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# Battery State-of-Charge Estimation Algorithm Using Dynamic Terminal Voltage Measurement

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** Short Paper*

***Abstract***: When a battery is discharging, the battery's current and terminal voltage must both be measured to estimate its state of charge (SOC). If the SOC can be estimated by using only the current or voltage, hardware costs will decrease. This paper proposes an SOC estimation algorithm that needs to measure only the terminal voltage while a battery is discharging. The battery's SOC can be deduced from its open circuit voltage (OCV) through the relationship between SOC and OCV. But when the battery is discharging, it is not possible to measure the OCV due to the voltage drop in the battery's internal resistance (IRdrop). The proposed algorithm calculates OCV by estimating IRdrop using a dynamic terminal voltage measurement. This paper confirms the results of applying the algorithm in a hardware environment via algorithm binarization. To evaluate the algorithm, a Simulink battery model based on actual values was used.

***Keywords***: Li-ion battery, State of charge (SOC), Terminal voltage

## 1. Introduction

Recently, as the performance of smart mobile devices evolves, battery life in these smart devices has become an important issue. Therefore, there is a need to be able to accurately estimate the remaining capacity for efficient battery management. So, research on various approaches to estimating remaining battery capacity has developed [1-7].

Kalman filter-based methods [4, 5], fuzzy logic approaches [6], and neural network [7] approaches provided high-performance SOC estimation. However, it is difficult to apply them to mobile systems with limited hardware, because they require complicated and extensive computing power.

At present, methods which can be applied in a mobile system environment are current measurement method using Coulomb counting equation and votage measurement method using the relationship between the open circuit voltage and the remaining capacity.

Voltage measurement methods [1] use the relationship between remaining capacity and the open circuit voltage of the battery. It is possible to directly determine the remaining capacity corresponding to the open circuit voltage of the battery. However, in a battery taking an external load, there is a problem in that open circuit voltage cannot be measured due to the voltage drop caused by the internal resistance of the battery. To measure OCV during battery discharge, the external load is must be taken off the battery. So, it is difficult to estimate SOC while the battery is being used, which constrains its use.

Coulomb counting is a method in which the current is measured [2] to obtain remaining capacity by integrating the amount of discharging current in the battery; determining the amount discharged from the battery is a method of estimating the remaining capacity. Coulomb counting is simple, easy to implement, and there is an advantage in that it is possible to estimate remaining capacity during battery use. However, this method has a problem in that SOC estimation accuracy drops because of measurement errors. And the characteristics of the algorithm make it impossible to estimate the initial SOC value of the battery.

In an attempt to address this point, an algorithm that is a mixture of Coulomb counting and the OCV method was recently studied [3]. The advantage of this method is that it is possible to estimate the SOC with OCV and solve the initial value problem, increasing correction performance. However, since it is necessary to measure both voltage and current systematically, the drawback is that hardware costs increase.

This paper proposes an algorithm to estimate the remaining capacity of the battery by only measuring the terminal voltage of the battery during use. A battery is modeled by using the circuit with internal resistance and a voltage source to calculate the voltage drop due to internal resistance.

This method, in which only the terminal voltage during battery use was measured, saves hardware configuration and cost, even during use of the battery, and can estimate the remaining capacity in real time, which is ideal for mobile systems. The rest of this paper is organized as follows. The next section describes the discharging battery circuit model. In the subsequent section, we explain the SOC estimation algorithm using terminal voltage. The performance evaluation section includes performance evaluations and discussion of the proposed algorithm by applying it in a battery simulator. Finally, we conclude the paper in the last section.

## 2. Battery Discharge Model

A battery can be modeled as a circuit with a single voltage source and internal resistance [8]. In this paper, the battery discharge situation was analyzed through the circuit model in Fig. 1.

A voltage source means the open circuit voltage (OCV) of the battery. Internal resistance means the internal chemical substance that provides resistance during battery discharge. In formula (1), if the external load (RL) is applied to the battery, current flows through the internal resistance, and voltage drop(IRdrop) occurs. So, it is impossible to measure OCV at terminal of battery.

$$\text{Terminal voltage} = \text{OCV} - \text{IRdrop} \qquad (1)$$

In formula (2), if internal resistance and discharging current can be determined, it is possible to calculate the voltage drop by internal resistance

$$\text{IRdrop} = \text{Ic x R} \qquad (2)$$

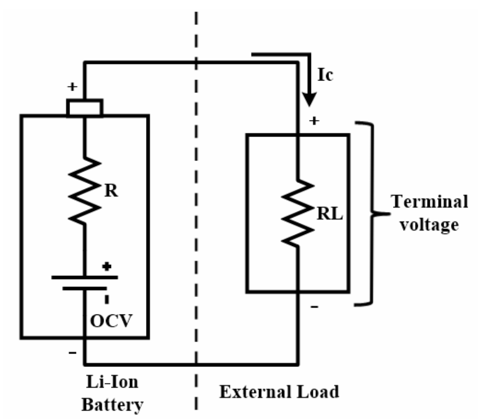


**Fig. 1. Battery circuit model with internal resistance.**

Then, it is possible to obtain the OCV by adding IRdrop to the terminal voltage.

## 3. The Proposed Algorithm

In this paper, we propose a battery SOC estimation algorithm using terminal voltage while the battery is being used, considering battery modeling and voltage drop by internal resistance. Considering the modeling and IR drop of the battery, we propose an algorithm that can estimate the remaining capacity by using only the terminal voltage during the use of the battery. Section 3.1 describes a discharge current estimation scheme by using the terminal voltage. Section 3.2 describes the relationship between SOC and internal resistance. Section 3.3 explains SOC estimation through the calculations and the OCV–SOC relationship. Finally, in Section 3.4, we describe the SOC estimation algorithm based on the contents of sections 3.1 to 3.3.

### 3.1 Discharging Current Estimation Algorithm

Coulomb counting was used by reverse modification to estimate the discharge current.

$$\mathrm{SOC}(t_2) = \mathrm{SOC}(t_1) + \frac{\int_{t_1}^{t_2} I(t)\,dt}{Ah_{nom}} \times 100 \qquad (3)$$

Eq. (3) indicates Coulomb counting equation. Coulomb counting equation calculates the SOC variation by integrating the discharging current.

I (t) in Eq. (3) is the discharge current of the battery. It becomes negative during discharge and positive during charging at the time. $Ah_{nom}$ means the nominal capacity of the battery.

$$(t_2 - t_1) \times I_{avr} = \int_{t_1}^{t_2} I(t)\,dt \qquad (4)$$

$$I_{avr} = \left(\mathrm{SOC}(t_2) - \mathrm{SOC}(t_1)\right) \times \frac{Ah_{nom}}{100} \times \frac{1}{t_2 - t_1} \qquad (5)$$

Using the SOC variation in Eqs. (4) and (5), it is possible to calculate the average discharge current $I_{avr}$ between $t_1$ and $t_2$.

### 3.2 The Relation Between SOC and Internal Resistance

The internal resistance of the lithium ion battery is closely related to SOC, age, and temperature. In this paper, we obtain the relationship between the SOC and internal resistance by experiment. Table in Fig. 2 shows the relationship between SOC and internal resistance.

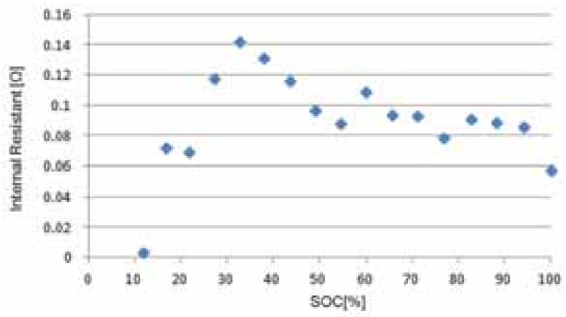


**Fig. 2. SOC-R relationship graph.**

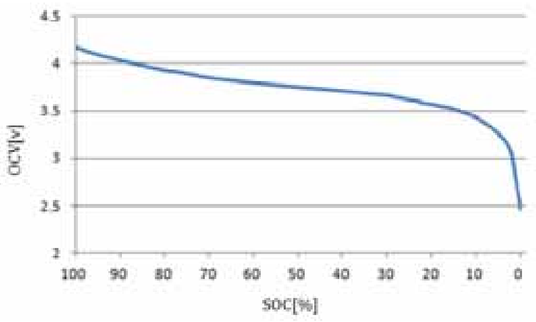


**Fig. 3. OCV-SOC relationship graph.**

## 3.3 OCV Calculation and OCV SOC Relationship

Multiplying the discharge current and the internal resistance obtained through 3.1-3.2, it is possible to calculate the voltage drop (IRdrop) due to internal resistance. It is possible to calculate the OCV by adding IRdrop and the terminal voltage in Eq. (6).

$$\text{OCV} = \text{Terminal voltage} + \text{IRdrop} \qquad (6)$$

Graph in Fig. 3 indicates relationship between OCV and SOC. It extracts the SOC through an OCV obtained with Eq. (6).

## 3.4 The Proposed Algorithm Flowchart

By applying the processes of sections 3.1 to 3.3, the algorithm for estimating battery SOC process was designed.

Fig. 4 presents SOC estimation algorithm flow chart. The algorithm is divided into an initial part and a subsequent part. Initial algorithm part is first SOC estimation process. First step is measuring terminal voltage of battery and SOC_c value was estimated by applying termanl voltage in SOC table. The estimated value SOC_c is put into the internal resistance R TABLE to estimate the value of internal resistance, R. The usage time of the battery is assumed to be 24 hours. Therefore Discharge current of the initial value algorithm was determined to 1/24 C-rate of nominal capacity. Voltage drop due to internal resistance (IRdrop) is calculated by multiplying the discharge current and the internal resistance. By adding IRdrop to terminal voltage, OCV is calculated and SOC is estimated using SOC table. Finally, the internal resistance (R) is obtained by placing R LUT for next step.

The following step is the after initial value algorithm part.

It contains section 3.1 process that estimate discharge current. The discharge current begins to be estimated using modifying coulomb counting equation.

First, terminal voltage is measured and SOC_c value was estimated by applying terminal voltage in SOC table in the same manner as initial value algorithm.

Then difference between the previous SOC_c value and current SOC_c value is determined, the value of the difference is initialized to 0 SOC_dif, if less than zero. The value of SOC_dif is applied to the inverse Coulomb counting equation to estimate the discharge current flowing between the previous time and current time. Running average filter is used to improve the estimation performance. Thereafter, the 1A clipping process considers the maximum allowable discharge current of the battery operation.

Through this, finally, discharge current is estimated. Then, the algorithm calculates the voltage drop due to internal resistance by multiplying the discharge current estimated and the internal resistance that was previously estimated, and calculates the OCV in addition to the terminal voltage. The calculated OCV is placed in SOC TABLE to estimate the SOC. Finally, the internal resistance (R) is obtained by placing R LUT for next step. Starting with measure terminal voltage, algorithm continues iterating this step.

## 4. Performance Evaluation

In this paper, the algorithm was implemented **by** C programming in a desktop environment. To analyze performance, the algorithm was tested using the Matlab Simulink battery simulator based on actual values. Through algorithm variable binarization, the algorithm's performance was confirmed in a digital hardware environment. By applying dynamic terminal voltage scenarios, we extracted the SOC and discharging current. The effects of temperature and age were not considered. The simulator and the algorithm were applied to a 2600mAh battery model with nominal capacity. Fig. 5 is the terminal voltage scenario that was used to validate the performance of the algorithm. It reflects an actual battery usage environment as dynamic terminal voltage by a change of external load. Fig. 6 is a graph comparing the discharge current coming out of the algorithm and the simulator. Looking at Fig. 6, it shows an estimate of the discharge current, overall, but the error is large at the portion where the terminal voltage changes. Estimated discharge current shows a down peak when the actual discharge current fell from a large value to a small value, and the estimated discharge current shows an up peak when the actual discharge current rises from a small value to a large value. In a battery, rapid rising discharge current from a change of external load causes rapid falling of the terminal voltage. In the algorithm, rapid falling of terminal voltage causes a huge discharge current estimation. In the


**Fig. 4. Algorithm flow chart.**

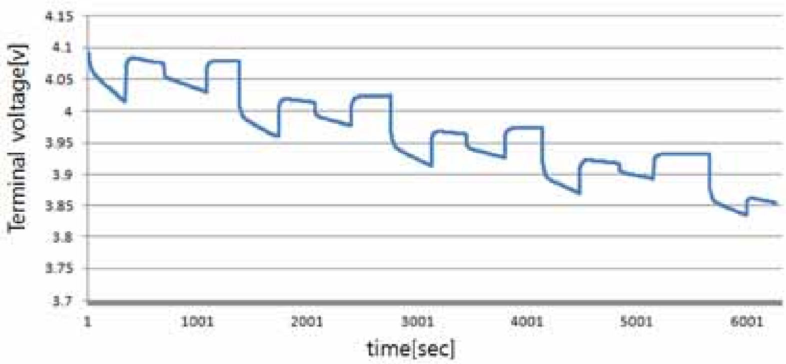


**Fig. 5. Dynamic terminal voltage scenario to evaluate the algorithm.**

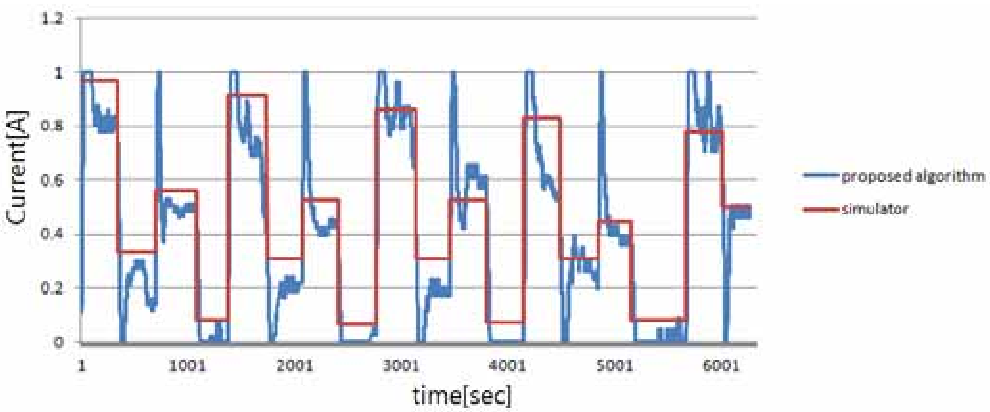


**Fig. 6. Algorithm discharge current estimation results.**

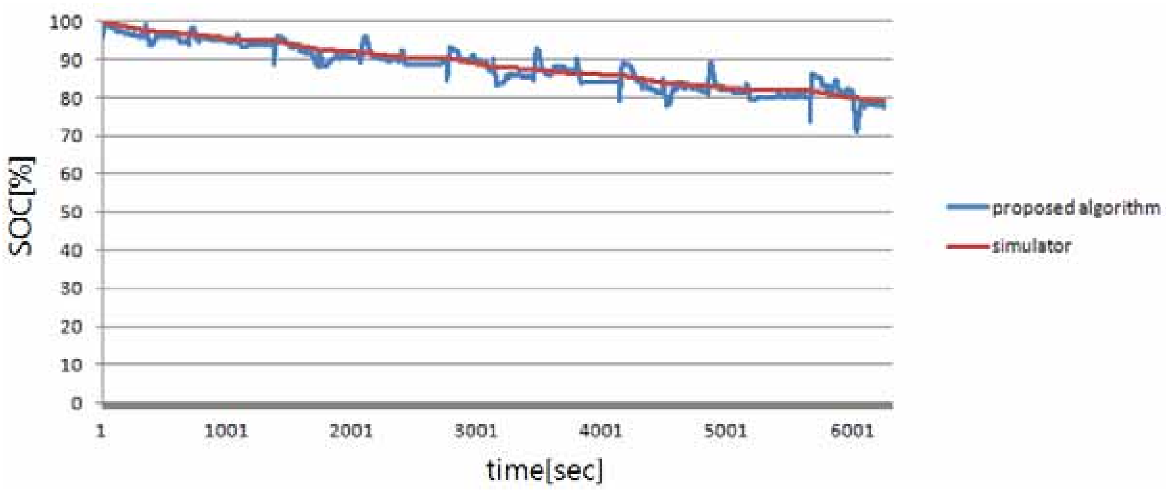


**Fig. 7. Algorithm SOC estimation result.**

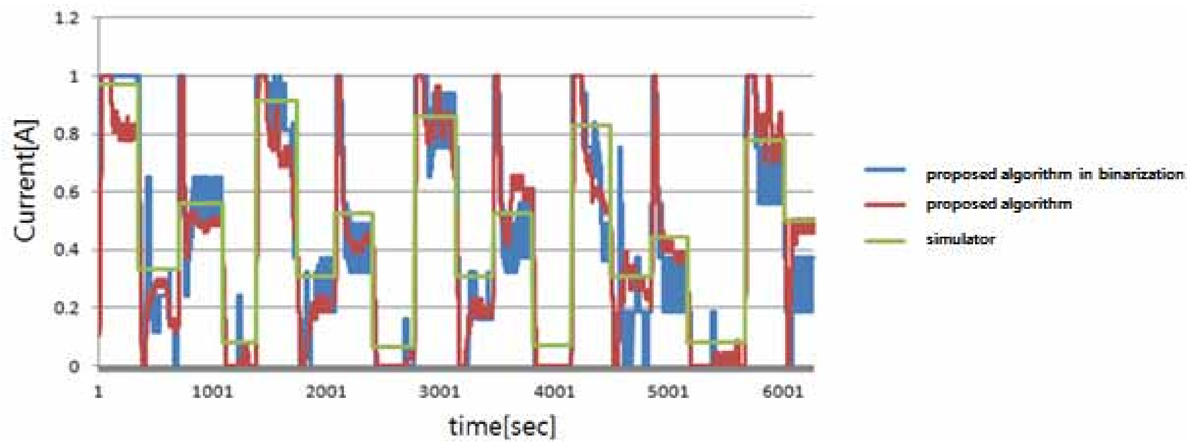


**Fig. 8. Algorithm binarization discharge current estimation result.**

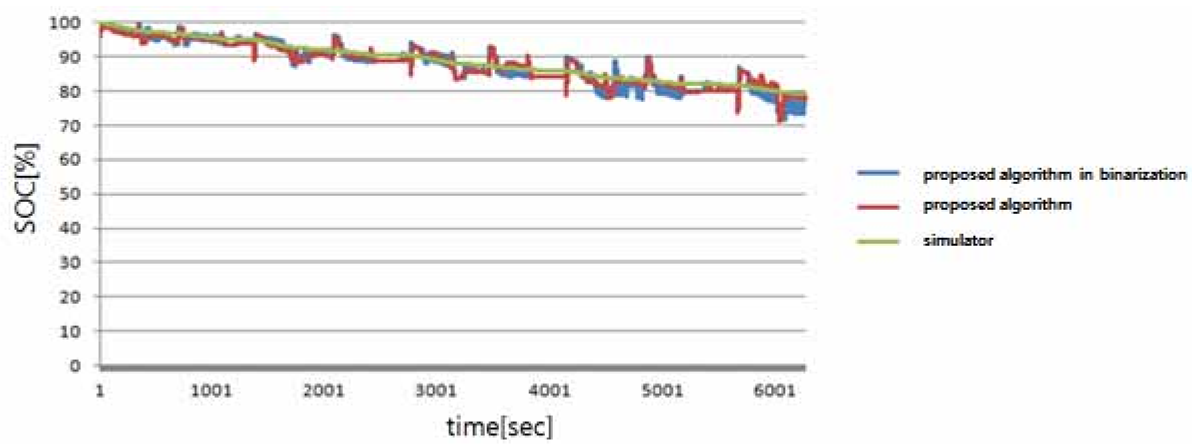


**Fig. 9. Algorithm binarization SOC estimation result.**

opposite case, with a sudden rise in terminal voltage, the algorithm estimates discharge current at zero. When the discharge current is large, the estimation performance of the discharge current is higher, and estimation performance was low when the discharge current is below 0.1A. This means that when the discharge current is large, it causes larger changes in the terminal voltage, and then discharge current estimation performance was good in the algorithm.

Fig. 7 is SOC estimation results obtained using the algorithm. As shown, the estimation error of the discharge current has been able to reflect how IRdrop and OCV affect SOC estimation. Figs. 8 and 9 provide an analysis of the test by adding the results obtained by applying algorithm binarization. By adopting binarization processing, it was confirmed that quantization errors showed the ability to effect the overall discharge current.

## 5. Conclusion

In this paper, we proposed an algorithm for estimating the remaining battery capacity by using the estimated voltage drop across the internal resistance model, and the internal resistance of the battery, to determine the discharge current by modifying Coulomb counting. We estimated internal resistance by using the relationship between the internal resistance and SOC, and calculating the voltage drop across internal resistance. While using only the terminal voltage in the battery, it was possible to estimate the SOC. However, there was an error in the current estimate due to the influence of instantaneous sampling when the terminal voltage changes suddenly. Through further research, there is a need for improved performance.

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