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ABSTRACT

This paper proposes an innovative and accurate method of estimating the internal conditions of rechargeable batteries for vehicles powered by electric motors, such as electric vehicles (EVs) and hybrid electric vehicles (HEVs). The proposed method is necessary to utilize battery power fully on vehicles powered by electric motors (especially HEVs) and thereby improve fuel economy or reduce the battery size.

As the first step in this study, the relationship between the current and terminal voltage of a rechargeable lithium-ion battery was described using a linear parameter varying (LPV) model. That made it possible to reduce the problem of estimating the internal battery conditions (internal resistance, time constant, and so on) to a problem of recursively estimating the model parameters with an adaptive digital filter. An up-to-date parameter identification algorithm has been applied in order to estimate the model parameters recursively with good accuracy at all times, since they vary greatly depending on the operating conditions (state of charge (SOC), temperature, degree of battery degradation, etc.). As the second step, the calculated model parameters (internal resistance, time constant) and another type of LPV battery model were used to derive the open voltage (one of the internal states). The calculated model parameters and open voltage facilitated accurate estimations of the SOC, available output power and acceptable input power using an inherent battery characteristic (the steady-state correlation between open voltage and SOC) and maximum power definitions regardless of the operating conditions.

This paper describes an example of the application of this method to a lithium-ion battery and presents the simulation and experimental results. Bench test results verified that SOC estimation accuracy was within ±4% and that of the available output power and acceptable input power was within ±10%.

INTRODUCTION

The automotive industry has been actively developing hybrid electric vehicles (HEVs) and other types of vehicles powered by electric motors in recent years out of concern for improving fuel economy and environmental protection. By using energy more efficiently, these vehicle systems improve fuel economy. Accordingly, in order to control the distribution of energy most efficiently, it is necessary to detect the internal conditions of the battery with high accuracy. The internal battery conditions that are particularly important are the state of charge (SOC) and power that the battery can accept or discharge, i.e., its charge and discharge limits.

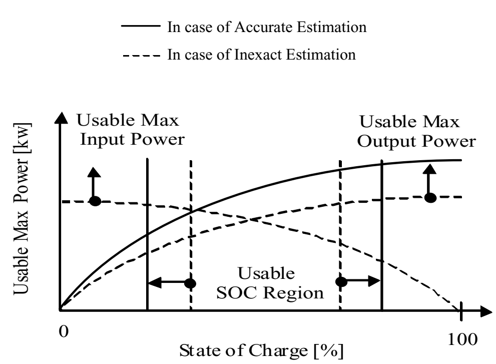

Fig. 1 Battery Characteristics

Because these conditions cannot be measured directly with a sensor while the battery is discharging or being charged, they are estimated on the basis of measurable quantities such as the battery terminal voltage or current. One method that has generally been used to date for estimating the SOC is to integrate the current values. Another commonly used method is to make a linear approximation of the immediate voltage and current histories, and then simply apply Ohm's law to find the open voltage (steady-state no-load terminal voltage), which corresponds directly to the SOC. However, deterioration of estimation accuracy with these methods is unavoidable owing to the effect of constantly changing battery characteristics due to the influence of transient battery properties or the operating conditions, such as the SOC, temperature, degree of battery degradation and so on.

In this study, the relationship between the current and terminal voltage of a storage battery was described using a linear parameter varying (LPV) model. That made it possible to reduce the problem of estimating the internal battery conditions to a problem of recursively estimating the model parameters with an adaptive digital filter[1]. Additionally, a parameter identification algorithm has been applied in order to estimate the model parameters recursively with good accuracy at all times, since they vary greatly depending on the operating conditions. This identification algorithm is a least squares algorithm[2] with upper and lower bounded trace of matrix gain. Moreover, a hybrid parameter identification method[3] has been adopted in order to make it easier to estimate accurately the parameters having physical significance. Through the application of these basic techniques, a parameter estimation system was constructed. This paper describes an example of the application of this system to a lithium-ion battery.

ADAPTIVE DIGITAL FILTER

The unknown plant is modeled as an adaptive digital filter (Fig. 2) given by the following equation

$$y = \omega^T \cdot \theta \qquad (1)$$

where y is the measurable plant output, ω is a vector consisting of the measurable plant input u and the output obtained by filtering u and y, and θ is an unmeasurable parameter vector. These signals are either discrete- or continuous-time signals. The estimated parameter vector θ of the model given in Eq. (1) is recursively adjusted using the least squares method, or a similar technique, such that error between the plant output y and the model output $\hat{y}$, representing the estimated plant output, approaches zero. This method constitutes recursive model parameter identification by means of an adaptive digital filter. By using only the measurable plant input u, plant output y and information about the structure of the plant model, the adaptive digital filter can be easily adapted to changes in the plant properties.

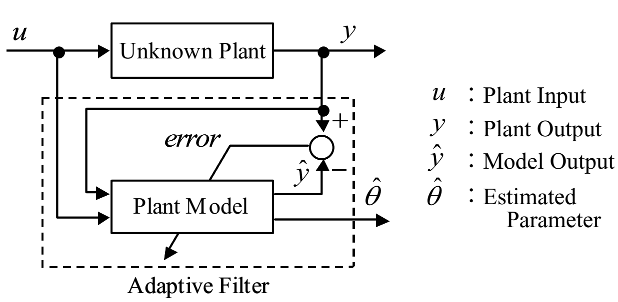

Fig. 2 Adaptive Digital Filter

LITHIUM-ION BATTERY CHARACTERISTICS

The steady-state correlation between the open circuit voltage and SOC is shown in Fig. 3. In general kinds of battery, these characteristics are inherent properties of the battery and are not influenced by temperature or the degree of battery degradation. SOC is defined as the ratio of the remaining capacity to the total capacity.

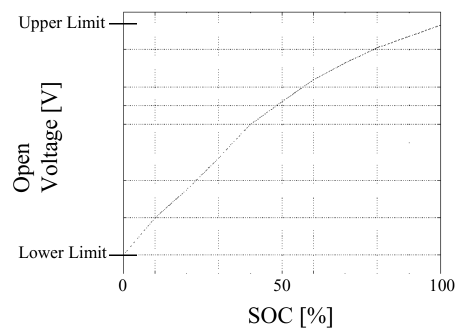

Fig. 3 Example of Battery Characteristics
(Open Voltage vs. SOC)

BATTERY MODEL

LPV MODEL

The relationship between the current and terminal voltage of a lithium-ion battery was represented by the simple model shown in Fig. 4, based on the structure of the battery.

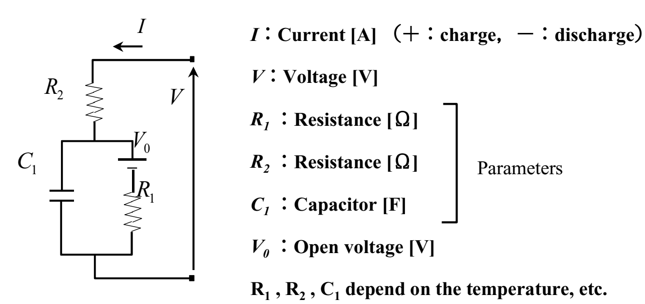

Fig. 4 Battery LPV Model

Equation (2) expresses the relationship between the charging/discharging currents $I(t)$ and the terminal voltage $V(t)$, and Eq. (3) shows the relationship between the open circuit voltage $V_0(t)$ and $V(t)$.

$$V(t) = \frac{C_1 \cdot R_1 \cdot R_2 \cdot s + R_1 + R_2}{C_1 \cdot R_1 \cdot s + 1} \cdot I(t) + \frac{1}{C_1 \cdot R_1 \cdot s + 1} \cdot V_0(t) \qquad (2)$$

$$V(t) = \frac{K \cdot (T_2 \cdot s + 1)}{T_1 \cdot s + 1} \cdot I(t) + \frac{1}{T_1 \cdot s + 1} \cdot V_0(t) \qquad (3)$$

where s is a differential operator, K is the internal resistance and T_1 and T_2 are time constants that are given as shown below.

$$K = R_1 + R_2 \quad T_1 = C_1 \cdot R_1 \quad T_2 = \frac{C_1 \cdot R_1 \cdot R_2}{R_1 + R_2}$$

Moreover, the open circuit voltage in Eq. (3) correlates closely with the integrated value of the charging and discharging currents and is described using the following equation.

$$V_0(t) = \frac{h}{s} \cdot I(t) \qquad (4)$$

where h is the open circuit voltage constant, which is proportional to the rate of change in the open circuit voltage relative to SOC in Fig. 3. In short, h varies constantly according to SOC. Substituting Eq. (4) into Eq. (3) yields the following equation.

$$V(t) = \frac{K \cdot T_2 \cdot s^2 + K \cdot s + h}{T_1 \cdot s^2 + s} \cdot I(t) \qquad (5)$$

As indicated here, the battery was modeled using the current as the input and the terminal voltage as the output. It will be noted that this model does not describe in detail the phenomena that occur inside the battery. Rather, the relationship between the input and the output under certain specific operating conditions (SOC, temperature, degree of battery degradation, etc.) is approximated as a linear model. Accordingly, this battery model presumes that the various model parameters, i.e., internal resistance K, time constants T_1 and T_2, and the open circuit voltage constant h, do not have fixed values but rather vary constantly according to changes in the operating conditions. In other words, the problem of estimating the internal battery conditions was simplified by defining the battery as a linear parameter varying (LPV) system.

EXPERIMENTAL VALIDATION OF BATTERY MODEL

A single-cell lithium-ion battery was charged and discharged using a square-wave current, and the measured current and terminal voltage data were then used in verifying the validity of the battery model given in Eq. (5). Specifically, the actual charging/discharging current data were input into the linear model in Eq. (5) and the terminal voltage was estimated as the model output. The battery model parameters were modified until good agreement was obtained between the measured and estimated terminal voltages by means of curve fitting. The experimental results for the discharge and charge modes are shown in Figs. 5 and 6, respectively. In the figures, the measured terminal voltage and the estimated terminal voltage obtained with the battery model are indicated in an offset manner for easy comparison. While these data represent just one example for each mode, it is clear that good agreement was obtained between the measured and estimated terminal voltages by suitably adjusting the battery model parameters, regardless of the operating conditions such as the temperature and SOC. Accordingly, these results confirmed that the LPV model given by Eqs. (3)-(5) is valid as a battery model for use with the adaptive digital filter.

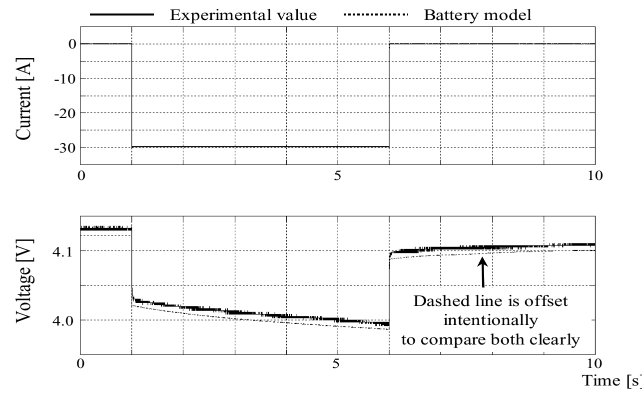

Fig. 5 Verification of Battery Model by Curve-fitting
（Discharge Mode）

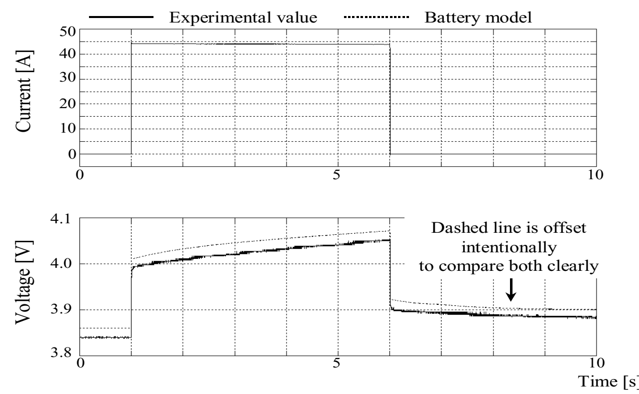

Fig. 6 Verification of Battery Model by Curve-fitting
（Charge Mode）

DESIGN OF ADAPTIVE DIGITAL FILTER

FORMULATION OF A STANDARD MODEL

A hybrid parameter identification method was applied to return the battery model described as a continuous-time type in Eq. (5) directly to the adaptive digital filter for recursive model parameter identification without discretizing the model. Three major reasons for applying this method are summarized below.

1) The parameters of a continuous-time model have physical significance, and it is easy to determine their estimation accuracy.

2) With a continuous-time model, parameter estimation error has less effect on the model calculations than in the case of a discrete-time model.

3) Because the filter output of the model input/output signals is used as the signal for parameter identification, the effect of observation noise can be mitigated.

Here, we will describe the formulation of the adaptive digital filter to make it applicable as a standard type of model. First, Eq. (5) is rewritten as the following expression.

$$\begin{aligned} & G_{lpf}(s)\cdot(T_1\cdot s^2+s)\cdot V(t) \\ & =G_{lpf}(s)\cdot(K\cdot T_2\cdot s^2+K\cdot s+h)\cdot I(t) \end{aligned} \tag{6}$$

The low-pass filter $G_{lpf}(s)$ is selected as indicated below so that both sides of Eq. (6) are strictly proper.

$$G_{lpf}(s)=\frac{1}{(\tau\cdot s+1)^3} \tag{7}$$

where τ is a time constant. By defining the filter output of the current and voltage as

$$\begin{aligned} & I_1(t)=G_{lpf}(s)\cdot I(t), \qquad I_2(t)=s\cdot G_{lpf}(s)\cdot I(t) \\ & I_3(t)=s^2\cdot G_{lpf}(s)\cdot I(t) \\ & V_1(t)=G_{lpf}(s)\cdot V(t), \qquad V_2(t)=s\cdot G_{lpf}(s)\cdot V(t) \\ & V_3(t)=s^2\cdot G_{lpf}(s)\cdot V(t) \end{aligned} \tag{8}$$

Eq. (6) can be written as

$$y(t)=\omega(t)^T\cdot\theta \tag{9}$$

$$y(t)=V_2(t), \quad \omega(t)=\begin{bmatrix} V_3(t) \\ I_3(t) \\ I_2(t) \\ I_1(t) \end{bmatrix}, \quad \theta=\begin{bmatrix} -T_1 \\ K\cdot T_2 \\ K \\ h \end{bmatrix}$$

Equation (9) is the standard model form of the adaptive digital filter and allows the adaptive digital filter to be applied to the problem. Except for θ, which is an unknown parameter, the other values are obtained by performing the filtering operation in Eq. (8) on the measurable signals.

PARAMETER IDENTIFICATION ALGORITHM

Letting $\hat{\theta}$ denote the estimated parameter and $\hat{y}$ the model output estimated by using $\hat{\theta}$, the following error equation is obtained.

$$\begin{aligned} e(t) & = y(t)-\hat{y}(t-\Delta t) \\ & = y(t)-\omega(t)^T\cdot\hat{\theta}(t-\Delta t) \end{aligned} \tag{10}$$

A recursive parameter identification algorithm was applied in relation to this error equation. For the specific purpose of accurately estimating the varying and unknown parameter θ, a least squares algorithm with upper and lower bounded trace of matrix gain was used in this study. The algorithm is described in Eq. (11) below in a discrete-time form.

$$\begin{aligned} & \hat{\theta}(k)=\hat{\theta}(k-1)-\gamma(k)\cdot P(k-1)\cdot\omega(k)\cdot[\omega^T(k)\cdot\hat{\theta}(k-1)-y(k)] \\ & \gamma(k)=\frac{\lambda_3}{1+\lambda_3\cdot\omega^T(k)\cdot P(k-1)\cdot\omega(k)} \\ & P(k)=\frac{1}{\lambda_1(k)}\left\{P(k-1)-\frac{\lambda_3\cdot P(k-1)\cdot\omega(k)\cdot\omega^T(k)\cdot P(k-1)}{1+\lambda_3\cdot\omega^T(k)\cdot P(k-1)\cdot\omega(k)}\right\} \\ & \quad =\frac{Q(k)}{\lambda_1(k)} \\ & \lambda_1(k)=\begin{cases} \dfrac{trace\{Q(k)\}}{\gamma_U} & if \quad \alpha_1\le\dfrac{trace\{Q(k)\}}{\gamma_U} \\ \alpha_1 & if \quad \dfrac{trace\{Q(k)\}}{\gamma_U}\le\alpha_1\le\dfrac{trace\{Q(k)\}}{\gamma_L} \\ \dfrac{trace\{Q(k)\}}{\gamma_L} & if \quad \dfrac{trace\{Q(k)\}}{\gamma_L}\le\alpha_1 \end{cases} \end{aligned} \tag{11}$$

where λ_3 and α_1 are the weights of the adaptive estimation and are set in a range of $0<\alpha_1<1,\ 0<\lambda_3<\infty$ and γ_U and γ_L are values that determine the upper and lower limits of the adaptive estimation.

CALCULATION OF OPEN CIRCUIT VOLTAGE BASED ON ESTIMATED PARAMETER

The estimated open circuit voltage $\hat{V}_0(t)$ is calculated from the parameter $\hat{\theta}(t)$ that is recursively estimated with the adaptive digital filter. Calculation of $\hat{V}_0(t)$ from Eq. (4) by means of the adaptive digital filter, however, would result in integrated accumulation of error. For that reason, $\hat{V}_0(t)$ is calculated directly with the battery model in Eq. (3) that does not include an integrator, instead of using Eq. (4). Using the same procedure as mentioned earlier, the polynomial denominator of Eq. (3) is cancelled and both sides are multiplied by the low-pass filter in Eq. (7) to yield the following equation

$$\begin{aligned} & G_{lpf}(s)\cdot V_0(t) \\ & =G_{lpf}(s)\cdot(T_1\cdot s+1)\cdot V(t)-G_{lpf}(s)\cdot(K\cdot T_2\cdot s+K)\cdot I(t) \end{aligned} \tag{12}$$

The left-hand side of Eq. (12) is the value obtained by performing the low-pass filtering operation on the open circuit voltage $V_0(t)$. This value is regarded as the estimated open circuit voltage $\hat{V}_0(t)$ because the change in the open circuit voltage $V_0(t)$ is relatively gradual. In addition, K and the other parameters are replaced by $\hat{K}(t), \hat{T}_1(t)$ and $\hat{T}_2(t)$, i.e., the parameters estimated with the continuous-time model calculated by means of the adaptive digital filter. Then, after performing the filtering operation shown in Eq. (8), the currents $I_1(t)$ and $I_2(t)$ and terminal voltages $V_1(t)$ and $V_2(t)$ are substituted into

Eq. (12), and the estimated open circuit voltage $\hat{V}_0(t)$ is calculated with the following equation.

$$\begin{aligned}\hat{V}_0(t) &\cong G_{lpf}(s)\cdot V_0(t)\\ &= \hat{T}_1\cdot V_2(t)+V_1(t)-\hat{K}\cdot\hat{T}_2\cdot I_2(t)-\hat{K}\cdot I_1(t)\end{aligned} \tag{13}$$

The structure of hybrid parameter identification is shown schematically in Fig. 7.

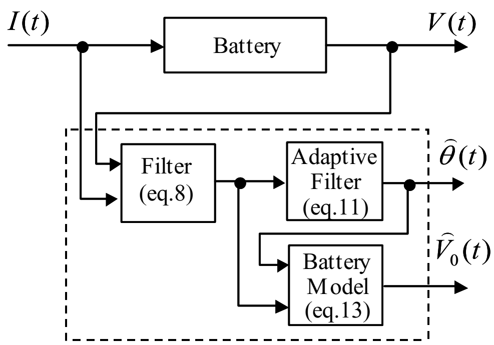

Fig. 7 Hybrid Parameter Identification

METHOD OF CALCULATING BATTERY'S INTERNAL STATE VARIABLES

Using the battery model parameter $\hat{\theta}(t)$, recursively estimated with the adaptive digital filter, and the estimated open circuit voltage $\hat{V}_0(t)$, which has already been calculated as an internal state variable, the estimated SOC $\hat{S}_{OC}(t)$, estimated acceptable input power $\hat{P}_{IN}(t)$ and estimated available output power $\hat{P}_{OUT}(t)$ are calculated. The estimated SOC $\hat{S}_{OC}(t)$ is calculated from the recursively estimated open circuit voltage $\hat{V}_0(t)$, using a battery characteristics map (Fig. 3) of the correlation between the open circuit voltage V_0 and SOC, which have been measured in advance. Estimated acceptable input power $\hat{P}_{IN}(t)$ and estimated available output power $\hat{P}_{OUT}(t)$ are calculated from the recursively estimated open circuit voltage $\hat{V}_0(t)$ and internal resistance $\hat{K}(t)$, using the following equation for the steady-state characteristic.

$$V(t) = \hat{K}(t)\cdot I(t) + \hat{V}_0(t) \tag{14}$$

The estimated acceptable input power $\hat{P}_{IN}(t)$ can be calculated with the following equation if it is defined as a critical value that reaches the upper limit of the battery terminal voltage V_{MAX}.

$$\hat{P}_{IN}(t) = \frac{V_{MAX}-\hat{V}_0(t)}{\hat{K}(t)}\cdot V_{MAX} \tag{15}$$

The estimated available output power $\hat{P}_{out}(t)$ can be calculated with Eq. (16) below if it is defined as a critical value that reaches the lower limit of the battery terminal voltage V_{MIN}.

$$\hat{P}_{OUT}(t) = \frac{\hat{V}_0(t)-V_{MIN}}{\hat{K}(t)}\cdot V_{MIN} \tag{16}$$

Figure 8 outlines the method for calculating the internal state variables of the battery.

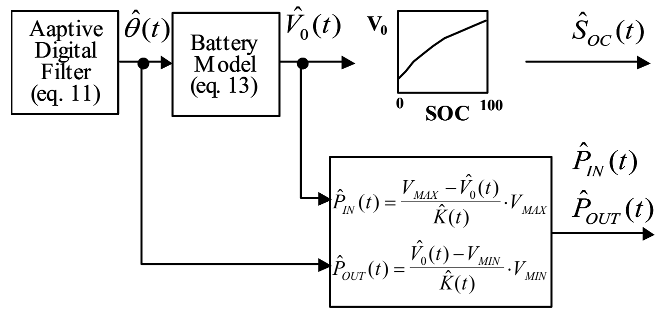

Fig. 8 Estimation of SOC, Pin and Pout

SIMULATION

A simulation was run to verify the estimation performance of the system designed in the foregoing section for estimating a battery's internal state variables by means of an adaptive digital filter. The target of the estimation was the battery model described by Eqs. (3) and (4). Figure 9 shows one example of the simulation results. The battery was charged and discharged for 800 s using a simple current cycle pattern that combined a step-like change and a lamp signal. The battery model parameters were changed in a step-like manner after a period of 400 s from values corresponding to a temperature of 25°C to those corresponding to a temperature of 0°C. This simulation experimentally induced abrupt parameter changes that are not actually possible in the real world. In addition, observation noise corresponding to that of an actual system implemented on a vehicle was added to the current and terminal voltage. The estimated values of the battery model parameters ($\hat{K}, \hat{T}_1, \hat{T}_2$) converged quickly to the actual values (those set for the battery model) right after the estimations began and also right after the step-like change in the parameters corresponding to the temperature change. As a result, the estimated open circuit voltage $\hat{V}_0(t)$, estimated SOC $\hat{S}_{OC}(t)$, estimated acceptable input power $\hat{P}_{in}(t)$ and estimated available output power $\hat{P}_{out}(t)$ calculated by using the above-mentioned estimated parameters all coincided with the actual values. The results of this simulation confirmed that the battery model parameters and internal state variables can be recursively estimated with good accuracy, even when the parameters that are the target of the estimation vary and observation noise is also present.

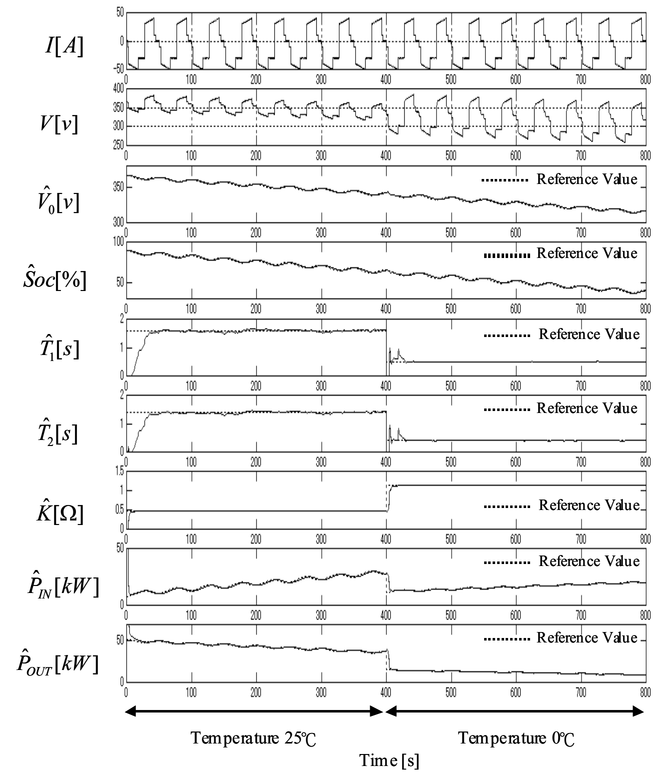

Fig. 9 Simulation Results
(Temperature 25→0℃) 《96 Cells》

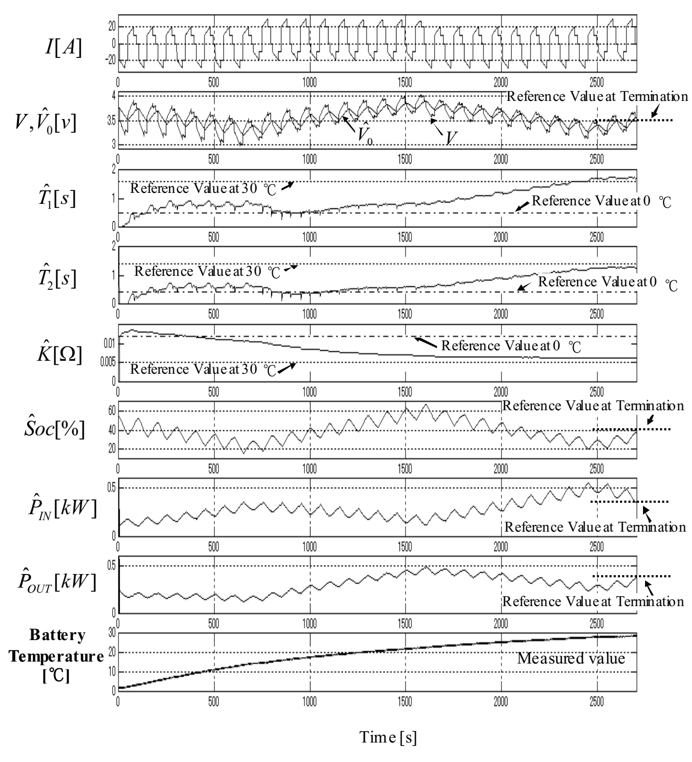

Fig. 10 Experimental Results 1
(Temperature 0→30℃) 《1 Cell》

BENCH TEST

A bench test of the charge/discharge modes of an actual lithium-ion battery was conducted to validate the estimation performance. The specifications of the estimator were the same as those examined in the simulation. However, in the case of an actual battery, the true values of the estimations cannot be ascertained during charging and discharging. Accordingly, values identified by the procedure described in the previous section about experimental validation of the battery model were regarded as the true values of the estimated parameters ($\hat{K}, \hat{T}_1, \hat{T}_2$). On the other hand, the battery terminal voltage that converged after the current was cut off was regarded as the true value of the estimated open circuit voltage $\hat{V}_0(t)$ at the end of charging or discharging. The value found by actually measuring the remaining battery capacity following a constant-current discharge after the current was cut off was regarded as the true value of the estimated SOC $\hat{S}_{OC}(t)$ at the end of charging or discharging. Similarly the true values of the estimated acceptable input power $\hat{P}_{in}(t)$ and available output power $\hat{P}_{out}(t)$ were measured after the current was cut off. By charging and discharging in short pulses, the true values can be measured without changing the battery conditions. The maximum power when the terminal voltage reached the limit voltage during charging or discharging was regarded as the true value. The battery was put in a constant-temperature tank for the purpose of controlling the internal temperature. However, the battery temperature could not be controlled accurately, so only the battery surface temperature was measured.

Figure 10 shows the results obtained when the battery was charged and discharged using the same specific simple current cycle pattern as that of the simulation (Fig. 9). However, the battery temperature was continuously changed from 0° to 30°C by changing the preset temperature of the tank. The estimated battery model parameters ($\hat{K}, \hat{T}_1, \hat{T}_2$) continuously changed from the true values at 0°C to the true values at 30°C, tracking the change in each true value. In addition, the estimated open circuit voltage $\hat{V}_0(t)$, the estimated SOC $\hat{S}_{OC}(t)$, the estimated acceptable input power $\hat{P}_{in}(t)$ and available output power $\hat{P}_{out}(t)$ at the time of current cut-off also coincided well with the respective true value.

Figure 11 summarizes the estimated SOC values that were obtained when bench tests were conducted repeatedly under various battery temperature conditions (approximately -20°~30°C) and SOC conditions (approximately 20~70%). It is seen that the estimated SOC values agreed well with the true SOC values under all of the test conditions, indicating that good SOC estimation accuracy (within ± 4%) was consistently obtained.

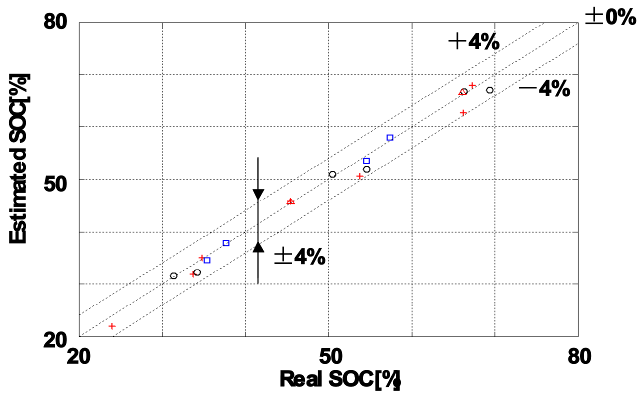

Fig. 11 Experimental Results 2
（SOC Estimation Accuracy / Temperature –20～30℃）

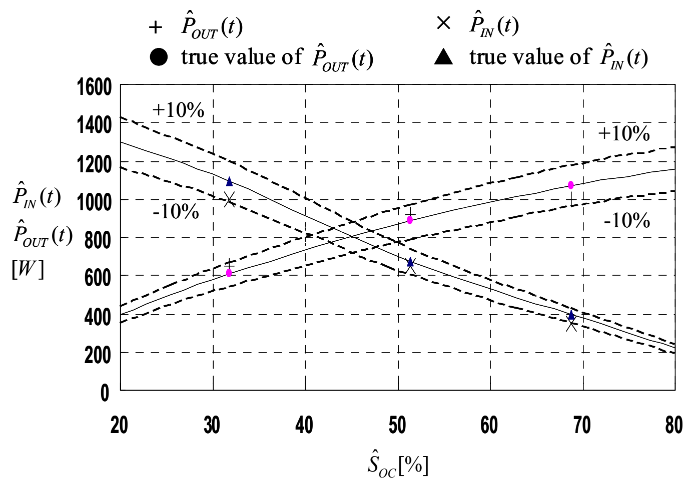

Fig. 12 Experimental Results 3
（Power Estimation Accuracy / Temperature 25℃）

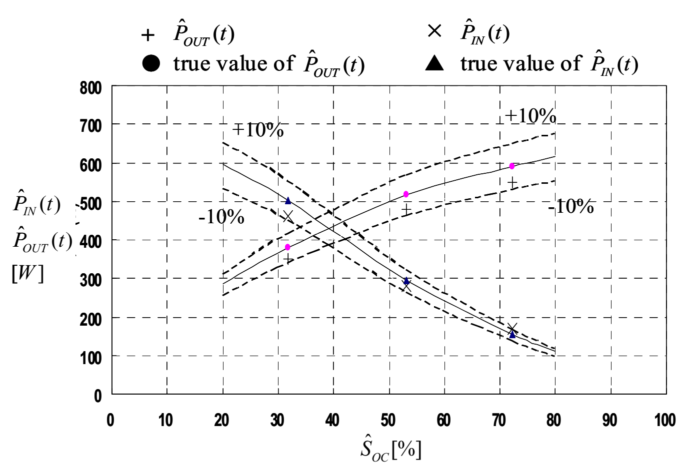

Fig. 13 Experimental Results 4
（Power Estimation Accuracy / Temperature 0℃）

Figures 12 and 13 summarize the estimated acceptable input power $\hat{P}_{in}(t)$ and available output power $\hat{P}_{out}(t)$ that were obtained when bench tests were conducted repeatedly under various battery temperature conditions (approximately 0~25°C) and SOC conditions (approximately 30~70%). It is seen that the estimated $\hat{P}_{in}(t)$, $\hat{P}_{out}(t)$ agreed well with the true values under all of the test conditions, indicating that good maximum power estimation accuracy (within ± 10%) was consistently obtained.

The results of the foregoing bench tests confirmed that this actual system, which differed in many respects from the LPV model represented by an adaptive digital filter, also provided good estimation performance like that seen in the simulation results.

CONCLUSION

The three methods noted below were applied in this research to the problem of estimating the internal state variables of a storage battery such as a lithium-ion battery. With these basic techniques, SOC, acceptable input power, available output power and other internal state variables of the battery that cannot be measured directly during charging or discharging can be estimated with good accuracy, regardless of the operating conditions (SOC, temperature, degree of battery degradation, etc.).

1) By describing the relationship between the current and terminal voltage of a storage battery as a linear parameter varying (LPV) model, the problem of estimating the internal state variables of the battery was reduced to a problem of recursive model parameter identification by means of an adaptive digital filter.

2) A least squares algorithm with upper and lower bounded trace of matrix gain was applied in order to recursively identify with good accuracy the battery model parameters that vary according to the operating conditions.

3) A hybrid parameter identification method was adopted that can directly estimate the parameters of a continuous-time model by means of an adaptive digital filter. That was done to take into account the influence of observation noise, presumed to be present in actual vehicle applications.

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