2016 2nd International Conference on Science and Technology-Computer (ICST), Yogyakarta, Indonesia

State of Charge (SOC) and State of Health (SOH) Estimation on Lithium Polymer Battery via Kalman Filter

Paris Ali Topan, M. Nisvo Ramadan, Ghufron Fathoni, Adha Imam Cahyadi, Oyas Wahyunggoro
Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada
Jalan Grafika No.2 Bulak Sumur, Yogyakarta 55281, Indonesia
paris.ali.t@mail.ugm.ac.id, ramadannisvo@gmail.com, ghufron.fathoni@mail.ugm.ac.id,
adha.imam@ugm.ac.id, oyas@ugm.ac.id,

***Abstract* —To avoid battery failure and keep the battery lifetime, a system needs control its use by considering two of several parameters of Battery Management System (BMS) such as State of Charge (SOH) and State of Health (SOH).The State of Charge in Battery Management System provides the percentage of battery capacity, while the State Of Health measures the battery health. The Thevenin battery model is used to describe polarization characteristic and dynamic behavior of the battery and estimared using KalmanFilter(KF). Parameters in the model were estimated using Recursive Least Square. As the results, KF is better then RLS to estimate SOH with a mean relative error as much as 5.26% while RLS has 7.08%.**

Keywords* — BMS; Battery model; State of Charge; State of Health; Kalman Filter; Recursive Least Square

I. INTRODUCTION

Electric vehicles are one of the several solutions for slowing down global warming, this is because electrical vehicles are powered up by a rechargeable battery for propulsion and produce no emission rather than internal combustion engine (ICEs) vehicles. Battery is one of the main part in electric vehicles therefore there is a need to control it by using Battery Management System (BMS) in order to keep the battery works in optimal conditions and long lifetime.

This research talk about Two of several parameters of BMS are State of Charge (SOC) and State of Health (SOH). SOC gives the information concerning how much the holding capacity when the battery is charged or it is discharged [1]. The provided information by SOC can support the right decision to start and stop both charging and discharging process in order to avoid battery failures such as overcharge and over discharge. The conducted research to estimate the value of SOC (expressed in percentage) has been done by employing some methodologies. Some of the researchers were applied conventional method, and some of them also applied intelligent system such as Neural Networks [5], and fuzzy logic[4].

The reducing battery performance information is provided by State of Health (SOH) parameter. By knowing its estimated value, the right decision to replace the worse battery performance in the electric vehicle with the new one battery can be taken. In most cases, the damages on the electrical vehicle are influenced by the worse battery performance, that is why the estimated value of SOH is very important in order to prevent the damages. Commonly, the decreased value of SOH shown by the loss of capacity, the change of charging curves and increased the internal resistance value of the battery [3],[8].Neural Networks [5], fuzzy logic [6], support vector machine (SVM) [7], and Kalman filter [4] are methods were employed by the researcher to estimate the value of SOH.

However, there are a few methods to estimate SOC and SOH simultaneously. In this research, the development of simultaneous, accurate estimation, and to reduce computational load of the BMS is developed and expected to be done by the Kalman filter algorithm.

II. BATTERY MODELING

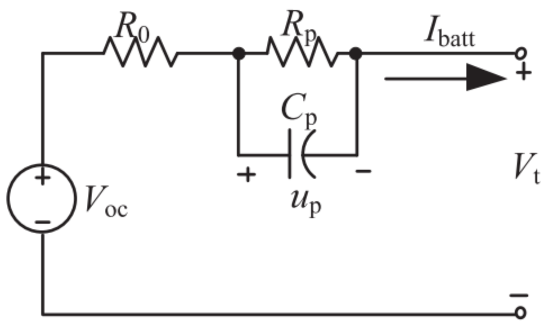

Figure 1. Thevenin battery model

Open circuit voltage V_{oc} in Figure 1 is a battery voltage that measured when the battery is not connected to the load, u_p is the voltage of the parallel R_p and C_p. The resistance R_0 is internal resistance of the battery while R_p, and C_p are the polarization resistance and capacitance, and I_{batt} is the current of the battery. The model in this research is based on conducted research by X Hu, et al [9], who did a comparative study on 12 electric circuits equivalent battery models. Concluded from his research, that the first order RC model or Thevenin battery model is the best option to consider the complexity, accuracy, and durability. Mathematical equations for Thevenin battery models are as follows:

$$\dot{u_p} = -\frac{u_p}{C_pR_p} + \frac{I_{batt}}{C_p}, \quad (1)$$

$$V_t = V_{oc} - u_p - I_{batt}R_0, \quad (2)$$

978-1-5090-4357-6/16/$31.00 ©2016 IEEE

$$V_t(s) - V_{oc}(s) = I_{batt}(s)\left(R_o + \frac{R_p}{1 + sR_pC_p}\right) \quad (3)$$

by using Bilinear Transformation method, the discrete equation can be formulated into.

$$V(k) + a_1V(k-1) = b_0I(k) + b_1(k-1). \quad (4)$$

The parameters a_1, b_0, and b_1 are estimated using *Recursive Least Square* (RLS). Where a_1, b_0, and $b_1$are parameters that determines the value of R_0, R_p, and C_p in Thevenin model as.

$$R_p = \frac{2(a_1b_0 + b_1)}{1 - {a_1}^2} \quad (5)$$

$$C_p = \frac{T(1 + a_1)^2}{4(a_1b_0 + b_1)} \quad (6)$$

$$R_0 = \frac{b_0 - b_1}{1 + a_1}. \quad (7)$$

III. SOC AND SOH

A. *(State of Charge) SOC*

The SOC value based on the remaining charge changes in accordance with the current flow into or out from the battery cell commonly estimated by using Coulomb Counting method. This method can be formulated into:

$$SOC = SOC_0 - \frac{1}{C_{cap}}\int_0^t \eta\, I_{batt}dt, \quad (8)$$

$$S\dot{O}C = -\frac{\eta\, I_{batt}}{C_{cap}} \quad (9)$$

With coulombic coefficient η is a constant value that defines charging and discharging process. SOC_0 is the initial value of SOC just before I_{batt} flow into or from the battery cell, and C_{cap} is the maximum ability of the new battery to store the current.

B. *State of Health (SOH)*

The changes of battery parameters indicate the SOH. One of the parameters that change over time and usage is the capacity. By looking at the changes of battery capacity, SOH is defined as [2]:

$$SOH_C = \frac{C_{act}}{C_{cap}}\ x\ 100\% \quad (10)$$

With SOH_C is the value of SOH, C_{act} is the battery maximum capacity. In case of battery capacity reaches below 80% of initial capacity, the BMS will give warning signal as it indicates the battery should be changed [3].

Another parameter which is internal resistance of the battery changes during degradation process. Battery internal resistance value will increase with time and battery usage.

When SOH value equal to 100%, the internal resistance Ro and internal resistance of the current condition of the new batteries R_i are identical. When SOH value equal to 0%, the R_o will be twice of R_i value. SOH can be formulated into.

$$SOH_{R_i} = \left(1 + \frac{R_i - R_o}{R_i}\right)\ x\ 100\%\ . \quad (11)$$

With SOH_{Ri} shows the value of SOH, Where Ri and Ro are internal resistance of the new battery and current internal resistance, respectively.

C. *Kalman Filter (KF)*

The uncertainty value of SOC and SOH is reduced by The Kalman Filter (KF) algorithm. This is because the algorithm of KF includes recursive equations which are evaluated repeatedly during system operation. Its means , the dynamic parameters of the battery are able to estimate.

The following equation is the state space form for Thevenin battery model.

$$x_{k+1} = Ax_k + BI_k + w_k \quad (12)$$

$$y_k = Cx_k + v_k \quad (13)$$

A, B, and C in (12, 13) describe the dynamic properties of the system, while x_k and I_k describe the state of the system and the inputs that affect the system. Variable w_k and v_k represent the process noise and measurement noise. The output system is y_k, computed with Equation (13) as a linear combination of state and input

The following equation is the matrix form to estimate the SOC and SOH simultaneously:

$$x(k) = \begin{bmatrix} SOC & u_p & R_0 & {}^1/_{C_{cap}} & {}^1/_{SOH} \end{bmatrix}^T, \quad (14)$$

$$A(k) = \begin{bmatrix} 1 & 0 & 0 & -\frac{\eta.\Delta t.I}{3600} & 0 \\ 0 & e^{-\frac{\Delta t}{RpCp}} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2{,}2 & 0 \end{bmatrix}, \quad (15)$$

$$B(k) = \begin{bmatrix} 0 \\ R_p.\left(1 - e^{-\frac{\Delta t}{RpCp}}\right) \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad (16)$$

$$C(k) = \begin{bmatrix} \frac{f(soc)}{x_1} & -1 & -I(k) & 0 & 0 \end{bmatrix}, \quad (17)$$

and

$$f(SOC) = a_1SOC^{12} + a_2SOC^{11} + a_3SOC^{10} + \cdots + a_{12}SOC^1 + a_{13}. \quad (18)$$

The initialization Kalman filter is as follows:
for $k = 0$,

$$\hat{x}_0^+ = x_0$$
$$P_0^+ = P_{x_0}, \quad (19)$$

Where P_o is the prediction error covariance matrix. For k = 1, 2, ..n.

Then, the step on the Kalman filter is as follows:

Step 1 : update the state estimation and estimate error covariance:

state estimation:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \tag{20}$$

error covariance:

$$P_k^- = A_{k-1}P_{k-1}^+A_{k-1}^T + Q_k \tag{21}$$

Step 2 : Kalman gain calculation:

Kalman gain:

$$K_k = P_k^- C_k^T [C_k P_{k-1}^- C_k^T + R_k]^{-1} \tag{22}$$

Step 3 : update the measurement value:

state estimation measurement:

$$\hat{x}_k^+ = \hat{x}_k^- + K_k[y_t - C_k\hat{x}_{k-1}] \tag{23}$$

error covariance measurement:

$$P_k^+ = (I - K_kC_k)P_k^-. \tag{24}$$

After going through iterations, the estimate will be closer to the terminal voltage measured value, so the value of SOC and another state also will be close to the actual values.

IV. Results and Discuss

A. Battery Model Parameter Identification

The Open Circuit Voltage (OCV) V_{oc} in Thevenin battery model is required as a voltage and obtained from pulse test when the battery is not connected to the load. $V_{oc}(SOC)$ is obtained by the form of 12-degree polynomial curve fitting functions, and formulated as follows:

$$V_{oc}(SOC) = k_1SOC^{12} + k_2SOC^{11} + \cdots + k_{11}SOC^2 + k_{12}SOC^1 + k_{13}\,, \tag{25}$$

With k is a constant value.

Battery model parameter values *Ro, Rp*, and *Cp* is obtained by running the RLS algorithm. And the results of parameter estimation using RLS are : R_0 = 0.03752 Ω, R_p = 0.01313 Ω, and C_p = 45.29 F.

B. SOH and SOC Estimation

To determine the SOH and SOC of the battery is needed some testing. The following explanation shows the estimation results for several testing.

1) Coulomb Counting -discharge and Coulomb counting -charge test

Figure 2 shows the results of the SOC value when the battery is tested by using Coulomb counting (CC) -charge and CC-discharge. Estimation results shown in the picture concluded that the estimation using the Kalman filter and Coulomb Counting is almost the same, this can be confirmed by noting that the relative error is less than 0.6%. Thus, we can conclude that Kalman Filter also accurate when applied to estimate the SOC by charging-discharging cycles more than one cycle

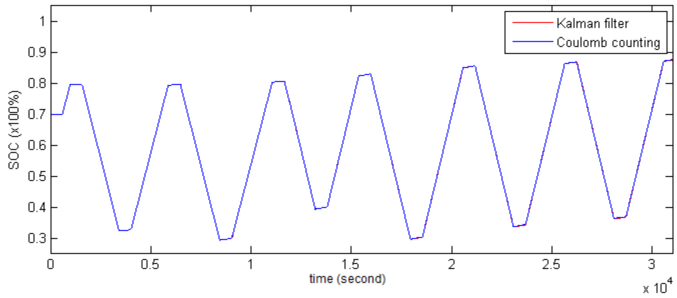

Figure 2. CC-charge and CC-discharge test SOC estimation

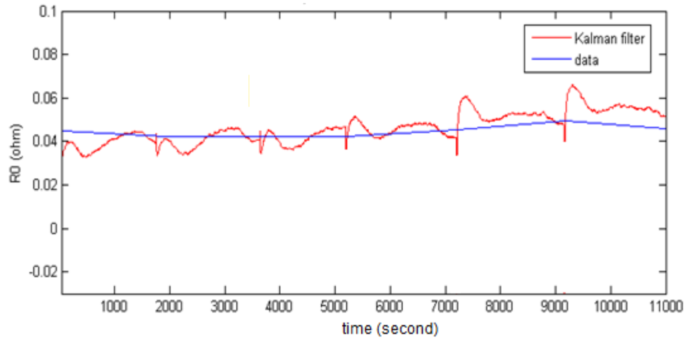

Figure 3. CC-charge and CC-discharge test internal resistance estimation

Figure 3 shows the change in the internal resistance that occurs during the test, and indicate a change in the value of SOH battery. The resistance value of the battery will always increase in proportion to the time length of usage and the age of the battery. SOH value estimation can be used as a reference to determine whether the battery is still proper to use.

2) 60 Cycles charging and discharging.

The SOH value of the battery can be determined by looking at the value of internal resistance which was estimated by RLS, and changes in the value of the battery capacity. Testing of 60 charging and discharging cycles will show the changes in the value of capacity and internal resistance of the battery in each cycle. Figure 4 shows the SOH value changes that occur in each cycle of charging and discharging process, and shows that the SOH based on the internal resistance and capacity decreased in the first 20 cycles. After 20 cycles, there are fluctuations in the value of SOH. It shows that when SOH value is less than 0%.

Figure 4, shows that the Kalman filter algorithm has a better accuracy than the RLS algorithm. This is indicated by the mean relative error of Kalman Filter that much smaller at 5.26% against 7.08% than RLS.

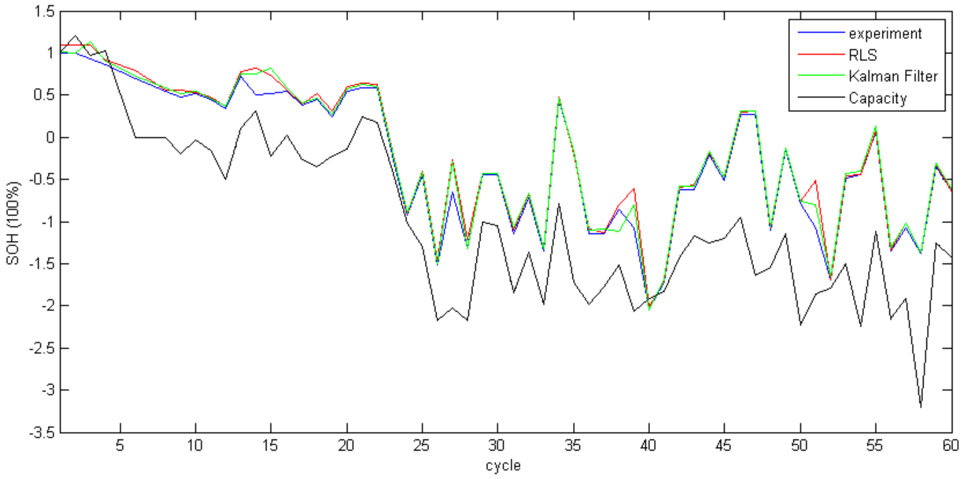

Figure 4. SOH-cycle

V. Conclusions

The conclusions that can be drawn based on conducted research is:

- RLS algorithm better estimates battery internal resistance R_o value than Kalman filter does by only 15% error.
- Kalman Filter can provide SOH estimation value better than RLS with a mean relative error of 5.26% while RLS provide 7.08% of mean relative error
- By applying Kalman filter algorithms, SOC and SOH can be estimated simultaneously.

References

.

[1] S. Yuan, H. Wu, and C. Yin, "State of charge estimation using the extended Kalman filter for battery management systems based on the ARX battery model," *Energies*, vol. 6, no. 1, pp. 444–470, Jan. 2013.

[2] J. Remmlinger, M. Buchholz, M. Meiler, P. Bernreuter, and K. Dietmayer, "State-of-health monitoring of lithium-ion batteries in electric vehicles by on-board internal resistance estimation," *Journal of Power Sources*, vol. 196, no. 12, pp. 5357–5363, Jun. 2011.

[3] Y. Zou, X. Hu, H. Ma, and S. E. Li, "Combined State of Charge and State of Health estimation over lithium-ion battery cell cycle lifespan for electric vehicles," *Journal of Power Sources*, vol. 273, pp. 793–803, Jan. 2015.

[4] X. Yan, Y. Yang, Q. Guo, H. Zhang, and W. Qu, "Electric vehicle battery SOC estimation based on fuzzy Kalman filter," *2013 2nd Int. Symp. Instrum. Meas. Sens. Netw. Autom.*, no. 1, pp. 863–866, Dec. 2013.

[5] D. Andre, A. Nuhic, T. Soczka-Guth, and D. U. Sauer, "Comparative study of a structured neural network and an extended Kalman filter for state of health determination of lithium-ion batteries in hybrid electric vehicles," *Eng. Appl. Artif. Intell.*, vol. 26, no. 3, pp. 951–961, 2013.

[6] H. T. Lin, T. J. Liang, and S. M. Chen, "The state-of-health diagnosis of Li-Co batteries with fuzzy identification," *Conf. Proc. - 2012 IEEE 7th Int. Power Electron. Motion Control Conf. - ECCE Asia, IPEMC 2012*, vol. 4, no. 101, pp. 2678–2682, 2012.

[7] V. Klass, M. Behm, and G. Lindbergh, "A support vector machine-based state-of-health estimation method for lithium-ion batteries under electric vehicle operation," *Journal of Power Sources*, vol. 270, pp. 262–272, 2014.

[8] Z. Guo, X. Qiu, G. Hou, B. Y. Liaw, and C. Zhang, "State of health estimation for lithium ion batteries based on charging curves," *Journal of Power Sources*, vol. 249, pp. 457–462, 2014.

[9] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.