State of Charge and State of Health Estimation of Lithium Battery using Dual Kalman Filter Method

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***Abstract*—In a Battery Management System (BMS), the determinations of state of charge (SOC) and state of health (SOH) of Lithium battery in hybrid electric vehicle (HEV) need to be accurate and reliable. Charging and discharging processes occurred in Lithium Battery used in HEV produce different SOC value over time, and an accurate prediction method is needed to estimate the SOC current condition. In the long run, both processes can reduce the SOH value of the lithium battery. One of the methods to estimate SOC and SOH values is Coulomb Counting which calculates the coulomb rate flowing out of the Lithium battery over time, but the calculation cannot be done in real time. In this paper, the dual Kalman filter method to predict Lithium Battery SOC and SOH values in real time are utilized. The experimental results show that the estimation of SOC and SOH by using the dual Kalman filter provides almost the same value with that by using the Coulomb counting method.**

***Index Terms*—State of charge (SOC), state of health (SOH), lithium battery, Kalman filter, unscented Kalman filter (UKF), Estimation**

I. Introduction

Fossil energy depletion had happened for decades and had affected lots of different industries in the world. This encourages experts in various industries to devise a new approach towards a sustainable energy vision ahead. One of industries that considers this vision is the automotive industry. For the past ten years, the automotive industry has adopted a new technology to find solutions in anticipating the fossil energy depletion issue. The answer leads to the development of electric vehicle, a vehicle that completely runs on a 100% electric as its source of energy. However, one challenge appeared when building this technology is the reliability of battery performance in the long run. State of Charge (SOC) of the battery needs to show an exact number with high accuracy to avoid any kind of incidents regarding to the maintenance of the battery.

Many fundamental formulas has been proposed to solve this problem, like Coulomb counting i.e. Ampere- Hour (AH) counting and Open Circuit Voltage (OCV) [1, 2, 3]. In resolving its dynamic characteristic, some papers used predictive methods like Kalman filter [4], nonlinear predictive filter [5], neural network [6], extended Kalman filter [7, 8], unscented particle filter [9], unscented Kalman filter [10, 11, 12], and support vector machine (SVM) [13].

In this paper, the domain-specific knowledge of lithium battery discussed in [14] and the basic concepts of Kalman filter in [15] are utilized. The predictive methods based on the Kalman filter and the unscented Kalman filter are proposed to estimate the battery SOC value to obtain a lower degree of error. The main contribution of this paper is the idea of combining 2 predictive methods to optimize the predicted SOC value of a lithium battery. In [4], the Kalman Filter as a method to support the local linearization approach, which creates a linear model in a small segment of the lines, is proposed. In [7], the extended Kalman filter to optimize SOC value estimation by generating best possible filter gain is used. In [10], unscented Kalman filter is proposed to obtain more robust solution than Kalman filter and extended Kalman filter in handling its nonlinear characteristics. Basically, the idea explained in this paper is to combine the accuracy of Kalman filter method proved in [4] for linear model and the reliability of unscented Kalman filter (UKF) has to handle nonlinear properties attached in the lithium battery, as shown in [10].

Dual Kalman Filter implementation thoroughly revealed in this paper primarily consists of battery model creation with Kalman filter and unscented Kalman filter as its compounds. The model is then validated by a comparison between SOC value estimation result and the actual SOC value derived from Coulomb Counting method. On the SOH estimation, this paper used capacity fade method, which is a comparison between the initial battery capacity and the latest battery charge-discharge cycle.

This paper consists of a brief introduction of the paper in section I. section II shows a brief explanation on the type of hardware and methods used in the experiment. section III elucidates how the hardware and software interact with each other under one big system. The discussions from the results of the experiments are represented in section IV. The overall conclusions of the paper, with a note on potential future work that can be done as an effort to advance the experiment further are in section V.

II. Materials and Methods

A. Materials

Hardware used in this experiment consists of the monitoring device and the experimental device. For monitoring device, the Powerlog 6S to record the system data flow is used. The computer codes and plots results in form of graphs. For experimental device, we use a $LiFePO_4$ China Aviation Lithium Battery (CALB) Battery

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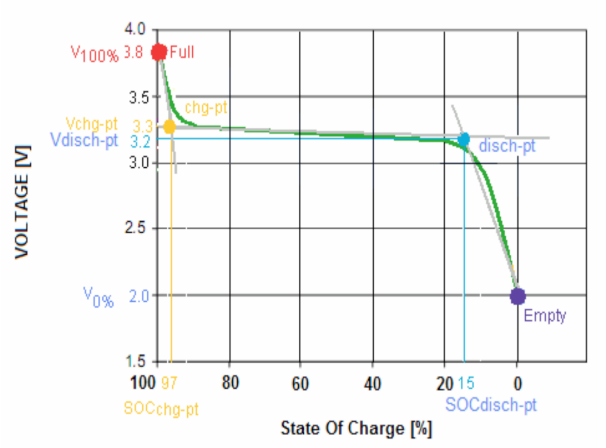

Fig. 1. Voltage translation graph

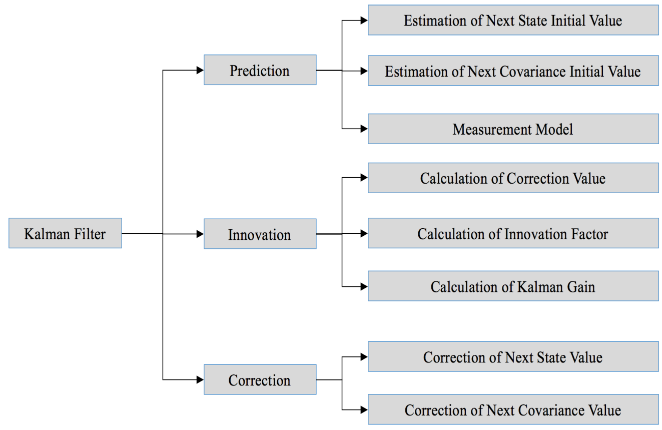

Fig. 2. Kalman filter method

with 10 Ampere-hour (Ah) capacity, a light bulb as the electric load, a power charger with the specification of 12V/20A, and an Elithion battery management system (BMS) to monitor the battery condition in real time. Software used in this experiment are Logview, Elithion BMS & Lithiumate.

Logview is the software attached to Powerlog 6s. It functions as a data logger and displays the received data to the computer screen. Logview also used to set and configure the data logger features of Powerlog 6s. The software version authors use in this experiment is the Logview version 2.7.5.

The Elithion battery management system (BMS) with Lithiumate software attached to it is used to monitor the battery condition. On the lithium battery, we use a cellboard plugged on the battery that acts as a sensor for current battery condition and as data transmission media from the battery to the BMS. Basically, cellboard gathers all data about battery current condition, and sends the data in the form of hexadecimal code via hub cable. This hexadecimal code is converted into decimal value, which expresses the battery actual condition.

B. Methods

The voltage translation and the Kalman filter are used for the estimation of SOC. The voltage translation sums up the total amount of current flowing (in Coulomb unit) for a period of time. The Powerlog 6s for recording the current flow data is used. Figure 1 shows that the battery voltage reaches 3.8 volt when it is fully charged, and drops down into 2 volt when it is fully drained.

Kalman filter is an estimator that calculates a variable to be estimated by minimizing noise attached to the variables, using a recursive algorithm. Kalman filter consists of three phases, which are prediction, innovation, and correction, as shown in Figure 2. The explanation of the steps are as follows:

1. Prediction Prediction phase determines the initial value and should be linear according to this formula:

$$\hat{x}_k^- = \mathbf{A}x_{k-1} + \mathbf{B}u_k + V_k \tag{1}$$

where $\hat{x}_k^-$ is the discrete random process/state vector of current phase, x_{k-1} is the discrete random process/state vector of previous phase, $\mathbf{A}$ is the state transition matrix, $\mathbf{B}$ is the control input matrix, u_k is the deterministic control vector, and V_k is the uncorrelated discrete random process (process noise).

The observation value, $Z_{model,k}$, is

$$Z_{model,k} = \mathbf{H}x_k + W_k \tag{2}$$

where $\mathbf{H}$ is the control input matrix, W_k is the uncorrelated discrete random process(measurement noise).

Then, the covariance value, P_k^-, is determined for the next phase, as follows:

$$P_k^- = \mathbf{A}P_{k-1}\mathbf{A}^T + Q \tag{3}$$

where P_{k-1} is the covariance value of the previous phase, and Q is the uncorrelated discrete random process (or covariance noise).

2. Innovation The innovation phase consists of three steps which are: (i) The determination of the correction value, $\bar{y}$

$$\bar{y} = (Z_{measure,k} - \mathbf{H}\hat{x}_k^-) \tag{4}$$

where $Z_{measure,k}$ is the measured value. (ii) The calculation of the innovation factor, $\mathbf{S}$

$$\mathbf{S} = \mathbf{H}P_k^-\mathbf{H}^T + \mathbf{R} \tag{5}$$

where $\mathbf{R}$ is the uncorrelated discrete random process (innovation factor noise). (iii) The assignment of the Kalman gain, K_K^-

$$K_K^- = P_k^-\mathbf{H}^T(\mathbf{S})^{-1} \tag{6}$$

3. Correction The generated Kalman gain value can be used to eliminate noise with recursive method stated in the following formula:

$$\hat{x}_k = \hat{x}_k^- + K_k(\bar{y}) \tag{7}$$

The Kalman gain value is used for updating previous covariance value, as follows:

$$P_k = (I - \mathbf{H}K_k)P_k^-. \tag{8}$$

The unscented Kalman filter (UKF) is used to linearize the nonlinear function of a random variables through linear regression between n points drawn from prior distribution of the random variables. The intuition behind this concept is that it is easier to approximate a probability distribution than it is to approximate an arbitrary nonlinear function or transformation. The steps of UKF are as the following.

1. Sigma point determination

Sigma point has a function as a sample point used for prominent reference of UKF method, to reconstruct updated mean and covariance value:

$$\mathbf{X}_o = \bar{x} \tag{9}$$

$$x_t = \bar{x} + \sqrt{(\mathbf{n}+k)\mathbf{P}_{xx}} \tag{10}$$

$$x_t = \bar{x} - \sqrt{(\mathbf{n}+k')\mathbf{P}_{xx}} \tag{11}$$

2. Weighting

Weighting process is used to optimize every sigma value existed before:

$$\mathbf{W}^{(0)} = \frac{k}{\mathbf{n}+k} \tag{12}$$

$$\mathbf{W}^{i} = \frac{1}{2(\mathbf{n}+k)} \qquad i = 1, ..., 2n \tag{13}$$

3. Unscented Transform

The unscented transform process propagates non-linear function into process and measurement models, which are, respectively, determined by

$$\mathbf{X}_{i,k} = \mathbf{F}\lfloor \mathbf{X}_{i,k-1}, \mathbf{u}_{k-1} \rfloor \tag{14}$$

$$\mathbf{Z}_{i,k} = \mathbf{H}\lfloor \mathbf{X}_{i,k-1} \rfloor \tag{15}$$

4. Prediction

The phase process and measurement models in the prediction step, respectively, are as follows:

$$\begin{aligned} \hat{x}_k^- &= \sum_{i=0}^{2n} \mathbf{W}_i \mathbf{X}_{i,k}, \\ \mathbf{P}_k^- &= \sum_{i=0}^{2n} \mathbf{W}_i \{\mathbf{X}_{i,k} - \hat{x}_k^-\}\{\mathbf{X}_{i,k} - \hat{x}_k^-\}^T, \end{aligned} \tag{16}$$

and

$$\begin{aligned} \hat{z}_k^- &= \sum_{i=0}^{2n} \mathbf{W}_i \mathbf{Z}_{i,k} \\ \mathbf{P}_{z_k z_k}^- &= \sum_{i=0}^{2n} \mathbf{W}_i \{\mathbf{Z}_{i,k} - \hat{z}_k^-\}\{\mathbf{Z}_{i,k} - \hat{z}_k^-\}^T. \end{aligned} \tag{17}$$

5. Innovation

On the innovation phase, the cross-covariance matrix value, $P_{x_k z_k}^-$, and the Kalman gain $\mathbf{K}$ value are determined, respectively, by the following

$$\mathbf{P}_{x_k z_k}^- = \sum_{i=0}^{2n} \mathbf{W}_i \{\mathbf{X}_{i,k} - \hat{x}_k^-\}\{\mathbf{Z}_{i,k} - \hat{z}_k^-\}^T, \tag{18}$$

and

$$\mathbf{K} = \mathbf{P}_{x_k z_k}^- \mathbf{P}_{z_k z_k}^{-1}. \tag{19}$$

6. Correction

The estimation process of real value ($\hat{x}_k$) and updated covariance value ($\mathbf{P}_k$) done by the use of correction value in Kalman gain ($\mathbf{K}_k$), is shown by the following equations:

$$\hat{x}_k = \hat{x}_k^- + \mathbf{K}_k(z_k - \hat{z}_k^-) \tag{20}$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{P}_{z_k z_k} \mathbf{K}_k^T. \tag{21}$$

The capacity fade method compares the amount of battery total capacity in each cycle, start from the first cycle done in the system. The formula used in this method is described as follows:

$$SOH = (\frac{Ci}{Co}) \times 100 \tag{22}$$

where C_i is the battery total capacity value after i times of cycles, and C_o is the initial battery total capacity value.

III. System Configuration

The SOC and SOH estimation system for lithium battery shown on Figure 3 consists of charge and discharge process, real-time monitoring on battery actual condition, and data acquisition system for all activities occurred inside the system. Charge and discharge process involved four parts, which are the charger, lithium battery, current limiter, and load. Charge process flows from the charger, as electric charge generator, to the battery, as charge storage. Current limiter is used to limit the amount of current flowing from

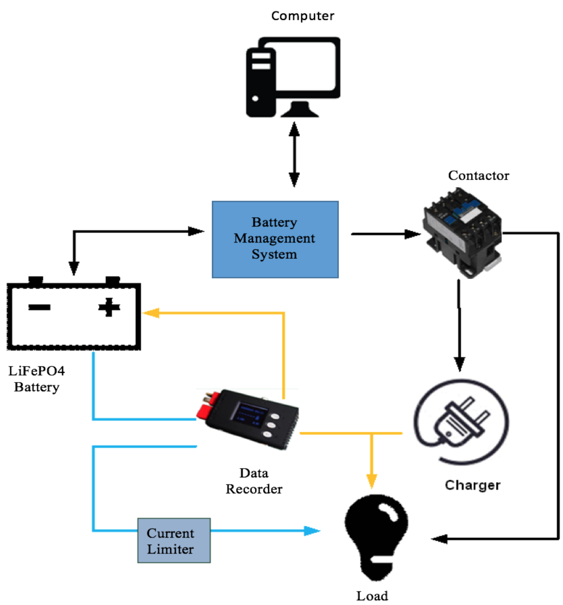

Fig. 3. System Configuration

the charger to the battery at a constant rate of 2A. The limitation of the current to 2A is to implement the C20 charging method in this experiment.

Monitoring system involved three parts, which are the BMS, the battery, and the safety module, which consists of a controller and a contactor. Since the lithium battery can not monitor its current condition and send it autonomously to the BMS, we utilize a cellboard plugged on the battery to do such task. BMS gives a signal to cellboard that translates into a request to send the actual data recorded by cellboard. Thus, the BMS receives the data in real-time.

The data acquisition system consists of four components, which are the battery, the data logger, the BMS and a computer. As explained above, to get battery current condition data, BMS needs to send a signal to cellboard for it to send the data back to BMS. The data is received by the BMS, and also by the computer through a data logger on the line of charge and discharge system. The data obtained by data logger is accessed by the computer via RS232 cable. On the computer, the data is processed to generate variable values and parameters needed to perform this experiment and displays the result in form of graphics.

IV. Results and Analysis

Figure 4 shows a comparison between SOC value of dual Kalman filter (blue line) and SOC value of actual data using Coulomb counting method (red line) for single discharge cycle. Figure 5 shows the zoom in version of the Figure 4 on SOC value around 87-88%.

The error between the SOC values calculation by using Coulomb counting and by using the dual Kalman filter methods are calculated by the following:

$$error_{rms} = \frac{\sum_{i=0}^{n} \sqrt[2]{(SOC_{est,i} - SOC_{cou,i})^2}}{n} \times 100\%, \tag{23}$$

where n is the sampling time. From Figures 4 and 5, both lines of SOC value are almost coincided each other. From this experiment, error rate value of 0.2% is achieved with red line as the reference. We can conclude that dual kalman filter method has given us a pretty good result in estimating SOC value. In the next experiment, we tried to use these methods to estimate SOC value in real time condition.

1. SOC estimation

On this phase, dual Kalman filter method is implemented along with two other methods, which are the Coulomb counting and the voltage translation.

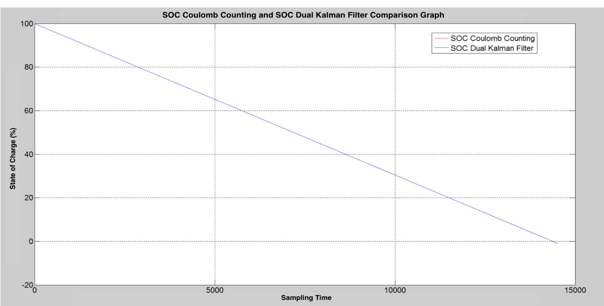

Fig. 4. SOC value : dual kalman filter vs coulomb counting

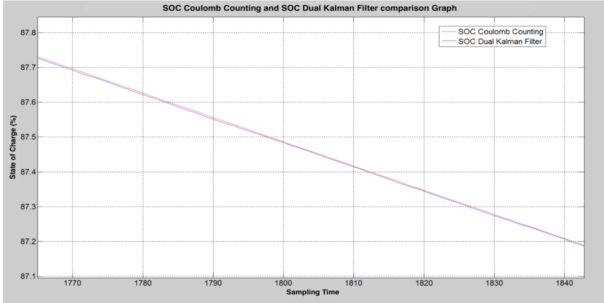

Fig. 5. The comparison of SOC value: zoom in 87-88%

In the previous experiment, the Coulomb counting method as the prominent reference for dual Kalman filter method. However, the Coulomb counting method can not be used for online SOC estimation, because Coulomb counting method needs a signal to start counting amount of current flowing through the battery. Thus, voltage translation method is used to complement Coulomb counting method.

Figure 6 shows how the voltage translation method is implemented in this experiment. Four lines existed in Figure 6 are explained as follows. The two vertical lines were used for sectioning the graph into three parts. The SOC value on area 1 and 2 can be approached by voltage translation method with following formulas described below for area 1 and area 2 respectively,

$$y = 10x - 33.2, \tag{24}$$

and

$$y = 15x - 175.5, \tag{25}$$

where y is the SOC value and x is the voltage value of the battery.

On area 3, the Coulomb counting approach is used to estimate the SOC value, with the following equation:

$$SOC_k = SOC_{k-1} - \frac{I \, . \, \Delta t}{C_{cell}} .100 \qquad [\%] \tag{26}$$

We note that the current I is constant 2A, Δt is a 10-second interval, and the Ampere-hour of the cell is 40 Ah.

With both methods stated above, we get overall SOC estimated value on Figure 7. Figure 7 shows the amount of SOC estimated value with methods explained in the previous paragraph. We can see that SOC starts at 100% and end at approximately 0%.

Figure 8 shows that the output of Kalman filter method is the value of V_1, V_2, and R_{Ω}, with V_1 and V_2 as the

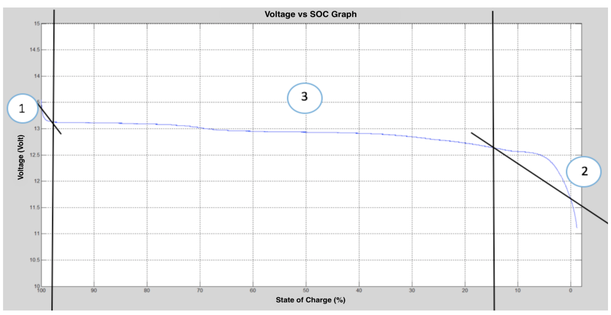

Fig. 6. Relation between battery voltage and battery SOC value

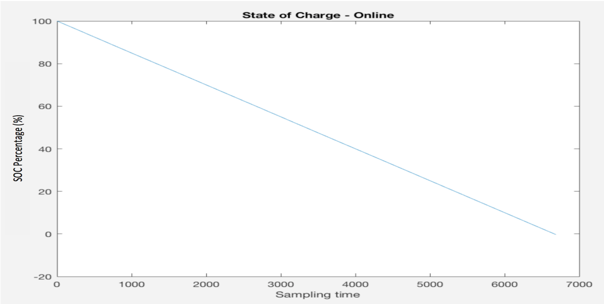

Fig. 7. Real-time SOC estimated value

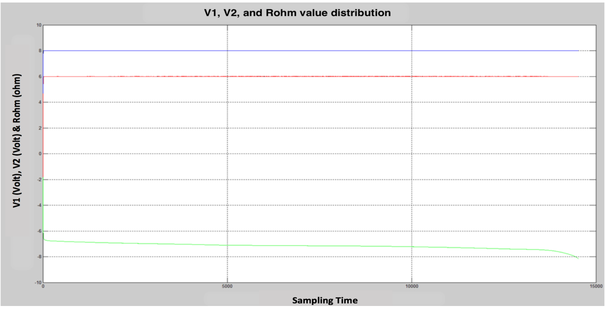

Fig. 8. Kalman filter result

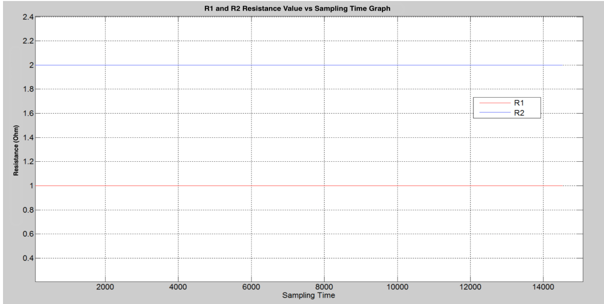

Fig. 9. R_1 and R_2 value graph

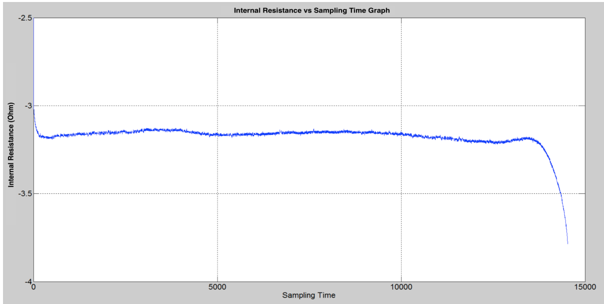

Fig. 10. The value of $R_(\Omega)$

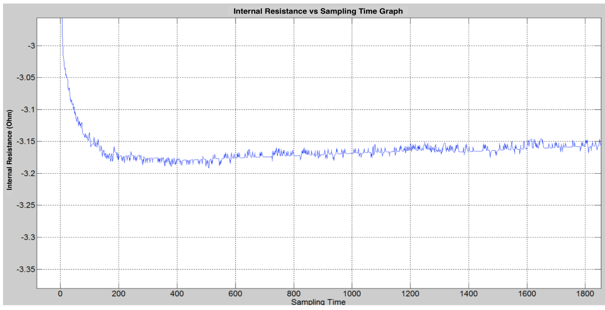

Fig. 11. Zoom of R value in 0-1800 sampling time

additional parameters used in the battery model, that can not be measured directly like V_{cell} and I_k value. R_Ω is the value of internal resistance existed inside the battery, but cannot be measured directly because no method can be used to measure the battery internal resistance without separating the battery from the system. Therefore, those three values were represented by estimated Z value with the following equation:

$$Z_k = V_1 + V_2 + I_k \,.\, R_\Omega. \tag{27}$$

In Figure 8, the value of V_1, V_2 and R_Ω shown with blue, red and green line respectively, with the x-axis represents the amount of data and y-axis represents the values of V_1, V_2 (with volt as the unit) and R_Ω (with Ω as the unit). As shown in Figure 8, V_1 value is oscillated around $2V$ and V_2 value is fluctuated around 4V. As seen from Figure 9, the value of R_1 stays at 2Ω and the value of R_2 stays at 1Ω. These values contribute to the correction process for the values of V_1 and V_2.

2. SOH Estimation

It has been konwn by resistance growth concept occurred in the $LiFePO_4$ battery that the battery internal resistance increases along with the increasing of the charge-discharge cycle. Unfortunately, this method has not worked since the value of internal resistance tend to be smaller from its estimated initial value with the increase of charge-discharge cycle. The estimate value of the internal resistance can be observed from Figure 10 and its zoomed in picture is shown in Figure 11.

On Figures 10 and 11, it can be clearly seen that the value of internal resistance acquired with dual Kalman filter method is stable at -3.18. While on the battery datasheet, the initial value of battery's internal resistance is $\pm 1m\Omega$. This difference happened because the use of V_{oc} value that did not derive directly from the experiment, but from the model stated in reference [8], where there is a possibility that the $LiFePO_4$ battery used in the experiment in reference [8] is a new battery (100% initial SOH), while $LiFePO_4$ battery used in our experiment has gone through a couple of charge-discharge cycles. This causes Z_k value became negative, and also affect the estimated value of V_1, V_2 and R_{ohm}. Biggest effect happens in R_Ω, since the estimated value of R_Ω is not used in the UKF, while V_1 and V_2 are. So even though V_1 and V_2 value have errors, it will be minimized in innovation phase of UKF method, so the error does not affect much to the estimated value of SOC.

So it can be concluded that the value of internal resistance is not valid and does not match with resistance growth theory. Therefore, the capacity fade method to estimate the SOH value. In this experiment, data used is gathered in date range June 24 July 14, 2014. During that time, the experiments apply 22 charge-discharge cycles. From those data, only 9 out of 22 data are considered valid, because there are some difficulties from the hardware aspects to make sure the system record the data correctly.

Figure 12 shows the amount of battery capacity measured in each cycle. There are two different lines, first is the

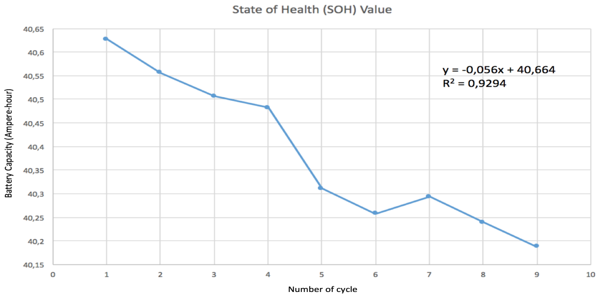

Fig. 12. SOH degradation value

straight line that represents actual battery capacity measured in each cycle, and second is the bullet line derived from the linear regression from the straight lines. Although there were oscillating happened in actual battery capacity, the graph trend tends to be consistent. This means a reduction in battery capacity has always happened in each charge-discharge cycle. The linear regression line generated the following as follows:

$$B_C = -0.056D + 40.664 \tag{28}$$

with B_C is the total battery capacity (Ah) and D as the total cycle. From the above formula, it can be concluded that for every charge-discharge cycle occurred, a reduction in battery capacity happened at a rate of 0.056 Ah. Value of correlation factor from the linear regression is $R^2 = 0.9294$

V. Conclusions & Future Work

In this experiment, the real-time SOC and SOH estimation systems have been developed. Using the dual Kalman filter method, the accuracy of SOC can be considered very superior, with estimation error below 1%. For SOH estimation using the capacity fade method, an estimated value of SOH with the error of 1,2% after 9 cycles of the charge-discharge process. Both estimation methods are implemented real time. In the next step, other method such as support vector machine method can be one of the options to compare SOH estimation method used in this experiment. Further research should also consider a test of the system in the actual vehicle data rather than laboratory data.

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