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Comparison of State-of-Charge (SOC) Estimation Performance Based on three Popular Methods: Coulomb Counting, Open Circuit Voltage, and Kalman Filter

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***Abstract*— In this research, three battery models are proposed, i.e., simple battery model, Thevenin battery model, and modified Thevenin battery model. State-of-Charge (SOC) estimation based on those battery models are conducted with coulomb counting, open circuit voltage, and Kalman Filter. Simulation about false on battery capacity initialization is tested over the battery. The results show that the proposed battery modeling can accurately provide SOC estimation. On the simulation of false initialization, SOC estimation method with coulomb counting, open circuit voltage model 1 and 2 methods cannot track the true value, while Kalman Filter method can accurately provide SOC estimation and is able to correct false SOC initialization in short time.**

Keywords—Battery modeling; State of Charge; Kalman Filter; Coulomb Counting; Open Circuit Voltages

I. INTRODUCTION

A battery is an element which has an ability to absorb, keep, and release electric charge. With this manner, it acts as an energy storage. In this era, batteries are widely applied ranging from simple low-power device up to critical high-power device such as Uninterruptible Power Supply (UPS). Development in automotive technology also places the battery as critical part of hybrid and fully-electric vehicle [1].

Development in transportation technology is addressed to reduce the use of fossil fuels. Gas emission from a fuel-based vehicle has a large contribution to global warming. Hybrid-vehicle can reduce the use of fossil fuels. While a fully-electric vehicle is a promising solution to eliminate the use of fossil fuels and is predicted to be able to reduce CO2 gas emission up to 21% by 2050 [2], [3].

Unfortunately, battery capacity in electric vehicles will decrease gradually since its chemical cells will be degraded over time along with charge-discharge cycle. Therefore, a Battery Management System (BMS) is needed to provide a proper conditioning process for the battery and hence maintaining its lifetime [4]. BMS will also ensure optimum usage and keeps the battery from the risk of damage.

Several studies of BMS modeling have been conducted. Battery modeling plays an important role in determining algorithm that will be used in the BMS. Equivalent Circuit Model (ECM) method is often used since it presents batteries in the form of electrical properties such as resistance, capacitance, and voltage [5].

Battery SOC estimation has become an integral part of BMS modeling. SOC is a representation of battery capacity which cannot be measured directly using any sensor [6], [9]. Battery SOC can be determined by integrating battery current over time. This approximation is known as Coulomb-Counting Method. However, this method has several disadvantages since it needs an accurate current measurement and error accumulation will also appear [7], [8]. Some research has been conducted to overcome this error by using ECM-based Kalman filter [9], [10].

Kalman filter is one method to estimate a problem using state of the system and how to make the minimum variance in finding the optimal estimates on a system as well as the solutions used to solve problems of linear discrete data screening [11]. This method is suitable for estimating SOC to obtain an effective and efficient BMS.

Another SOC estimation method has been developed on the base of battery Open Circuit Voltage (OCV). The result of this method is only valid while the battery is in an unloaded condition. Of course, this method is impractical to be implemented in an electric vehicle under operation.

II. BATTERY MODELING

A. Thevenin Battery Modeling (Model 1)

An example of a series battery model that is commonly used is a parallel RC circuit model which is called the Thevenin as shown in Fig. 1. Thevenin equivalent battery model can be derived by some equations.

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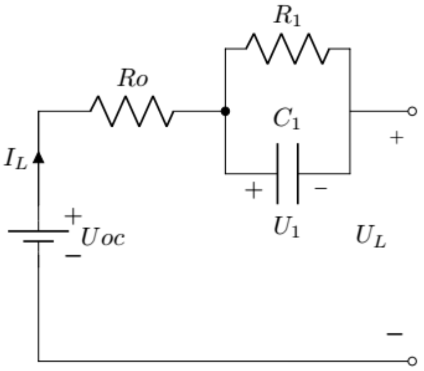

Fig. 1. Thevenin battery model.

$$U_{0c} = U_L + U_{R0} + U_{1.} \tag{1}$$

The equation for the current value on the parallel RC circuit can be written as follows.

$$I_L = C_1 \frac{dU_1}{d_t} + \frac{U_1}{R_1}, \tag{2}$$

then the value $\dot{U}_1$ can be expressed by

$$\dot{U}_1 = \frac{I_L}{C_1} - \frac{U_1}{R_1 C_1}. \tag{3}$$

The SOC equation uses coulomb counting method is written as follows.

$$SOC = SOC_0 + \frac{1}{C_N} \int_{t_0}^{t} I dt, \tag{4}$$

and the value $S\dot{O}C$ is expressed by

$$S\dot{O}C = \frac{1}{C_N} I\,. \tag{5}$$

By combining (3) and (5), the model of state space can be established as follows.

$$\begin{bmatrix} \dot{U}_1 \\ S\dot{O}C \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} U_1 \\ SOC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_N} \end{bmatrix} I_L. \tag{6}$$

B. Modified Thevenin Model (Model 2)

Model 2 uses modified Thevenin battery model (Model 1) [12]. The source voltage of the battery is shown in Fig. 2. If the model 1 is U_{0c}, at this U_{0c} model 2 is modeled as C so that the parameters in this model 2 to 4, namely C, R_0, R_1, and C_1. Based on these two models, the model can be derived from the equation as follows.

$$U_{0c} = \frac{1}{C} I_L\, dt. \tag{7}$$

with $U_C = U_{0c}$,

$$\dot{U}_{0c} = \frac{1}{C} I_L. \tag{8}$$

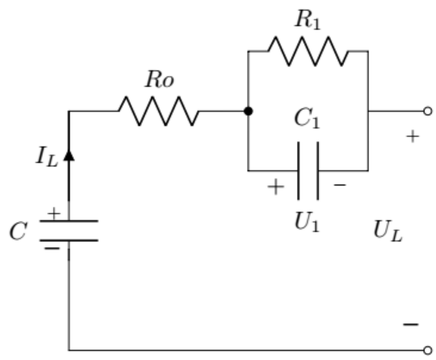

Fig. 2. Modified Thevenin battery model.

By using (7) and (8), the model of state space it can be established as follows.

$$\begin{bmatrix} \dot{U}_1 \\ \dot{U}_{0c} \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_1 C_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} U_1 \\ U_{0c} \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C} \end{bmatrix} I_L. \tag{9}$$

C. Simple model (Model 3)

The circuit of the simple model is shown in Fig. 3. It consists of an internal resistance R, capacitor C, the capacitor voltage V_C and the voltage V_R barrier [13]. The relationship between the terminal voltage Vt and the voltage on the capacitor voltage at the V_C and V_R barriers can be represented by the Laplace equation as shown by (10), (11) and (12).

$$V_c[k] = V_c[k-1].(1-\alpha) + V_t[k].\alpha, \tag{10}$$

$$\alpha = \frac{T_S}{T_S + RC}, \tag{11}$$

$$I[k] = (1-\alpha).(I[k-1] + \frac{V_t[k] - V_t[k-1]}{R}). \tag{12}$$

III. State of Charge Estimation

A. Coulomb Counting

Coulomb counting method is the most common method to estimate SOC wherein this method, the battery capacity is measured by looking at the changes remaining the charge on the basis of electrical current into or out the battery cells [5]. This method can be formulated as follows.

$$SOC = SOC_0 + \frac{1}{C_{Cap}} \int_{t_0}^{t} I_{Batt}\, dt, \tag{13}$$

$$S\dot{O}C = -\frac{\eta\, I_{Batt}}{C_{Cap}}, \tag{14}$$

where coulombic coefficient □ is a constant value of 1 for discharging and 0.98 for charging [4]. SOC_0 is the initial value that indicates the value of SOC shortly before I_{batt} flows into or out of cells of the battery. C_{cap} indicates the maximum capacity of new battery cells.

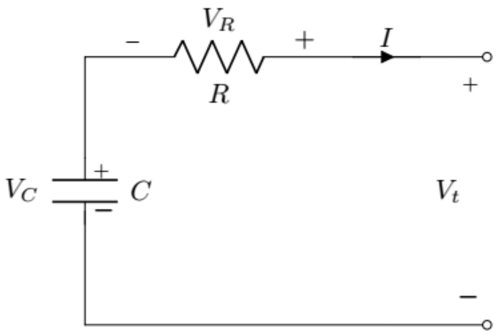

Fig. 3. Rint model.

B. Open Circuit Voltage

Open Circuit Voltage (OCV) is the battery voltage when the circuit is open or disconnected to the load. In an initialization of battery conditions, it is necessary to test the relationship between SOC and OCV.

To achieve a balanced voltage, the value of OCV after sufficient resting batteries can be considered since there is a correspondence between OCV and SOC and supporting little relation to battery life. It is an effective method to estimate SOC of the battery [14].

C. Kalman Filter

Kalman Filter method is a recursive process. It is an effective method when is used to deal with measurement data containing noise either by way of combining it with other sensor measurement data or the noise filter.

Kalman Filters is a solution to solve the problems of data screening discrete linear recursive process which was first introduced by Rudolf. E Kalman in 1960. In the Kalman Filter method, system is assumed linear and all of the observed variables are represented in a Gaussian distribution [15]. This supports previous and current state estimation. The state will be determined and can work even when the nature of the modeled system is unknown.

The state estimation can be written as follows.

$$x_{k|k-1} = Ax_{k-1|k-1} + Bu_{k}, \tag{15}$$

and the error covariance matrix is calculated by

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k \tag{16}$$

The Kalman Gain can be calculated by

$$K_k = Pk_{k|k-1}C^T(CP_{k|k-1}C^T + R)^{-1} \tag{17}$$

and the state update is expressed by

$$x_{k|k} = xk_{k|k-1} + K_k\,(Z_k - Cx_{k|k-1}), \tag{18}$$

The update of the error covariance matrix is calculated by

$$P_k = (I - K_kC)P_{k|k-1}. \tag{19}$$

where, K is Kalman gain, P is error covariance, Q is process noise covariance, R is measurement noise covariance, and I is identity matrix.

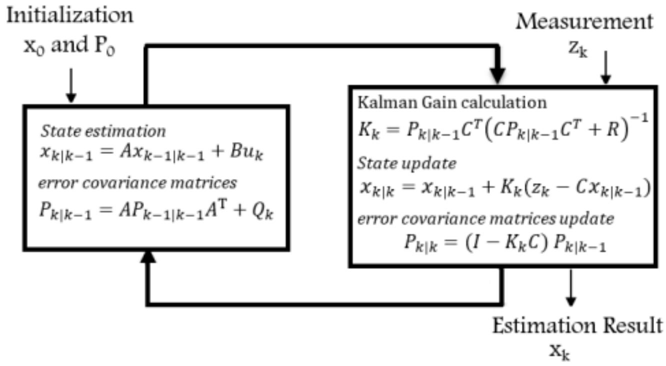

Fig. 4. Kalman filter algorithm.

IV. Experimental Setup

A. Design of the system

Experiments were performed to test lithium polymer battery. This subchapter describes the tools and materials used for the experiment, and also design and methods used for data retrieval. Fig. 5 shows the experimental system. The battery is the object of research and the testing is conducted to determine the open circuit voltage and battery characteristics during the charge and discharge condition. The used switching circuit is a tool to connect the battery to the dummy load, charger, measuring and controlling part for switching and save the data to a computer via serial communication.

B. Battery Testing

Testing is conducted by connecting a load to the battery to provide the desired current flow. The first test is a static capacity test with 1C discharge current. This test was conducted not only to determine both of the battery capacity but also to get a real-time connection to the SOC battery. The next test is a pulse test. It is conducted to identify parameters on battery model equivalent circuit. The next step is pulse variation test. It is used to validate the equivalent circuit model parameters. The final test consists of Constant-Current (CC) and Constant-Voltage (CV), charge-discharge which is conducted to increase the number of cycles the battery.

V. Results and Analysis

A. SOC Estimation Results with Pulse Test Data

The results of the SOC estimation for each method can be seen in Fig 6.

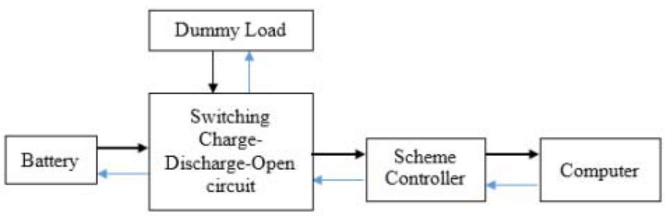

Fig. 5. Experimental scheme.

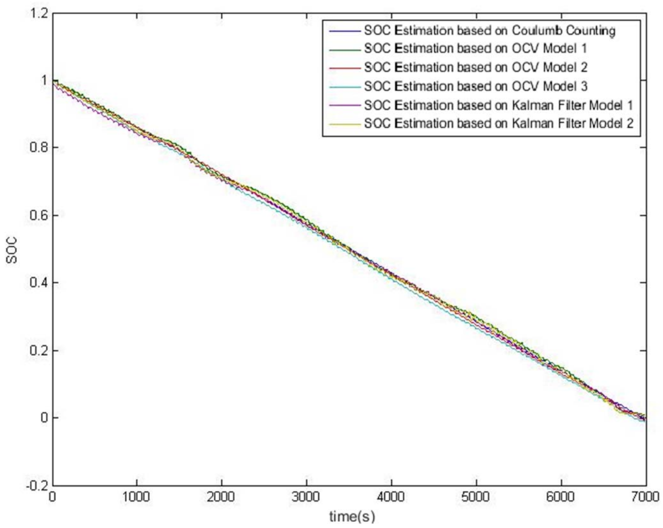

Fig. 6. SOC estimation with pulse test data.

Using the same data of the test pulse, the obtained SOC final value is different. The more detail of quantitative data error can be seen in Table I. The estimated value of SOC in its application does not often escape from the initialization process.

Some analysis parameters are used to determine the level of accuracy by looking at the rate of error of the used method. The error analysis includes percentage of Error (e_i), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The percentage of Error is the difference between the actual value and the estimated value. MSE is calculated to show the average square between actual data and data estimation. As for RMSE, it is calculated to show the square root of the average difference between the actual data and estimates. The percentage Error (e_i) can be calculated by

$$e_i = x_i - \dot{x}_{i,} \tag{20}$$

then the value MSE is given by

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \dot{x}_{i,})^2, \tag{21}$$

and the RMSE is calculated by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \dot{x}_{i,})^2} \tag{22}$$

Initialization process becomes significant if the method cannot make corrections to the initialization error. In this research, there are two methods cannot perform error correction initialization. There are the SOC method of Coulumb Counting and OCV based on the model 2. However, the three models of the OCV method, Kalman Filter model 1, and Kalman Filter model 2 can perform the correction.

TABLE I. ERROR SOC ESTIMATION WITH PULSE TEST DATA

Methode	SOC Final	%Error	MSE	RMSE
OCV 1 OCV 2 OCV 3 KF 1 KF 2	1,32 % -0,11 % 1,23 % 0,00 % 0,00 %	1,49 1,013 2,36 0,76 0,92	6,6 x 10↖5□ 2,9 x 10↖5□ 14,5 x 10↖ 5□□	0,0081 0,0054 0,0121 0,0038 0,0045

			1,4 x 10↖5□ 2,05 x 10↖ 5□	

Initialization SOC of 0% is shown in Fig 7. It can be seen that all three methods can make a correction value initialization error to SOC even though it is very far from the true value. the three models of the OCV method take 1600 seconds while the Kalman Filter only takes 60 seconds to correct the value of SOC.

B. SOC Estimation Results with DST Data

Dynamic Stress Test (DST) is used to show the dynamic nature of a battery. It is conducted by varying battery loads. Fig. 8 shows a comparison SOC estimation methods. Testing is conducted until the battery reaches 20% of capacity. Data error for each SOC estimation method is shown in Table II. The test of the reliability of the SOC estimation methods is investigated.

Testing initialization error in the extreme condition has been conducted with SOC initialization of 0%. Fig. 9 shows that all three methods can correct SOC value. However, for the three models of the OCV method require a longer time about 1600 sec compared with two Kalman Filter which takes only 50 seconds.

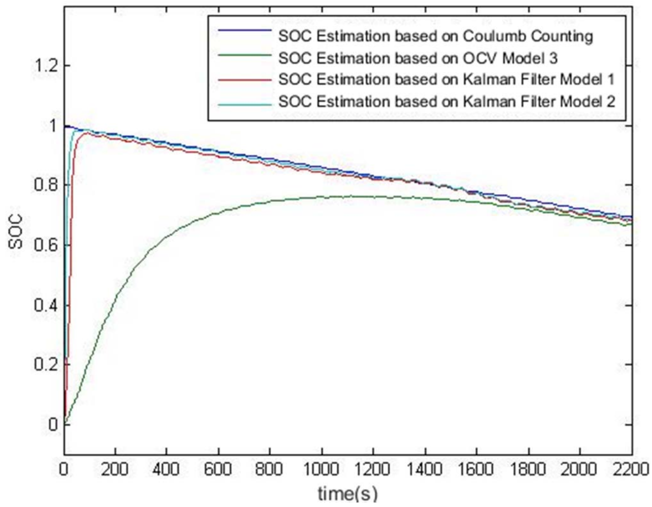

Fig. 7. Comparison correction capability SOC estimation method.

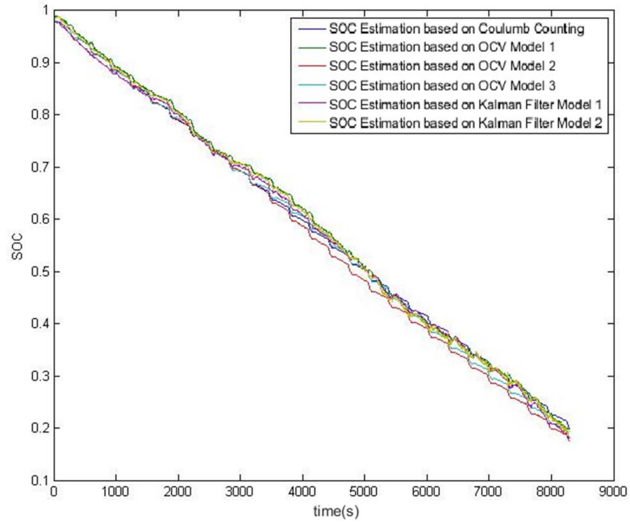

Fig. 8. SOC estimation with pulse test data.

TABLE II. ERROR SOC ESTIMATION WITH DST DATA

Methode	**S**OC Final	**%**Error	MSE	**R**MSE
OCV 1	19,77 %	1,9184	17,55 x 10↖5□	0,0132
OCV 2	17,38 %	3,44	27,3 x 10↖5□□	0,0165
OCV 3	18,20 %	1,86	7,725 x 10↖5□	0,088
KF 1	20,04 %	0,2612	0,19 x 10↖5□□	0,0014
KF 2	19,42 %	0,6661	12,44 x 10↖5□	0,0031

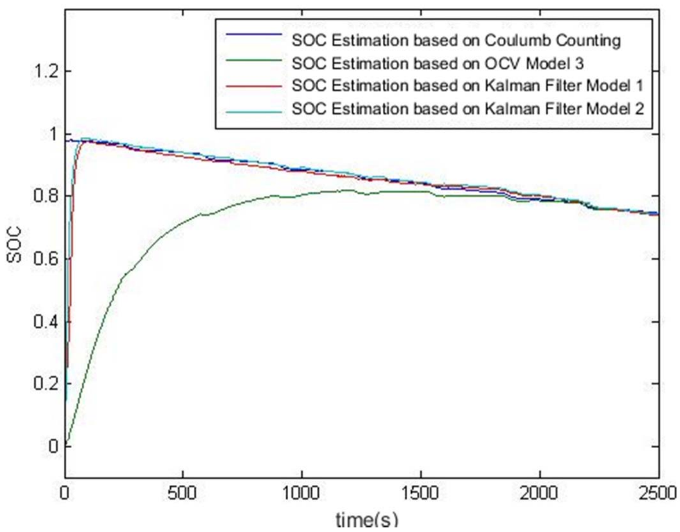

Fig. 9. Comparison correction capability SOC estimation method.

VI. CONCLUSIONS

Based on experimental results, it can be concluded that the SOC estimation using Coulomb Counting method relies heavily on the accuracy of the current sensor. Therefore, SOC estimation based on battery model can generate an accurate estimation. Estimation of SOC using Coulomb Counting and OCV model 1 and 2 cannot correct errors initialization value of SOC. However, the method of Kalman Filter can produce accurate SOC estimation and corrects errors initialization SOC value quickly.

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