A Battery Smart Sensor and Its SOC Estimation Function for Assembled Lithium-Ion Batteries

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Abstract – This paper discusses about the smart sensor which is the important technology in a smart grid. We have developed the system to monitor the battery condition by the attached sensor. It accumulates the measured data onto the WEB. The battery sensor is implemented with a microcomputer. We have first developed a high accurate and practical SOC sensor using the Extended Kalman filter as a function of the battery sensor. Based on the SOC estimation function for a single cell, the SOC estimation function for assembled Lithium-ion batteries is also developed.

I. Introduction

The energy resources which produce electric power do not exist infinitely. Introduction of renewable energy is required in the power supply side, and efficient electric power using is demanded by the power consumer. However, renewable energy such as solar power and wind power are difficult to stable power supply because of effects of renewable energy using environment. Electric power obtained by these power generation methods is achieved stabilized by using a power storage system. There is a storage battery as a representative of the power storage system. Storage batteries conventional mainstream was lead-acid battery. In recent years, high-performance lithium ion batteries are becoming the mainstream. The lithium ion battery is excellent in energy density and charge and discharge efficiency in comparison. Therefore, the lithium ion battery has advantages in performance and compactness. However, there are problems such as safety and degradation in lithium ion battery, so management and control of the lithium ion battery is important.

In this paper, the battery smart sensor system [1] that stores data on the WEB, and it monitors a lithium ion battery state equipped with a wireless function is described. The battery smart sensor is a real-time monitoring system of the lithium ion battery which used a sensor network. Then, an accurate and practical battery SOC (State-of-charge) estimation algorithm which is mounted on the battery sensor system is introduced. Finally, SOC estimation system of assembled Lithium-ion batteries is introduced.

The battery SOC is an index which shows the battery charging rate. Grasp of the battery SOC is a fundamental subject of battery control, it is an important function for battery management system. Various battery SOC estimation methods have been proposed. Output voltage method [2], internal resistance method [3], current integration method [4], etc are used for SOC estimation in the battery control. Output voltage and internal resistance method can be easily constructed system, but SOC estimation accuracy is not good. Current integration method calculates the SOC by integrating electric current of each time period. This method is capable of accurate battery SOC estimation if the initial capacity and the current value are accurate. SOC estimation accuracy of this method is relatively better, and this technique is used for various devices that require battery since it can be easily implemented. However, this method is susceptible to measurement noise and noise caused by the bias deviation of the initial capacity, and it does not have a structure for feedback of such noise. Then, the proposed SOC estimation method is Extended Kalman Filter method. This method is a statistical method for estimating battery SOC accurately by setting the error in advance. In order to accurately estimate a battery SOC is also important to select the appropriate SOC estimation method by the characteristics and usage of the battery. Especially electric vehicles and power storage systems that require high output and high capacity are used as assembled Lithium-ion batteries connecting the battery cell in series and parallel. SOC estimation of assembled Lithium-ion batteries is different from the case of the single battery cell in case of the variation of the battery cells. There are various factors such as voltage, capacity, internal resistance, degradation and so on in variation. So, this paper shows the assembled Lithium-ion batteries SOC definition and its calculation method.

II. Battery Smart Sensor

The battery smart sensor is a system which supervises the state of a battery in real time. This system can store the battery data in the storage server on WEB. This system is based on IEEE1888 standard. IEEE1888 protocol that replaces control data and the sensor data by the network is an open standard. The battery smart sensor system consists of a radio node, a gateway and a storage server (Fig.1). The sensor node (Fig.2) consists of 4 series assembled Lithium-ion batteries, a sensor board and a logger board. The sensor board measures 4 series assembled Lithium-ion batteries voltages, current and temperature. Logger board sends measured battery data to the gateway by the Bluetooth communication standard. The Logger board uses ARM mbedLPCNXP1768 microcomputer. mbed microcomputer is implemented the IEEE1888 standard. The gateway converts the data to the IEEE1888 format, and it is a device that transfers the data to the storage server. Communications between the gateway and the sensor nodes is carried out in Bluetooth wireless communication, communications between the gateway and the storage server is carried out in IEEE1888 standard. This gateway is a Windows application that is defined in IEEE1888.

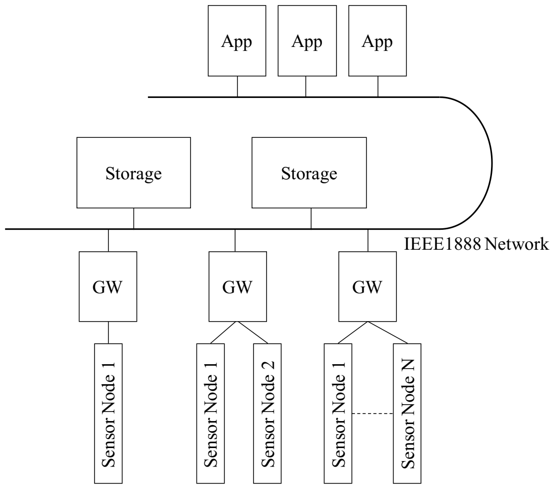


Fig. 1. Battery smart sensor

Fig.3 is a schematic diagram of the sensor node. The Sensor board uses IC "BQ76920" for monitoring a battery to measure an assembled Lithium-ion batteries voltages and current. Current is obtained by using the current detection resistor 0.001 [Ω] (Rs) installed at the "BQ76920" outside. "BQ76920" sampling interval is 0.25 [Sec]. "BQ76920" is equipped with a 14-bit AD converter and I2C interface. The measured data converts analog into digital, and transfers these data to the logger board in an I2C standard. The sensor board implements a temperature sensor "ADT7410" connector. "ADT7410" is equipped with a temperature sensor, a 16-bit AD converter and an I2C interface. Temperature measured by "ADT7410" is converted analog into digital, and the data is transferred to logger board the I2C standard. Data logger board is mainly implemented a microcomputer "mbed" and the Bluetooth module "ZEAL-CO02". Microcomputer have implemented assembled Lithium-ion batteries SOC estimation program. Microcomputer calculates SOC by the measured data that transferred from the sensor board.

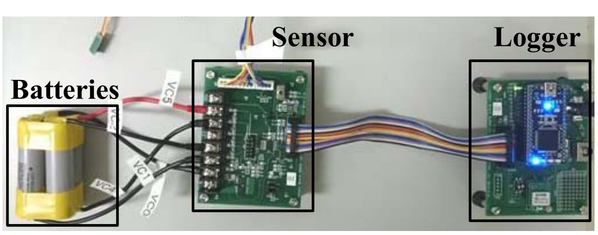


Fig. 2. Sensor node

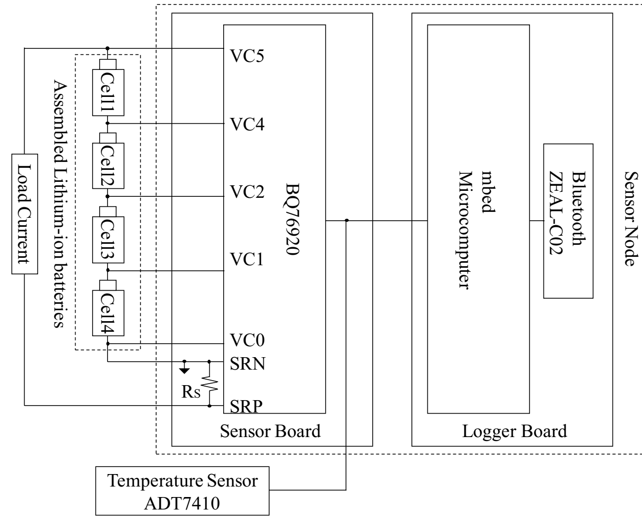
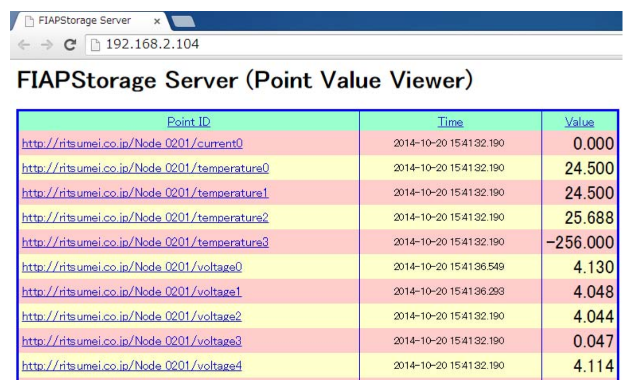


Fig. 3. Sensor node composition

The Storage server can confirm the stored battery data by Web browser in real time. Fig.4 is the storage server, it manages the measurement data as a point. Each battery cell Voltages, current, three locations temperature data of 4 series assembled Lithium-ion batteries has been registered as the point.



FIAPStorage Server (Point Value Viewer)

Point ID	Time	Value
http://ritsumei.co.jp/Node 0201/current0	2014-10-20 15:41:32.190	0.000
http://ritsumei.co.jp/Node 0201/temperature0	2014-10-20 15:41:32.190	24.500
http://ritsumei.co.jp/Node 0201/temperature1	2014-10-20 15:41:32.190	24.500
http://ritsumei.co.jp/Node 0201/temperature2	2014-10-20 15:41:32.190	25.688
http://ritsumei.co.jp/Node 0201/temperature3	2014-10-20 15:41:32.190	-256.000
http://ritsumei.co.jp/Node 0201/voltage0	2014-10-20 15:41:36.549	4.130
http://ritsumei.co.jp/Node 0201/voltage1	2014-10-20 15:41:36.293	4.048
http://ritsumei.co.jp/Node 0201/voltage2	2014-10-20 15:41:32.190	4.044
http://ritsumei.co.jp/Node 0201/voltage3	2014-10-20 15:41:32.190	0.047
http://ritsumei.co.jp/Node 0201/voltage4	2014-10-20 15:41:32.190	4.114

Fig. 4. IEEE1888 storage server

III. Single Battery Cell SOC Estimation

A. SOC estimation by Extended Kalman Filter

Lithium-ion battery used in the experiment subject is a commercially 18650 type battery. Specifications of Lithium-ion battery are referred to TABLE I.

TABLE I
Lithium-ion battery

Nominal Voltage	3.6V
Nominal Capacity	2250.0mAh
Maximum Voltage	4.2V
Minimum Voltage	3.0V

The Kalman Filter is used to estimate and control the state of the dynamic system by using the observed value with errors. The battery SOC estimation uses Extended Kalman Filter (EKF) to perform appropriate weighting according to the size of each noise when the random noise is applied to the system and measurement values. The method estimates accurately the state of ever-changing system [5].

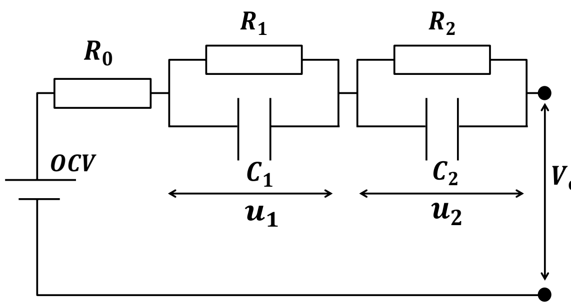


Fig. 5. Equivalent circuit model of a Li-ion battery

Also serving as the base of the EKF is an accurate characterization of the battery [6]. Therefore it is necessary to measure the characteristics of the battery from the pre-experimental. Model used to measure the battery characteristics is an equivalent circuit model of Fig.5. This model is a representation schematically a chemical reaction inside a Li-ion battery by two RC circuit and internal resistance.
This model OCV (Open-Circuit-Voltage) is shown in Fig.6. Other parameters (R_1, C_1, R_0) are measured in advance experiment.

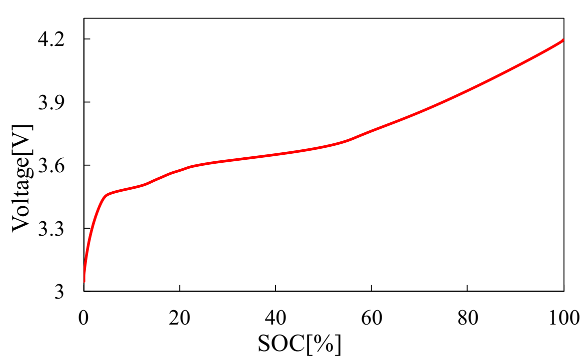


Fig. 6. OCV

To use the Kalman filter requires a state equation connecting the state of the system. Equation (1) is the equation of state. Observation equation showing the relationship between observed values and the system state is shown in equation (2).

$$x_{k+1} = f(x_k) + \boldsymbol{b}_u u_k + \boldsymbol{b}\omega_k \quad (1)$$

$$y_k = h(x_k) + v_k \quad (2)$$

Here, b_u associate control input u_k and state variable x. ω_k is a observation noise, and v_k is process noise. The state equation and observation equation for the battery equivalent circuit model is shown in equation (3) and (4).

$$x(k+1) = \begin{bmatrix} SOC(k+1) \\ u_1(k+1) \\ u_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \left(1 - \frac{\Delta t}{R_1 C_1}\right) & 0 \\ 0 & 0 & \left(1 - \frac{\Delta t}{R_2 C_2}\right) \end{bmatrix} \times \begin{bmatrix} SOC(k) \\ U_1(k) \\ U_2(k) \end{bmatrix} + \begin{bmatrix} \frac{\Delta t}{FCC} \\ \frac{\Delta t}{C_1} \\ \frac{\Delta t}{C_2} \end{bmatrix} \times i(k) + \boldsymbol{b}\omega(k) \quad (3)$$

$$y(k) = OCV(SOC) + i(k)R_0(k) + U_1(k) + U_2(k) + v_k \quad (4)$$

In equation (3), state variable $x(k)$ is the battery SOC and the battery equivalent circuit model parameters. Δt is the sampling interval, and FCC is the capacitance of the battery. $y(k)$ is a sum of the observation noise and the model terminal voltage $V_o(k)$. $i(k)$ is shown a current load applied to a battery. Linearization computation of the nonlinear model is shown in Equation (5) (6).

$$\widehat{A_k} = \left.\frac{\partial f(x_k, u_k)}{\partial x_k}\right|_{x_k = \hat{x}_{\frac{k}{k}}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \left(1 - \frac{\Delta t}{R_1 C_1}\right) & 0 \\ 0 & 0 & \left(1 - \frac{\Delta t}{R_2 C_2}\right) \end{bmatrix} \quad (5)$$

$$\widehat{C_k} = \left.\frac{\partial h(x_k, u_k)}{\partial x_k}\right|_{x_k = \hat{x}_{\frac{k}{k}}} = \begin{bmatrix} \left.\frac{dOCV}{dSOC} + \frac{dR_0}{dSOC} \times i_k\right|_{SOC = \widehat{SOC}_{k+1/k}}, & 1, & 1, & i_k \end{bmatrix} \quad (6)$$

Kalman filter has two steps which is a observation step and time update step. In the observation step, equation (7) ~ (9) is performed. Initially, the step calculates the Kalman gain shown in equation (7). Here, R_k is the observation noise covariance, P is a error covariance. Equation (8) is shown an update of the estimated value (post-estimation).

$$K_k = \frac{P_{k/k-1} C_k^T}{C_k P_{k/k-1} C_k^T + R_k} \quad (7)$$

Equation (8) is shown an update of the estimated value (post-estimation).

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k\{y_k - h(\hat{x}_{k+1/k})\} \quad (8)$$

Equation (9) is updating of the error covariance.

$$P_{k/k} = (1 - K_k C_k) P_{k/k+1} \quad (9)$$

Time update step predicts a step $(k+1)$ state. Equation (10) is shown prediction of the estimated value (pre-estimation).

$$\hat{x}_{\mathrm{k+1/k}} = f(\hat{x}_{\mathrm{k/k}}) \tag{10}$$

Equation (11) is calculated a pre-error covariance.

$$P_{\mathrm{k+1/k}} = A_{\mathrm{k}} P_{\mathrm{k/k}} A_{\mathrm{k}}^{T} + Q_{\mathrm{k}} \tag{11}$$

Q_{k} is the covariance of the system noise.

Microcomputer used in implementation of SOC estimation system is mbed, it is the same as the battery smart sensor. We also use the mbed evaluation board with modules such as LCD and SD as shown in Fig.7. Basic characteristics such as voltage and current of the battery are required for EKF processing, so we create an amplification circuit of each. Each amplification value enters the 12-bit analog input pin of the mbed. Then, the operation flow of the SOC estimation system is showed. Fig.8 is the representation of schematic operation flow. The beginning of the operation flow measures the voltage of the target cell. Battery initial parameters are determined based on measurement voltage values from tables. Initial SOC is determined from the relationship table of OCV-SOC. Performing low-pass filtering when the voltage and current values measured. After above mentioned steps are finished, the flow moves to the loop processing of SOC estimation. After measuring the cell parameters necessary for processing EKF, EKF estimates SOC. The estimation results of the SOC output to the LCD and SD are a module mbed evaluation board. This loop step repeat until the battery SOC becomes zero. The sampling interval is adjusted using the mbed Timer library. SOC estimation accuracy and the sampling interval is a trade-off, therefore SOC estimation accuracy increases as the sampling interval decreases. We set it 1.0 [Sec] in this experimentation.

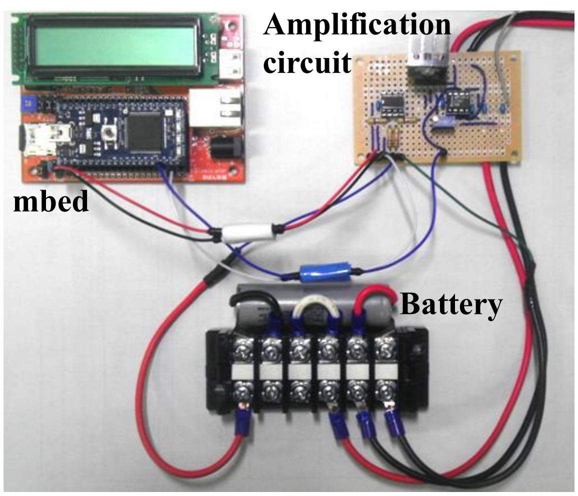


Fig.7. SOC estimation system

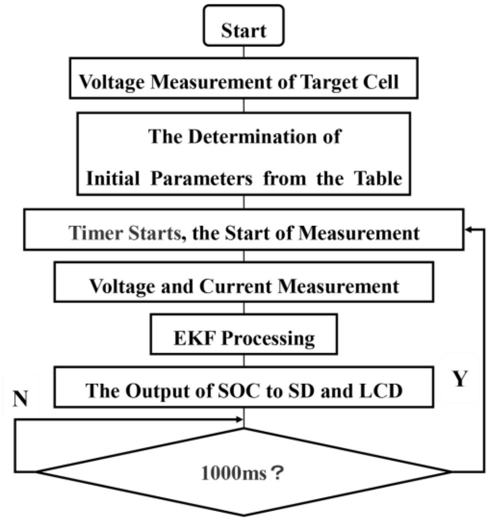


Fig.8. SOC estimation flow

We evaluated the accuracy of the SOC estimation. The current load applied to the target Lithium-ion battery are Fig.9. Experiments are discharged at above current patterns until battery SOC reaches 0.0 [%]. Experiments are evaluated by comparing the estimated SOC by Extended Kalman Filter that implements mbed microcomputer and SOC calculated by the charging and discharging machine. Here SOC = 100.0 [%] is defined that battery is charged constant voltage for 2 hours after the battery is charged constant current 2.25 [A] until the battery output voltage is 4.2 [V]. SOC = 0.0 [%] refers to the state in which the battery output voltage becomes 3.0 [V].

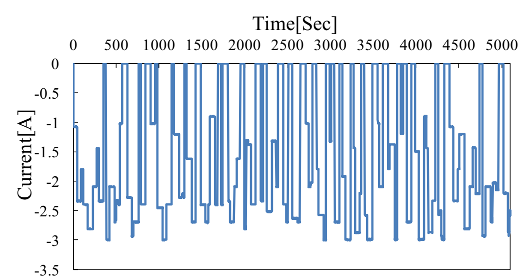


Fig. 9. Discharge current load

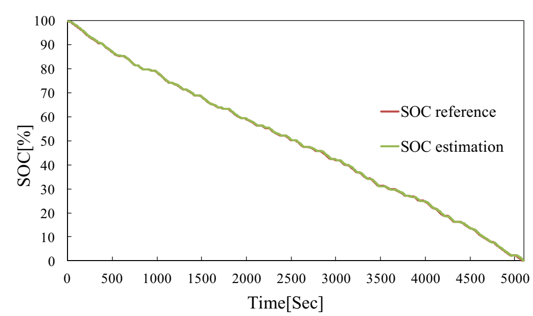


Fig. 10. SOC estimation result

SOC estimation accuracy evaluates the absolute value of subtracting the true SOC from the estimated SOC in percentage. The true SOC is given by the SOC value given by high accurate experimental equipment. The time transition of the estimated SOC and reference SOC is shown in Fig.10. The average error for SOC estimation experiment is 0.15 [%].

IV. Assembled Lithium-ion batteries

A. charge and discharge of assembled Lithium-ion batteries

The 4 series assembled Lithium-ion batteries uses the Lithium-ion batteries shown in TABLE I. The 4 series assembled Lithium-ion batteries were created from aligned each battery cell SOC before the assembled battery is connected in 4 series. Charging method is a CC-CV (Constant Current - Constant Voltage) charging. In order to charge by CC-CV charging method may need to set the maximum battery voltage value. The maximum voltage of the 4 series assembled Lithium-ion batteries is sum of the maximum voltage of each battery cell. However, each battery cell voltage varies. If the maximum voltage of assembled Lithium-ion batteries is set as described above, overcharged battery cell occurs. Therefore, maximum voltage (Vmax) of each battery cell is set to be lower. Discharge of the 4 series assembled Lithium-ion batteries stops when one of battery cell has reached the lower limit voltage (Vmin). Vmax and Vmin of applied battery cells are set up by Vmax=4.0 [V] and Vmin=3.0 [V]. CV charging voltage of the 4 series assembled Lithium-ion batteries is 16.0 [V].

B. Capacity and SOC of assembled Lithium-ion batteries

As indicated in the previous section, when operating assembled Lithium-ion batteries, the variations occur in each battery cell. In BMS (Battery Management System), balancing function is incorporated to keep of each battery cell voltage equal. The capacity and SOC of each battery cell vary by repeating charge and discharge. In addition, the degree of degradation varies by each battery cell. In order to define the capacity and SOC of assembled battery, we must consider these matters.

Figs.11 and 12 depict fully discharged state and fully charged state, respectively. In both pictures, capacity of each cell is different. Thus, let each battery cell capacity be C_1, $C_2, C_3 \ldots C_n$. For a degraded cell i, C_i is smaller than others. As you can see, degraded cell tends to reach upper bound earlier than others when charging. Also, it tends to reach lower bound earlier than others when discharging. Consequently, the degraded cell tends to degrade more. Next, the state of charge of each cell is defined as the ratio of charge in the cell to the capacity of the cell. Let's define the SOC of a cell i by SOC_i. SOC_i is estimated by Extended Kalman Filter shown in section III.

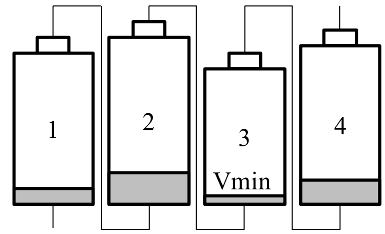


Fig. 11. Fully discharged state of an assembled battery

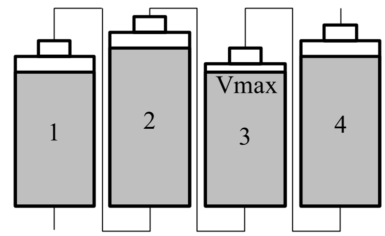


Fig. 12. Fully charged state of an assembled battery

In Fig.11, one cell has reached to minimum voltage V_{min} (see TABLE I), however, other cells have space (gray area in Fig.11) to discharge. At this time, SOC of each cell i is SOC_min_i. Sum of the spaces is defined as discharge capacity loss, LL, which is given by equation (12).

$$LL = \sum_{i=1}^{n} (SOC\_min_i \times C_i) \quad (12)$$

In Fig.12, one cell has reached to maximum voltage V_{max} (see TABLE I), however, other cells have space (white area in Fig.12) to charge. At this time, SOC of each cell i is SOC_max_i. Sum of the spaces is defined as charge capacity loss, LU, which is given by equation (13).

$$LU = \sum_{i=1}^{n} \{(1 - SOC\_max_i) \times C_i\} \quad (13)$$

LL and LU are also given by formulas (14) and (15).

$$LL = \sum_{i=1}^{n} \left(\frac{SOC\_min_i}{|SOC\_max_i - SOC\_min_i|} \times Discharge\ capacity\right) \quad (14)$$

$$LU = \sum_{i=1}^{n} \left(\frac{1 - SOC\_max_i}{|SOC\_max_i - SOC\_min_i|} \times Charge\ capacity\right) \quad (15)$$

Here, $Discharge\ capacity$ and $Charge\ capacity$ are obtained by current integration method. Considering these losses, the sum of capacity distributed in the cells of the assembled battery, C_{all} is given by equation (16). (note: This does not mean the capacity of the assembled battery.)

$$C_{all} = \sum_{i=1}^{n} C_i - (LL + LU) \quad (16)$$

Thus, SOC of the assembled battery, SOC_{all} is given by equation (17).

$$SOC_{all} = min(SOC_i) \quad (17)$$

C. Charge and discharge experiment by the smart sensor

In this section, we describe charge and discharge experiment of the assembled Lithium-ion batteries using the smart sensor. As indicated in the previous section, SOC_i, LL, LU, C_{all} and SOC_{all} are given by this experiment. Charge and discharge do the following current load pattern (Fig. 13). Charging method is CC-CV charging.

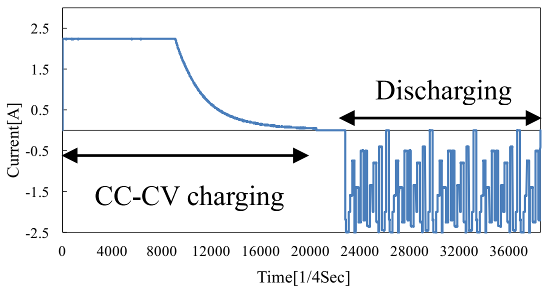


Fig. 13.Charge and discharge current

Fig. 14 is shown each cell terminal voltage .

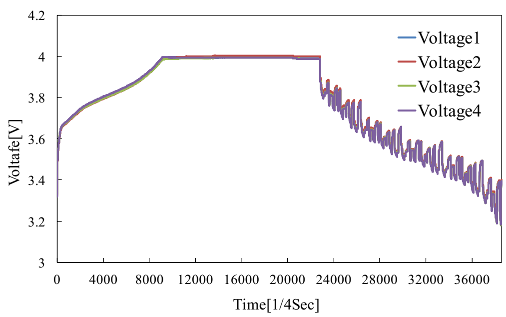


Fig. 14. Each cell terminal voltage

Each battery cell SOC shown in Fig. 15.

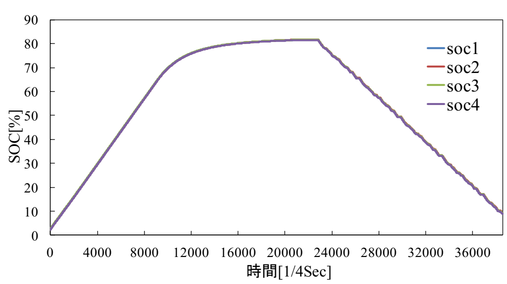


Fig. 15. Each cell SOC

LL, LU, C_{all} calculated by the above charge and discharge current are shown in Table II. SOC_{all} is 8.8 [%].

TABLE II
LL, LU, C_{all}

Capacity	[Ah]
LL (discharge capacity loss)	0.83
LU (charge capacity loss)	1.67
C_{all} (sum of capacity)	6.49

V. Conclusions

This paper showed a battery sensor technology in the smart grid. With the growing demand for battery, the battery control technology that related to maintainability and safety of the battery is necessary. In addition, each battery differs in the characteristic by each use history and manufacture variation, so that unific control and management are difficult. By grasping the real time characteristics of the individual cells, development of the system which can apply control suitable for each battery is desired.

Moreover, implementation of high accurate SOC estimation system to the microcomputer was described. The experimental results showed the SOC estimation function obtains very accurate results. The SOC estimation algorithm for 4 series assembled Lithium-ion batteries was also shown. Unfortunately, the program has not been implemented. We implement the SOC estimation program for the 4 series assembled Lithium-ion batteries to the smart sensor, and show the accuracy at the workshop.

Acknowledgement

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