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On-line SOH Recognition for Large Capacity Lithium-ion Batteries on Electric Vehicle

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Abstract

In application of battery system on electric and hybrid electric vehicles, on-line prediction of its performance relative to the initial conditions such as instantaneous power and nominal capacity over the life time is essential for proper use of a battery and extending its lifetime. In this paper, algorithms are developed for estimating the available power and capacity as a state of health (SOH) of a battery system. The algorithms are based on a simple dynamic model and parameter identification. The feasibility of the proposed algorithms is verified through experiment of a Li-ion battery for EV.

Keywords: EV(Electric Vehicle), Lithium Battery, battery Soh(State of Health)

1 Introduction

The electrochemical degradation of battery will be accelerated by instantaneous load changes based on charge • discharge strategy of vehicle and environmental conditions especially temperature fluctuations. It can be expressed by battery's parameter changes in electrical equivalent circuit and battery's capacity fading.

Battery's parameter changes adversely affect the dynamic response characteristics of terminal voltage. It means battery's power is faded in the admissible voltage range for the safe battery operation. Battery's capacity fading means that the remained mileage of EV is reduced.

Therefore, the quantitative diagnosis of battery degradation necessarily has to be implemented in battery management system for admissible endurance management, the optimal controls to prevent battery's overcharge•discharge and real-time display of remaining mileage according to battery degradation.

In this paper, we present the terminal voltage transient response analysis on a pulse current input and recursive least mean square method on the driving load pattern to identify battery's parameter changes using simple circuit model of high-capacity lithium-ion battery. Using these methods, the degree of power fading (SOH_p) is estimated. In addition, the algorithm to diagnose degree of capacity fading (SOH_c) is developed based on the battery remaining capacity estimation.

2 Battery circuit model

A dynamic response characteristic of the battery can be modelled as a simple equivalent electrical circuit ignored Warburg impedance. It is shown in Fig.1. In this model, parameters R_i is a internal ohmic resistance and parameters R_S , C_S represent the polarization that lead to delay or hysteresis of the battery terminal voltage. v_e, open circuit voltage of the battery is a function of SOC (State Of Charge) to describe the relationship between OCV and SOC.

Terminal voltage, v_t could be expressed as

$$v_t = v_e(SOC) + iR_i + v_p \quad (1)$$

and v_p is a polarization voltage derived from

$$\dot{v}_p = -\frac{1}{R_S C_S} v_p + \frac{1}{C_S} i \quad (2)$$

$R_S C_S$ is a time constant (T_S) of polarization voltage to represent the transient response characteristic of terminal voltage in Eq.(2).

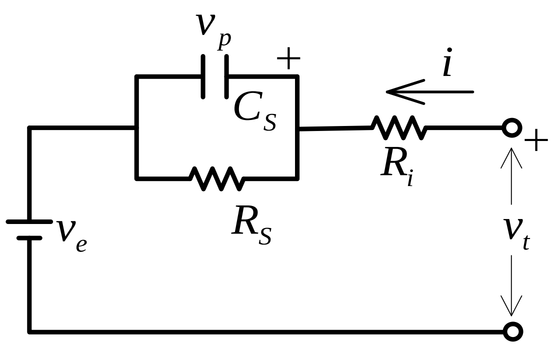

Figure1: Equivalent Circuit Model

3 Parameter Identification

3.1 Voltage transient response analysis

A terminal voltage response of the unit cell on a charge pulse current is shown in Fig.2 and Fig.3. Since the terminal voltage has almost the same response characteristics at the same temperature and SOC state, battery parameters (R_i , R_S , C_S) can be estimated by a simple response analysis.

Each parameter is a solution of battery model Eq.(1) for the pulse current input i $(0 \le t \le t_1)$ and obtained as follows.

$$\begin{cases} v_t(t) - v_e(t) = i \cdot R_i + i \cdot R_S(1 - e^{-\frac{t}{T_S}}), & t \le t_1 \\ v_t(t) - v_e(t) + i \cdot R_S(e^{-\frac{t-t_1}{R_T}} - e^{-\frac{t}{T_S}}), & t > t_1 \end{cases} \quad (3)$$

at t = 0 in (3)

$$R_i = \frac{v_t(t=0) - v_e(t=0)}{i} \quad (4)$$

and at $t = t_1$ in the case of $t >> T_S$

$$R_S = \frac{v_t(t_1) - v_e(t_1) - i \cdot R_i}{i} \quad (5)$$

C_S is given by differential equation of (3) at t = 0

$$C_S = -\frac{i}{(v_t(t) - v_e(t))/dt}\bigg|_{t=0} \quad (6)$$

or

$$C_S = -\frac{i \cdot t_1}{v_t(t_1) - v_e(t_1) - i \cdot R_i} \quad (7)$$

with exponential function approximation in the case of $t << T_S$.

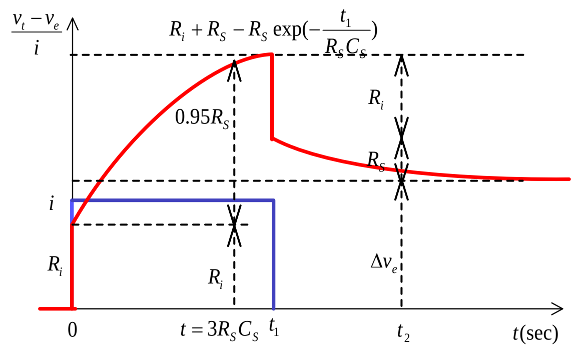

Figure2: terminal voltage response (t >> Ts)

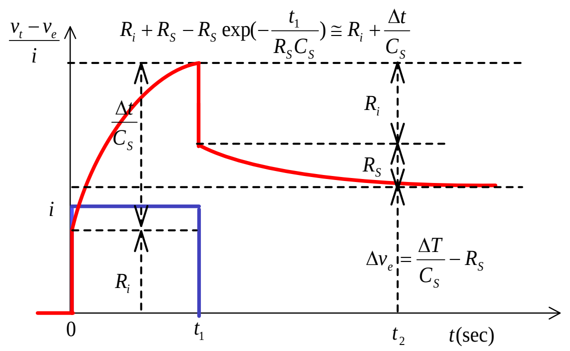

Figure3: terminal voltage response (t << Ts)

3.2 Recursive least mean square method

Model parameter can also be estimated by system identification, the recursive least mean square method using correction factor is applied and it is shown in Fig.4.

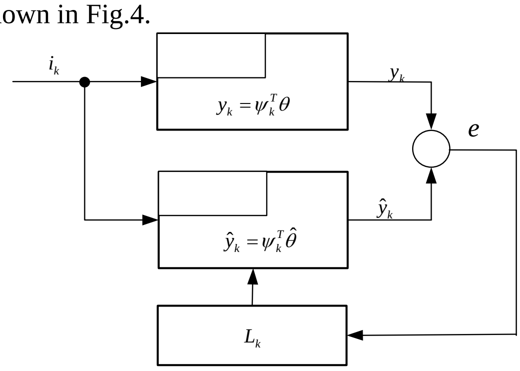

Figure4: Structure of Parameter estimation

The model output is

$$y_k = \psi_k{}^T \theta \quad (8)$$

θ : parameter vector, y_k :output vector

ψ_k : system matrix, T_{samp} : sampling time(sec)

in Fig.4 and each vector is expressed as follows.

$$\theta = [(1 - \frac{1}{T_S} T_{samp}) \quad R_i \quad R_i \left\{ \frac{1}{T_S R_i}(R_i + R_S)T_{samp} - 1 \right\}]^T \quad (9)$$

$$y_k = v_t(k) - v_e(k) \quad (10)$$

$$\psi_k = [y_{k-1} \quad i_k \quad i_{k-1}]^T \tag{11}$$

The result in the recursive parameter estimation is obtained.

$$\hat{\theta}_k = \hat{\theta}_{k-1} + L_k (y_k - \psi_k{}^T \hat{\theta}_{k-1}) \tag{12}$$

L_k is a correction factor in (11) and is given by

$$L_k = P_{k-1}\psi_k{}^T [1 + \psi_{k+1} P_{k-1} \psi_k{}^T]^{-1} \tag{13}$$

$$P_k = P_{k-1} - L_k \psi_k{}^T p_{k-1} \tag{14}$$

4 Degree of power fading

4.1 Case of constant current charging

A terminal voltage is consistently increased by constant current input. The time that the terminal voltage reaches to maximum admissible voltage $v_{t\max}$ is calculated as follows.

$$\begin{cases} t_{\max} = T_S \ln\left(1 - \dfrac{v_{t\max} - v_e(t_{\max}) - iR_i}{iR_S}\right)^{-1}, & t_1 >> T_S \\ t_{\max} = \dfrac{C_S}{i}\{v_{t\max} - v_e(0) - iR_i\}, & t_1 << T_S \end{cases} \tag{15}$$

Since $t_{\max}$ is a function of the model parameters and OCV, it can be decreased by parameter changes due to power fading and it means performance degradation of battery power.

4.2 Case of constant power charging

Fig.5 represents terminal voltage response on the constant power. For analyzing power fading characteristic, the current input is assumed $i = a + bt$. Coefficients a, b for any given constant power are calculated as follows.

$$\begin{cases} a = \dfrac{P_{const}}{v_e(0) + (P_{const}/v_e(0))R_i}, \\ b = \dfrac{(P_{const}/v_{t\max}) - a}{\Delta t} \end{cases} \tag{16}$$

The solution of battery model Eq.(1) for the current input expressed by first order time function described above is as follows.

$$v_t = v_e + a(R_i + R_S) - bR_S{}^2 C_S + b(R_i + R_S)t + (bR_S{}^2 C_S - aR_S)e^{-\frac{t}{R_S C_S}} \tag{17}$$

And $t_{\max}$ on the constant power input is calculated as follows.

$$\begin{cases} t_{\max} = \dfrac{\left(a - \dfrac{P_{const}}{v_{t\max}}\right) \cdot R_S{}^2 C_S}{v_{t\max} - v_e(t_{\max}) - \dfrac{P_{const}}{v_{t\max}} \cdot (R_i + R_S)}, & t_1 >> T_S \\ t_{\max} = \dfrac{C_S}{a}\left(v_{t\max} - v_e(t_0) - \dfrac{P_{const}}{v_{t\max}} R_i\right), & t_1 << T_S \end{cases} \tag{18}$$

Eq.(17) is similar to Eq.(14) because current input is assumed a linear function.

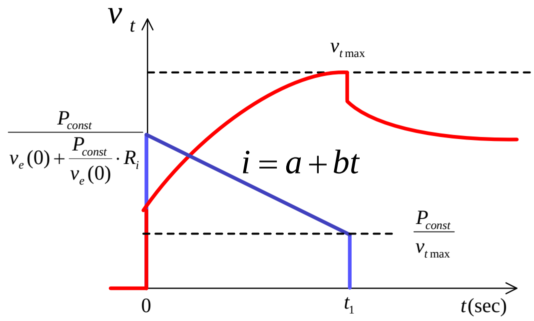

Figure5: Terminal voltage response on the constant power charging

The calculated $t_{\max}$ in Eq.(15) and (18) can be decreased by parameter changes due to power fading, therefore it can represent the degree of power fading.

5 Degree of capacity fading

The capacity fading of battery means available energy reduction. It will adversely affect the remaining mileage of EV. The remaining energy capacity of battery (SOC) is defined as the accumulation of charge and discharge currents.

$$SOC = \frac{\eta}{C_n} \cdot \int idt \tag{19}$$

C_n is a nominal capacity of the battery and η is a efficiency in Eq.(19). Since the capacity is decreased by battery degradation, the variation of SOC on the same amount of charge•discharge current can be increased. The relationship between the SOC variation and amount of current is illustrated in Fig.6.

Since many SOC estimation algorithms have been implemented using OCV rather than current integration, the capacity degradation can be diagnosed based on SOC in this article.

The degree of capacity fading is defined as a ratio of SOC variation.

$$SOH_C \equiv \frac{C_{na}}{C_{ni}} = \frac{\eta_a}{\eta_i} \cdot \frac{\Delta SOC_i}{\Delta SOC_a} \tag{20}$$

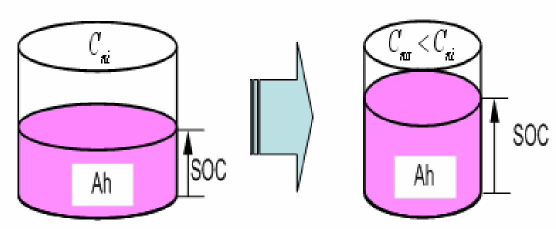

Figure6: SOC variation according to degradation

The SOC variation by an arbitrary current in real time is represented in Fig.7 and is expressed as following equations.

$$\Delta SOC = a \cdot \Delta Ah + b$$

$$a = \frac{\eta}{C_n} \tag{21}$$

$$b = \Delta SOC^{+} + \Delta SOC^{-} = \frac{\eta^{+} - \eta^{-}}{C_n} \sum_j \Delta Ah_j$$

Assuming that efficiencies of charge and discharge are equal,

$$SOH_C = \frac{a_i}{a_a}, \eta_a \cong \eta \tag{22}$$

Therefore, the degree of capacity fading can be diagnosed by comparing between initial battery's current-SOC Characteristic and degraded battery's.

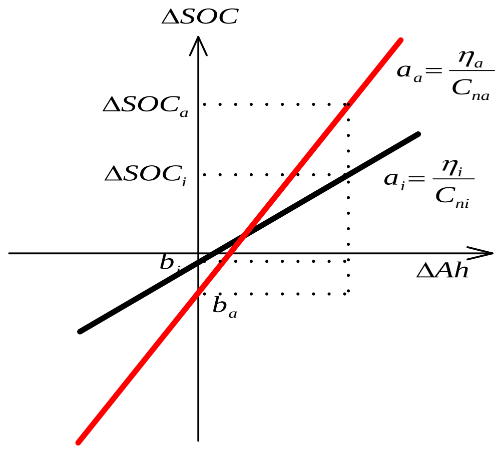

Figure7: SOC variation characteristic according to battery degradation

6 Verification

6.1 Parameter identification of battery

Test environment is composed of charge-discharge device, thermostatic room chamber and battery cell. Using this environment, the terminal voltage is measured on a pulse current. Fig.8 is a transient response of terminal voltage on a 50A pulse current for 1sec with estimated parameters by Eq.(4)~(6) at 25℃.

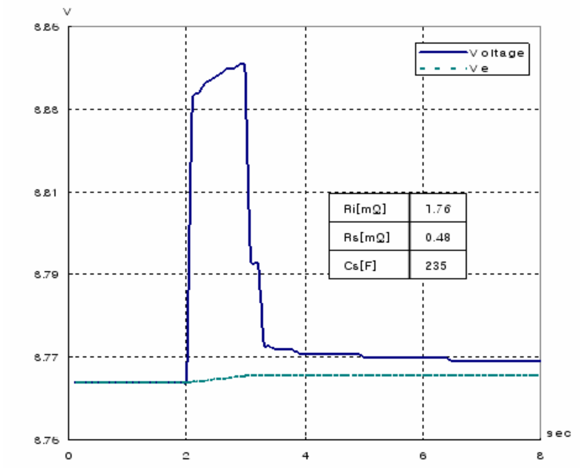

Figure8: Terminal voltage response analysis at 25℃

Estimated parameters are matched with results of recursive least mean square. By this method, the terminal voltage transient response characteristics on a small pulse current for a short time can be analyzed simply and intuitively. Therefore, it can be applied to real-time battery management system (BMS) in the diagnostic service mode as well as the off-line simulation.

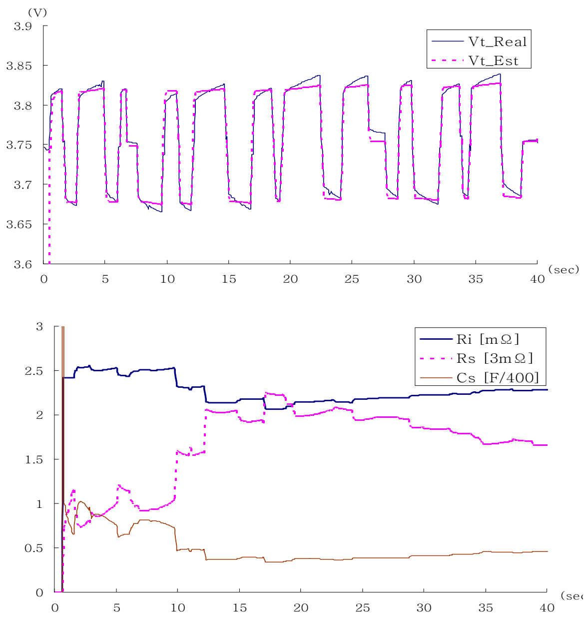

Figure9: parameter estimation using recursive least mean square method

Fig.9 is a result of parameter estimation using recursive least mean square method on arbitrary current pattern. Model parameters converge to a steady state after 20sec. The simulated terminal voltage using these parameters is agreement with the measured values in ± 2% error.

Table 1 shows a result of parameter estimation for degraded batteries.

Table1: Estimated parameters for degraded batteries

	Cell#1	Cell#2	Cell#3
$R_i(m\Omega)$	1.36	1.60	1.63
$R_S(m\Omega)$	0.47	0.48	0.50
$C_S(F)$	230	220	222
T_S(sec)	0.11	0.10	0.10

6.2 Estimation of power fading

The theoretical estimation of the time ($t_{\max}$) to reach admissible limit voltage on a constant current using Eq.(15) requires the information about OCV. Since the battery used in electric vehicles should guarantee the minimum power performance even if degradation, $t_{\max}$ is more than a few seconds and is much larger than the time constant (T_S ≒ 105ms) of polarization voltage. Therefore, $t_{\max}$ is estimated by Eq.(15) in case of $t_1 >> T$ and the degree of power fading relative to initial parameters of BOL(Begin of Life) can be estimated by Eq.(23).

$$SOH_p = \left(1 - \frac{t_{\max}}{t_{\max BOL}}\right) \times 100(\%) \qquad (23)$$

Fig.10 is a result of a power test performed for the verification according to battery degradation. Table.2 represents a estimation of the relative degree of power fading.

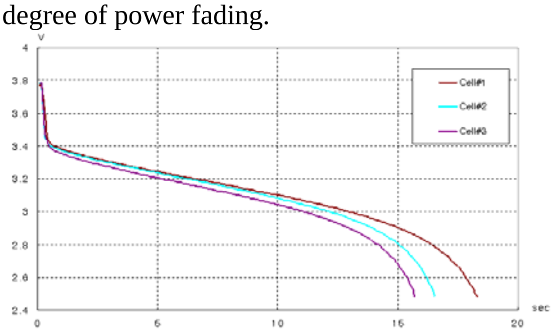

Figure10: The result of power test

Table2: Estimation of relative degree of power fading

	Cell#1	Cell#2	Cell#3
SOH_P	0	8.3	11.4
SOH_P (real)	0	10.9	14.8

Estimated results have a similar tendency to measurement results, however, has a difference caused by linearization of the exponential function.

6.3 Estimation of capacity Fading

Fig.11 represents measured terminal voltages of batteries which have a different degradation on a same pulse current. It shows that terminal voltage fluctuates according to the degree of capacity fading. Therefore capacity is a state variable of battery and capacity fading is caused mainly by battery degradation.

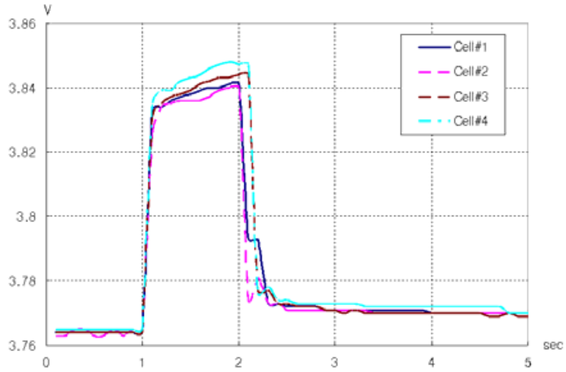

Figure11: Measured terminal voltage according to capacity fading

Fig.12 is a measured amount of SOC changes for the current input and table.3 shows a result of the estimated capacity by Eq.(22)

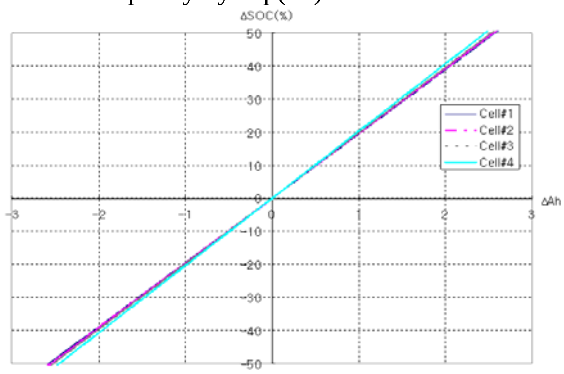

Figure12: Measured SOC according to capacity fading

Table3: Estimated degree of capacity fading

	Cell#1	Cell#2	Cell #3	Cell #4
a_a	19.3	19.6	19.8	20.4
SOH_C	100	98.4	97.5	94.6
SOH_C (real)	100	98.3	96.7	94.1

The SOC estimation accuracy affects on the estimated degree of capacity fading directly in this method. Therefore further study about state observer design that has a $C_n \cdot SOC$ as new state in Eq.(1) is required for the robust capacity estimation.

7 Conclusion

In this paper, a new battery degradation diagnostic algorithm is proposed and the battery model parameter estimation methods are developed for the algorithm. It is tested and verified for degraded high-capacity battery cells in arbitrary driving patterns and environmental conditions.

(1) The estimated results by proposed battery model and parameter identification method are agreement with measured values within ± 5% margin of error. It can be used to diagnosis of power, capacity fading and prediction, simulation of battery performances.

(2) The estimation of power fading by parameter identification has a similar tendency to measured data, is slightly underestimated.

(3) The degree of capacity fading is estimated well, however, the study is required for enhancing the robustness through sensitivity analysis according to the SOC estimation.

Therefore, the result of this study can be applied to real-time state monitoring, degradation diagnosis and estimation of remaining mileage in battery management system for electric vehicles.

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