Battery State Estimation System for Automobiles

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Recently lithium-ion batteries have been widely used for electric vehicles. The states of batteries should be estimated accurately for their safe and effective use. We have developed a battery state estimation system that has a parameter estimation algorithm for a battery model. This paper describes the estimation results, including the state of charge (SOC) and state of health (SOH) for each battery cell, and presents the system that transmits these results to a server.

Keywords: electric vehicle, lithium-ion battery, battery state estimation, IoT

1. Introduction

In response to a growing public concern about reducing the consumption of oil and other fossil energy resources and the necessity for global warming countermeasures, the popularity of hybrid electric vehicles (HEVs), electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs) and other battery-powered vehicles has been expanding in the world. With the advancement of IoT technology, the development of connected car technology has also been promoted.(1) Equipped with Internet access, connected cars are expected to provide a diversity of services.

Lithium-ion batteries (LiBs) have recently become the mainstream of the power sources for electrified vehicles. LiBs have an advantage over lead-acid batteries in energy density and weight. However, to use LiBs safely and efficiently, it is indispensable to have a method of diagnosing their state and thus protecting them properly. All the electrified vehicles are equipped with battery packs in which two or more battery cells are connected to each other to achieve the required capacity and voltage. Since the performance of each cell varies in response to the operating temperature and other conditions of use, it becomes necessary to grasp the state of each cell depending on the purpose of use of the battery.

Sumitomo Electric Industries, Ltd. has developed a state estimation unit into which a LiB state estimation technology is incorporated, and built this unit into an on-board system which can be linked to a server through the Internet. This paper describes the in-vehicle evaluation results of the system.

2. System Configuration

The configuration of the on-board system we evaluated in this study is shown in Fig. 1. The system consists of a battery state estimation unit and on-board wireless communication unit. The former is incorporated with a LiB state estimation algorithm, while the latter has a function to communicate with a cloud server. The battery state estimation unit receives sensor information on the on-board battery, such as current and voltage, from the system installed in the vehicle, estimates the state of the battery, and transmits the estimation results to the cloud server through the on-board wireless communication unit.

The on-board system used for this study was configured to receive sensor information from the electric vehicle and compute the state of each cell of the in-vehicle battery. This study was carried out by incorporating the battery state estimation function into an independent unit. However, this function can be also incorporated into an on-board wireless communication device, battery management unit (BMU), or other unit.

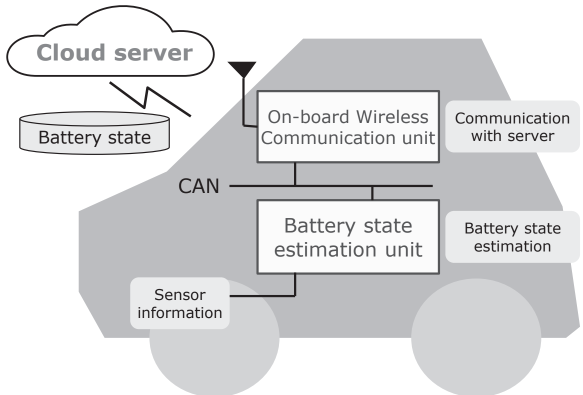

Fig. 1. System Configuration

3. Outline of Battery State Estimation System

3-1 State quantity of battery

For a secondary battery, the state of charge (SOC*1) and the state of health (SOH*2) are the key state quantities for representing the remaining capacity or the charge remaining in the battery. SOH is further divided into capacity retention rate (SOH-C) and an increase in internal resistance (SOH-R). SOH-C is defined as the ratio of the measured capacity of the battery to the initial fully charged capacity of the battery when it was new. SOH-R increases as the battery deteriorates. The state of power (SOP) is also used in practice as an important parameter representing the electric power that can be charged/discharged into/from the battery.

Estimating these quantities is important to check if the vehicle is controlled optimally to retard the deterioration of the battery, use it efficiently, and maximize the fuel efficiency. However, the physical quantities of a battery that can be externally measured are only the current, voltage, and temperature. It is impossible to directly measure SOC and other state quantities. Various techniques are being studied at present to estimate these quantities, including an open-circuit voltage (OCV) estimation technique, an equivalent circuit model technique that uses an electric circuit to represent a battery, and a nonlinear Kalman filter technique.[(2), (3)]

Figure 2 shows the schematic block diagram of the battery state estimation system we evaluated in this study. The system combines a few techniques, such as an extended Kalman filter (EKF) and a parameter estimation method that uses an equivalent circuit model of the secondary battery. When externally measurable current, voltage, and temperature are inputted in the system, it outputs the estimates of various state quantities of the battery.

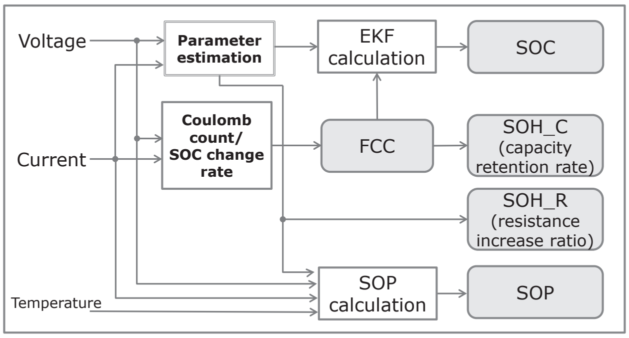

Fig. 2. Block Diagram of Battery State Estimation System

3-2 Estimation of the SOC of battery

The equivalent circuit model shown in Fig. 3 was used to estimate the state quantities of a battery. When a battery is charged/discharged, the voltage changes due to a rapid (about several tens of milliseconds) reaction and slow (between 10 and 20 milliseconds to a few minutes) reaction. The rapid reaction is caused by an electrolyte resistance and charge transfer resistance, while the slow reaction is derived from an increase in diffusion resistance. In the equivalent circuit model used for this study, the rapid reaction was approximated by Ra, the sum of a resistance component and electrolyte resistance. The diffusion phenomenon inside the electrode, which causes the slow reaction, was represented by the parallel circuit of Rb and Cb.

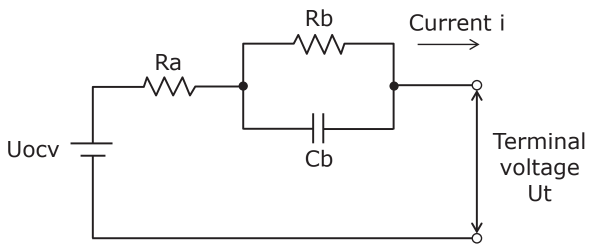

Fig. 3. Battery Equivalent Circuit Model for Parameter Estimation

For the parameters of the equivalent circuit model shown in Fig. 3, the following approximation formulas (identification formulas) (1) through (5) hold.[(4)]

$$Ut(k) = b0 \cdot i(k) + b1 \cdot i(k-1) - a1 \cdot Ut(k-1) + f \quad (1)$$
$$b0 = Ra \quad (2)$$
$$b1 = Ts \cdot Ra/(Rb \cdot Cb) + Ts/Cb - Ra \quad (3)$$
$$a1 = Ts/(Rb \cdot Cb) - 1 \quad (4)$$
$$f = (1 + a1)Uocv \quad (5)$$

where, Ut: terminal voltage, i: charge/discharge current, Ts: measuring period, k: an integer representing measuring time point

In this model, θ = (b0, b1, a1, f) is defined as an unknown parameter for estimating θ using the forgetting factor iterative least square method. Once θ is estimated, parameters Ra, Rb, Cb, and Uocv can be determined from formulas (6) through (9), which are derived from the inverse operation of formulas (1) through (5).

$$Ra = b0 \quad (6)$$
$$Rb = (b1 - a1 \cdot b0)/(1 + a1) \quad (7)$$
$$Cb = Ts/(b1 - a1 \cdot b0) \quad (8)$$
$$Uocv = f/(1 + a1) \quad (9)$$

To estimate SOC, a sequential computation is carried out by applying the equivalent circuit parameters, which are obtained according to the above procedures, to the battery model for EKF. The open circuit voltage Uocv, which is a component of the linear regression formula (1), is a physical variable that varies depending on the state of charge (SOC). In this study, we obtained a value by the following procedures and used it as a substitute for the Uocv. First, we estimated the SOC one period before EKF. Subsequently, we calculated the value by substituting the estimated SOC into the SOC – OCV relation.

In this model, the parameter estimation error increases when the absolute value of the current is small or the change amount is small. As a measure to minimize the estimation error, we added a judgment/treatment procedure to the model.

4. In-Vehicle Evaluation

We installed in a commercial electric vehicle (travel distance: over 70,000 km) the state estimation unit incorporated with the battery state estimation algorithm discussed in the preceding section, and carried out an in-vehicle evaluation of the unit by inputting sensor information on the on-board battery.

Figure 4 shows the graph of the current and voltage (the average of all cell voltages) measured when the test electric vehicle was driven in an urban area for about 2.5

hours. The battery repeated discharging (negative value) when it is used to drive the vehicle and charging (positive value) when it stored the regenerative energy. Finally, the current was maintained within the approximate range of -250 to + 60 A. The average cell voltage dropped from about 4.1 V, which was measured when the vehicle started running, to about 3.8 V due to charging and discharging.

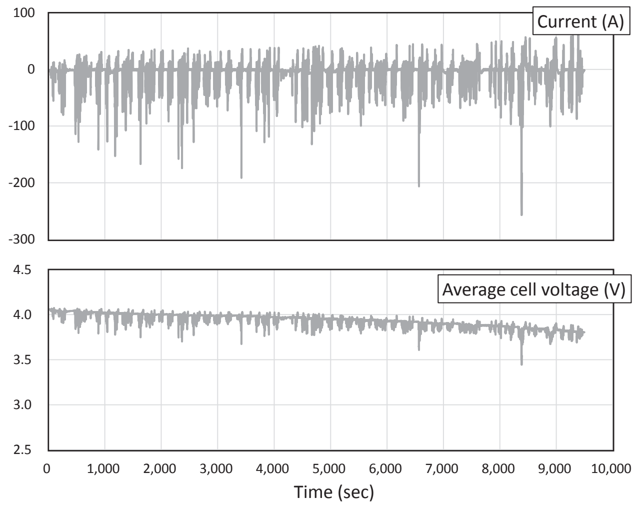

Fig. 4. Variation in Battery Current/Voltage with Time When Vehicle Was Driven in Urban Area

In this study, we estimated the state of each of the cells connected in series to each other in the on-board battery pack, using the above current and the voltage of each cell. An example of the estimation result for the battery equivalent circuit model parameter of a cell is shown in Fig. 5. This figure shows the time dependence of the estimated value of solution resistance Ra of the battery, which is one of the battery equivalent circuit model parameters relating to rapid reaction. After the initial estimation value of Ra was calculated when the predetermined time passed after the test electric vehicle was driven, the Ra was estimated at given time intervals. As a result, the estimated Ra converged with time to a finite value.

The Ra of the battery, when it was new, was preliminarily measured under the same temperature condition as that for Ra estimation. It was confirmed from the Ra estimation result that the internal resistance increases as the battery deteriorates.

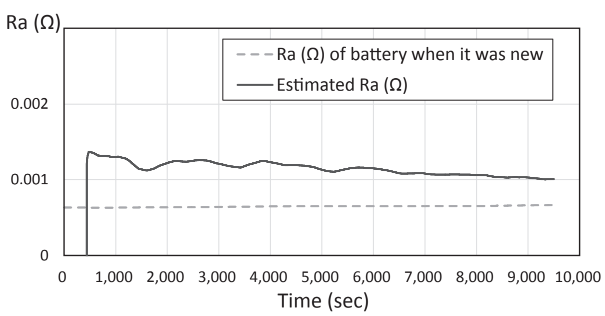

Fig. 5. Parameter Estimation Result (Solution Resistance RO)

The full charge capacity (FCC) of the battery used for this study was also calculated from the travel data of the test electric vehicle. The calculated FCC was used as an input value for EKF, the next calculation step. The SOH-Cs of individual cells were determined from the ratio of calculated FCC to the full charge capacity of the battery that was measured when it was new. The result is shown in Fig. 6. The SOH-Cs of individual cells varied in the approximate range of 67 to 74% and their capacity retention rates also differed depending on the usage environment and the characteristics of individual cells, as shown in Fig. 6.

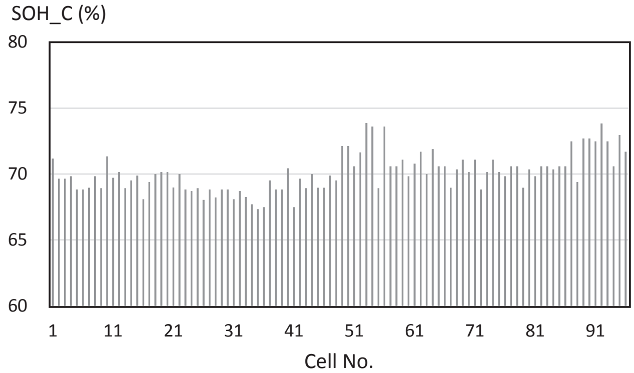

Fig. 6. SOH-C (Capacity Retention Rate) Calculation Result

Subsequent to the above procedure, we substituted a group of estimated parameters into the battery equivalent circuit model to sequentially estimate the SOC of each battery cell using the EKF method. An example of the SOC estimation result for a cell is shown in Fig. 7. The battery equivalent circuit model achieved a satisfactory SOC estimation result as shown in this figure. In particular, the root mean square error (RMSE) of the estimated SOCs was less than 1% with respect to the true SOC value that was determined from the accurately measured coulomb count, and the maximum error fell within 2%.

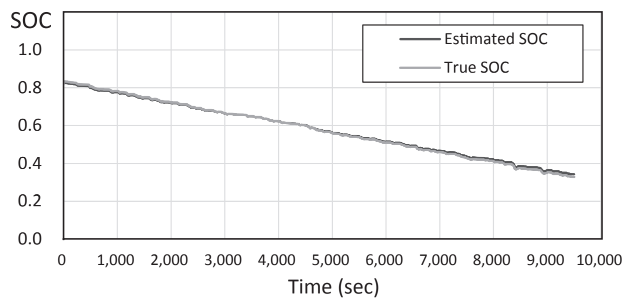

Fig. 7. Estimation Result for SOC of Electric Vehicle Battery

It was confirmed that the states of each cell estimated as above can be periodically uploaded to the server through an on-board communication unit as battery state data and used to control the state of the battery installed in the electric vehicle.

5. Conclusion

In association with the recent growing demand for batteries for electric vehicle applications, we have developed a LiB state estimation unit. Test results confirmed that the new unit can estimate with a high degree of accuracy the SOC, SOH, and other state quantities of each cell of the battery installed in a commercial electric vehicle. We have also established a system that can store the estimated battery states in a server as battery state data.

We will continue the study on the establishment of a battery reuse system and server-stored information utilization system both based on the newly developed battery IoT infrastructure system.

6. Acknowledgements

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Technical Terms

∗1 State of charge (SOC): A capacity available in a battery pack or system. It is expressed as a percentage of rated capacity.

∗2 State of health (SOH): The actual physical condition of a battery in comparison with a completely new battery (100%).

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