_s/\tau} V_{p,k} + R_p(1 - e^{-T_s/\tau}) I_{L,k}, && (2) \\ V_{t,k+1} &= V_{oc}(SOC_{k+1}) + V_{p,k+1} + R_0 I_{L,k+1} && (3) \end{aligned}$$

  where the time constant $\tau = R_p C_p$.

- Eliminating V_p from (2)-(3) yields an ARX model (1,2,0):

$$y_{k+1} = a_0 y_k + b_0 I_{L,k} + b_1 I_{L,k+1}, \qquad (4)$$

  where

$$\begin{aligned} a_0 &= e^{-T_s/\tau} \\ b_0 &= -e^{-T_s/\tau} R_o + (1 - e^{-T_s/\tau}) R_p \\ b_1 &= R_o \\ y_{k+1} &= V_{t,k+1} - V_{oc}(SOC_{k+1}) \end{aligned}$$

Battery Parameter Estimation....

- the SR-RLS algorithm is chosen to estimate the battery parameters, which are related to a_0, b_0 and b_1 as follows:

$$\hat{R}_o = b_1 \tag{5}$$

$$\hat{R}_p = \frac{b_0 + a_0 b_1}{1 - a_0} \tag{6}$$

$$\hat{C}_p = \frac{(a_0 - 1)T_s}{(a_0 b_1 + b_0)\log(a_0)} \tag{7}$$

- The sequential RLS algorithm with a forgetting factor (λ) minimizes the sum of error-squared cost function:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{N} \lambda^{N-i}\left(V_{t,i} - \theta^T \mathbf{\Phi}_i\right)^2 \tag{8}$$

where λ: real, positive,< 1, and $\to 1$

- λ trades off the tracking capability for noise filtering; For our battery experiment, λ of 0.995 was found to be sufficient

Battery State Estimation

- State-space model:

$$\begin{pmatrix} \dot{SOC} \\ \dot{V}_p \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & -\frac{1}{\tau} \end{pmatrix} \begin{pmatrix} SOC \\ V_p \end{pmatrix} + \begin{pmatrix} \frac{1}{Q_{batt}} \\ \frac{1}{C_p} \end{pmatrix} I_L \tag{9}$$

$$V_t = V_{oc}(SOC) + V_p + R_o I_L, \tag{10}$$

- Since the state space model is a continuous-time nonlinear model, the extended Kalman-Bucy filter (EKBF) is applied to estimate the states.
- EKBF steps:

$$\begin{aligned} \mathbf{C} &= \frac{\partial V_t}{\partial \mathbf{x}} \\ \mathbf{P} &= \mathbf{AP} + \mathbf{PA}^T - \mathbf{KRK}^T + \mathbf{Q}, \mathbf{P}(0) = \mathbf{P}_0 \\ \mathbf{K} &= \mathbf{PCR}^{-1}, \\ \dot{\hat{\mathbf{x}}} &= \mathbf{Ax} + \mathbf{B}I_L + \mathbf{K}(V_t - \hat{V}_t) \end{aligned}$$

Computer Experiment

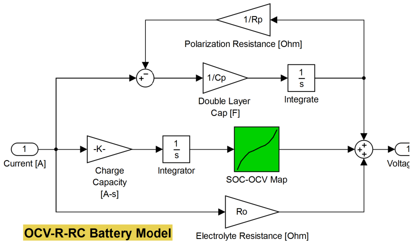
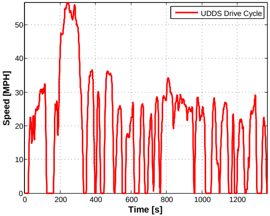


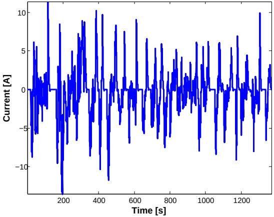
Figure 5 : OCV-R-RC type Battery Model Implemented in Matlab/Simulink

- SOC estimators:
  - Coulomb Counting (CC)
  - Regressed Voltage (RV) Estimator
- Assumed the initial SOC for both of these two estimators to be 64% whereas the true initial SOC was set to be 80%
- A current profile from a UDDS velocity profile was obtained by simulating a mid-size EV in Matlab/Simulink

Computer Experiment (Cont'd)

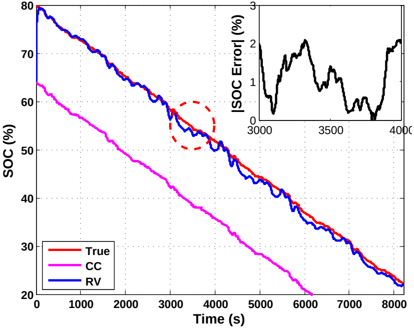


(a) UDDS Speed Profile

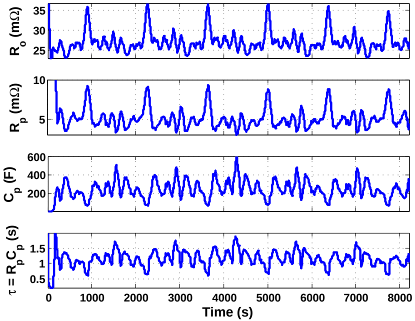


(b) Current Profile

Figure 6 : Speed and current profiles for one UDDS drive cycle



(a)



(b)

Figure 7 :

Parameter	R_o [mΩ]	R_p [mΩ]	C_p [F]	Max. SOC Err. [%]
True	25	5	300	
RV Estimator	26.1	4.8	286.8	3.1

Table 1 :

Virtues of the Dual Estimator

- Unlike the CC which uses the current measurement only, the dual method systematically fuses the current measurement with the voltage measurement
- Applicable to any other types of battery chemistries whose SOC and OCV relationship s one-to-one and monotonically increasing.
- Modular: The parameter identification block can be re-used for other battery control tasks such as battery SOP and SOH.

Open Questions

Table 2 :

Issues	Root Causes	Solution
Covariance Wind-up	Poor input excitation	Upper bound covariance Time varying forgetting fa Switch on/off RLS based o statistics
Convergence	Model mismatch Time varying parameter V_{oc}	Open question? Separate V_{oc}
SOC error $\leq 3\%$ at low temperature		ROM Voting/weighted average o methods (CC, RV, Data-dr

Thank you!