Novel state-of-health prediction method for lithium-ion batteries in battery storage system by using voltage variation at rest period after discharge

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***Abstract*—We have developed a diagnostic architecture of lithium-ion batteries that finds the variation of State of Health (SOH) by actively sensing the voltage transient response at rest period after discharge, that is where each battery cell returns to an equilibrium state. We found that this transient response represents SOH of the battery cells. Since at this rest period after discharge the cell balance controller is not activated, by sensing the voltage variation we can also predict the SOH variation inside the Battery Storage System (BSS). This architecture was applied to a 20 kVA BSS. We have experimentally verified this architecture. We have estimate the BSS's SOH by also considering this SOH distribution only using limited data from the Battery Management System (BMS). Through the analyses of both data from accelerated cycle test and data from the BSS, a robust parameter strongly correlated with battery SOH is identified. This parameter is extracted by using the voltage standing state characteristics of the battery at the rest period after discharge. By measuring the voltage time differential at the transient state in the rest period, we can estimate the BSS's average SOH with the accuracy under 1% with a short period of measurement time (within seconds). By monitoring the minimum voltage, average voltage and maximum voltage at the standing state characteristic that are available from BSS, we can estimate the SOH distribution inside BSS.**

***Index Terms*—battery, state of health, stationary battery, online estimation**

I. Introduction

Nowadays, lithium-ion battery (LiB) is the most attractive energy storage device. The scope of implementation is very wide because it offers portability and flexibility. From consumer electronics, IoT, electric vehicle (EV) to the battery storage system (BSS). The increasing mass production of batteries will decrease its production cost, hence, it will offer another advantage: affordability. This advantage is expected to accelerate the implementation of batteries in the renewable-energy system through BSS since BSS is the most battery consuming application in terms of capacity volume.

Estimating the State of Health (SOH) of the battery system has been a challenging task. A robust onboard and online method is required especially for a system with a busy charge and discharge schedule such in EV and BSS. Huang et al. [1] proposed a method to estimate the State of Charge (SOC) and SOH of the battery using the amount of voltage change per unit time during discharge period of battery. They found that the SOH has a linear relationship with the reciprocal of the unit time voltage drop, which is the function of the SOC. This method shows that online estimation is possible and proved to have robustness. Other SOH online estimation methods are using Extended Kalman Filters or Adaptive Extended Kalman filters to improve the prediction accuracy provided by the traditional Kalman Filter [2], [3].

In BSS, we predict that there is a temperature distribution inside the battery stacks. This temperature distribution can accelerate local degradation of specific battery cells. The battery cells exposed to higher temperatures should degrade faster than those exposed with lower temperatures. Therefore, it causes the state-of-health (SOH) variation. To understand the system's overall SOH, we have to also consider this SOH variation, because the overall performance is affected by the battery cells with the lowest SOH.

There are several methods for the SOH prediction, including mathematical approach, sampling based method, etc. [4]–[6]. Our method is to also consider the SOH variation inside the BSS in predicting system's SOH, so that we can predict the overall SOH more accurately. It is possible if we can see the voltage deviation of the battery cells. We use the voltage variation to predict the battery-cell SOH distribution inside the BSS. However, the BSS usually comes with a

978-1-7281-3153-5/19/$31.00 ©2019 IEEE

cell balance controller system that hides the voltage deviation during charge and discharge. Fig. 1 shows the BSS configuration. The information that can be extracted from the battery management unit (BMU) inside of the BSS is limited. Usually, the BMU provides the information of the cell's maximum voltage (V_{max}), average voltage (V_{ave}), and minimum voltage (V_{min}).

We have developed a diagnostic architecture that finds the variation of SOH by actively sensing the voltage transient response at the rest period after discharge, that is where each battery cell returns to an equilibrium state. We found that this transient response represents SOH of the battery cells. Since at this rest period after discharge the cell balance controller is not activated, by sensing the voltage variation we can also predict the SOH variation inside the BSS.

In this study, we have predicted a 3% SOH decrease in our BSS using our methods. This value is close to the reference SOH from the BMU, that is 3.6%.

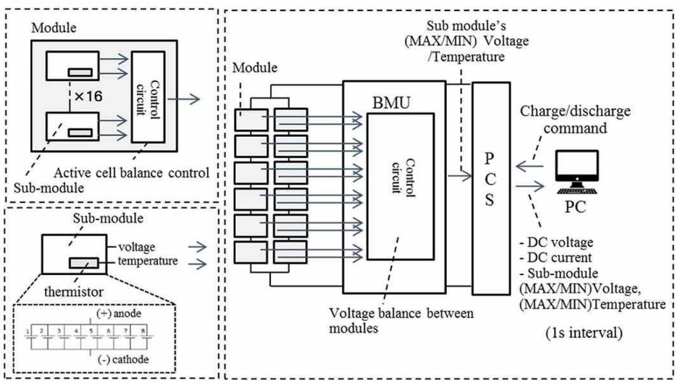

Fig. 1. BSS configuration.

II. Technical Background

Fig. 2 (a) shows the V_{max}, V_{ave}, and V_{min} during discharge, rest, and charge periods. The Fig. 2 (b) shows the corresponding V_{max}-V_{min} values. During the charge or discharge process, the difference between V_{max} and V_{min} is comparably small. While in the rest period after discharge, the difference is very pronounced (red dotted line). We can detect the SOH variation using V_{max}, V_{ave}, and V_{min} at the rest period after discharge. This finding is our core idea to develop our SOH estimation method.

We evaluated the validity of using the voltage-time differentiation at rest period after discharge dVt/dt to predict the system SOH. We performed an accelerated charge and discharge test for $LiFePO_4$ batteries with different temperatures and capacity rates (C-rates) and examined the correlation between SOH and dVt/dt, and investigated how different stress condition affects them. A C-rate here is a measure of the rate at which a battery is discharged relative to its maximum capacity. 1C means that the discharge current will discharge the entire battery capacity in 1 hour.

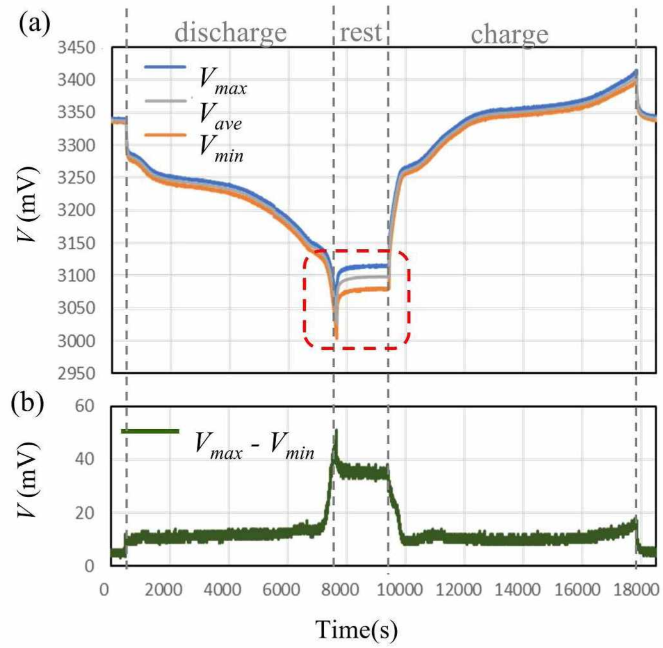

Fig. 2. V_{max}, V_{ave}, and V_{min} (up) and the different between V_{max} and V_{min} (bottom) during discharge-rest-charge.

III. Experiment

BSS cycle test

Charge and discharge cycle test has been conducted in BSS with charge and discharge power P set to up to 15 kW, between 99%-7% SOC. Since the total capacity of our BSS is 20 kW, the maximum C-rate we can use is up to around 0.75 C. The limitation of SOC range was set for protection of batteries.

We collected the data of total voltage, total current, sub-module maximum voltage, sub-module minimum voltage, sub-module maximum temperature, sub-module minimum temperature, cycle and also SOC. The data are recorded in one-second interval.

Battery-cells cycle test

We conducted a battery-cell cycle test with temperature and C-rate as a degradation accelerating factor. The experimental conditions for each cell are presented in Table I. Samples A, B, and C were accelerated under 45°C with C-rate being set to 1, 2, and 3.5 C respectively. Sample D and E were accelerated under 60°C with C-rate being set to 1 and 2 respectively. Since the rated capacity of the battery used in this experiment is 2.85 Ah, a charge and discharge in 1 C mean charge and discharge using 2.85 A. The temperatures (45°C and 60°C) here were the ambient temperature, not the inside temperatures of cells.

The battery cycle test was done by discharging the cells using specified C-rate until the voltage drop to its cutoff voltage (V_{cutoff} = 2.00 V), give a rest period for 15 minutes by set the charging current to 0 A, and charge the cells at the specified C-rate until the voltage reaches its float voltage (V_{float} = 3.60 V).

TABLE I
BATTERY CELLS CYCLE TEST CONDITIONS

Sample	Temperature (°C)	C-rate
A	45	1
B	45	2
C	45	3.5
D	60	1
E	60	2

IV. RESULT AND DISCUSSION

A. *Battery cells cycle test*

SOH vs cycle

Fig. 3 shows the SOH vs number of charge and discharge cycles at different C-rates and ambient temperatures of 45 and 60°C. The SOH here is a relative value to the capacity at the beginning of the test, presented in percent.

As we had expected, the accelerated test under 60°C gave faster SOH decrease compared to the case accelerated under 45°C. Cells accelerated in 1 C and 2 C gave comparably the same SOH decrease rate for each temperature.

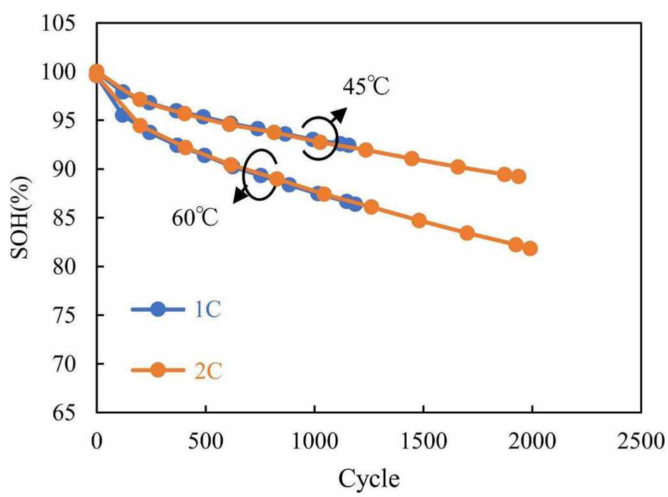

Fig. 3. SOH vs cycle number for samples cycled in 1 and 2 C rates under 45 and 60°C.

dV/dt vs SOH

The data of time differential dV/dt at rest period after discharge from the cycle test is analyzed to test the feasibility to derived SOH from dV/dt. Using Equation 1, we set the Δt to be the 1 s interval simply because we want to compare the data with the data from the BSS, which is available in 1 s interval.

$$\frac{dV}{dt} = \frac{\Delta V}{\Delta t} = \frac{V(t2) - V(t1)}{t2 - t1} \tag{1}$$

The graph of dVt/dt vs SOH is shown in Fig. 4. The starting point of dVt/dt in SOH near 100% was almost the same under the same C-rate regardless of temperature. The slope m of SOH decrease was roughly the same regardless of the C-rate but it strongly depends on temperature. It shows that predicting SOH from dV/dt could be estimated using the simple linear equation with temperature as a parameter that affects the slope.

We would like to know whether the dV/dt value is dependent on the C rate during the cycle test or merely dependent on the C-rate at discharge before the rest period. We took the sample out in every two weeks during the cycle test, put it in room temperature and discharge the sample at 3 C and give the rest period. We got the discharge-rest pattern in SOC 10%, 30%, and 50%. We measured the dV/dt and plotted them against SOH for samples A, B, and C in Fig. 5.

Even though samples A, B, and C were cycled with different C-rates (1,2, and 3.5, respectively), in Fig. 5 we found that all the samples exhibit the similar linear SOH vs dV/dt curves. This is because all samples were discharged at the same C-rate (3 C) during this measurement. The dV/dt value in every SOH also depends on the SOC where the measurement takes place. The lower the SOC the higher dV/dt value.

From the above analysis, we can conclude that it is possible to predict the SOH by using the dV/dt at rest period after discharge as long as we know the C-rate during discharge and the SOC where the measurement takes place. Regarding the SOC, even if we do not know the exact value, we still can get the SOH accuracy of around 5% if the SOC is somewhere between 10% and 50%.

B. *Comparison of BSS data and accelerated test results*

Next, we compare the predicted SOHs using the accelerated test data and the data we collected from our BSS. First, we tested whether the predicted SOH using dVt/dt using system data is reasonable or not. We picked the system's average voltage V_{ave} from the early cycle and compared it with the latest cycle. Both were experiencing the same charge-discharge condition, that is under $P = \pm 10$ kW and the rest period was taken at SOC 7%.

We calculated the dVt/dt value which is shown in Fig. 6. The figure shows that the dVt/dt difference between the 20s cycle and 290s cycle was around 12 mV/s. If we plot the difference of this dVt/dt value to the accelerated data, we calculated that the SOH difference between 20-s and 290-s cycles was around 3%. In this approximation, we assumed that the battery condition at the beginning of the system usage is already experiencing the rapid SOH decrease due to the tuning done by the manufacturer, so we compared it to the SOH in linear decrease region.

We also have the SOH reference data collected from the BMU. The BMU required to be fully charged and discharged at least once every month. The SOH value is presumably come from the recalculation result of the battery total capacity during this calibration time. The SOH reference value provided by the BMU shows that in 290s cycles, the SOH is 96.4%. So, according to the BMU data, the SOH has been decreased by 3.6% of the new condition. This value is reasonable compared to our estimation using dVt/dt, regardless of what method they are using. The errors might also come from the difference in SOC value during the dVt/dt calculation, or due to the

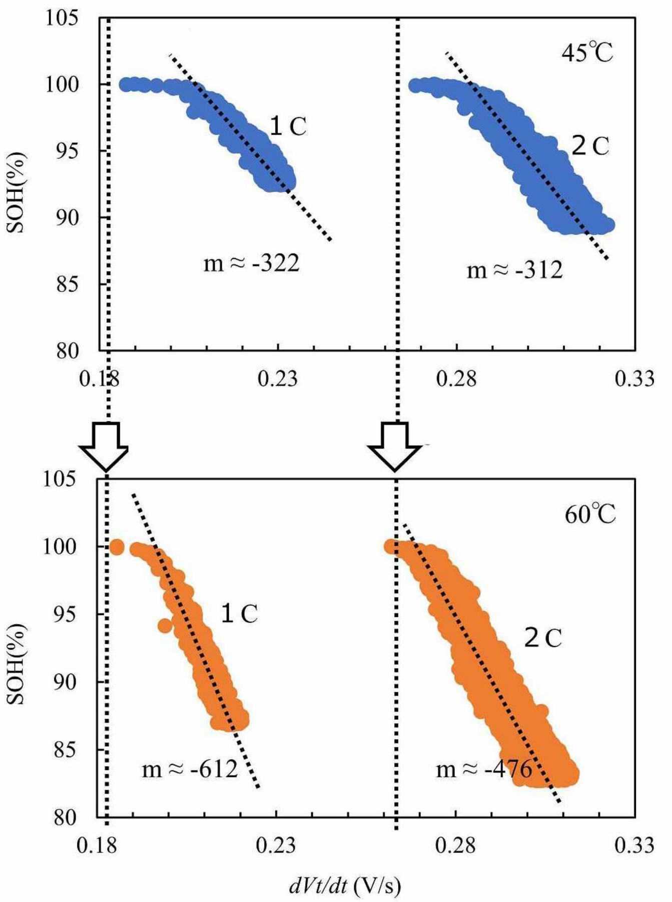

Fig. 4. SOH vs dVt/dt for samples accelerated under 45°C (up) and 60°C (bottom).

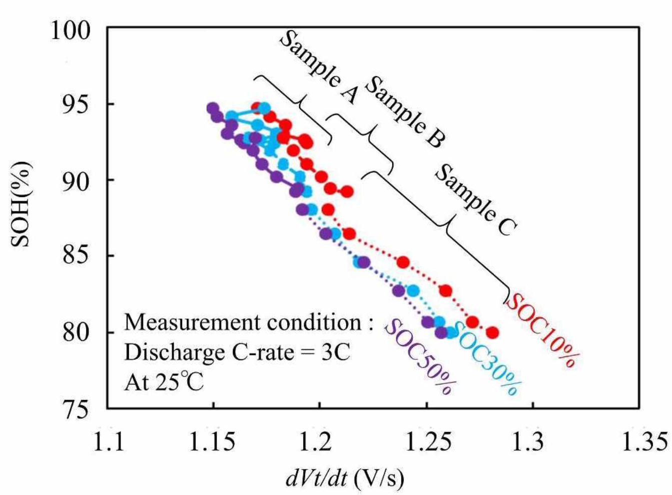

Fig. 5. SOH vs dVt/dt for samples taken at Room temperature using C-rate of 3 C in SOC10%, 30% and 50%.

temperature difference between the accelerated test and the actual battery system's temperature.

From the above results, we can deduce that the dVt/dt method is dependable to predict the system's SOH on the go, without having to fully charge and discharge the battery system.

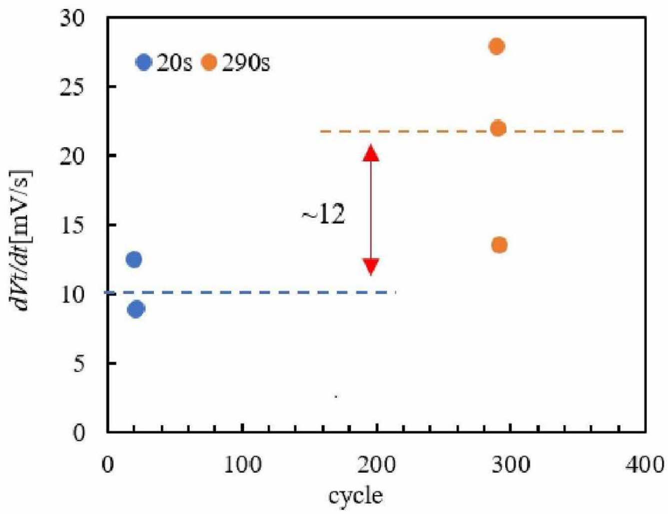

Fig. 6. dVt/dt of battery system at (blue) 20s cycle and in (orange) 290s cycle.

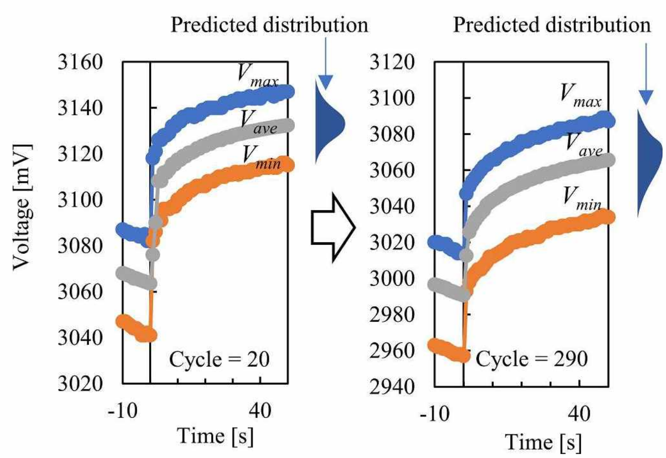

Fig. 7. System's V_{max}, V_{ave}, and V_{min} reading at cycle 20 (left) and 290 cycle (right).

Voltage distribution in battery system

We compared the V_{max}, V_{ave}, and V_{min} of 20-s and 290-s cycles in the battery system. The time dependence of voltage is shown in Fig. 7.

As we had predicted, the distribution of the V_{max}, V_{ave}, and V_{min} changed as the cycle increased. Since the V_{min} gives higher dVt/dt value than V_{max}, this distribution changes corresponding well to our prediction, where the V_{min} stretches away from the V_{ave}. This result shows the possibility of predicting SOH distribution inside BSS by monitoring the voltage distribution at rest period after discharge.

CONCLUSION

We found that the variation of voltage at rest period after discharge is strongly correlated to the SOH. Using this phenomenon, we built a new method to estimate the SOH. The accelerated test revealed that the SOH can be predicted by using dVt/dt at the rest period after discharge, as long as we can control the discharge C-rate and ambient temperature. We calculated the SOH decrease of our BSS using dVt/dt method as a verification. The calculated value was 3%, that is close to the reference value of 3.6% from the BMU.

ACKNOWLEDGMENT

The authors thank the member of the Energy Business Unit of Hitachi, Ltd., Hitachi Industrial Equipment System Co., Ltd. for the construction of the battery storage system, fruitful discussion, and their valuable advices.

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