Estimation of SOC and SOH for Lithium Batteries

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Abstract- **This paper proposes a SOC (State-of-Charge) estimation and temperature detection system for a Li-ion battery cell. By using the proposed VCT detector IC, the battery voltage, current, and temperature could be detected. The sensed voltage and current are used to estimate the SOC using the algorithm in this paper. The computed SOC and detected temperature is revealed on a LCD display by the Arduino MCU module in the mini self-propelled vehicles. 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).**

Index Terms- **BMS; Battery model; State of Charge; State of Health; Lithium-ion, battery+**

I. INTRODUCTION

The State of Charge (SOC) of a rechargeable chemical cell is a proportional to the amount of energy available. It is commonly expressed as a real value from 0 to 1, or as a percent from 0% to 100%, where 0% indicates that the cell cannot be safely discharged any further, and 100% indicates it cannot be charged any further. It is a unitless, normalized metric making it ideal for use as a "fuel gauge" for all kinds of battery technologies. A closely related concept is State of Health (SOH), which is related to the age of a cell. It usually is an estimation of either cell impedance or capacity. For example, a cell could be fully charged (100% SOC), but have severely degraded runtime (low SOH).

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.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.Due to the increasing demands of battery-powered applications, much research has been done on developing the architecture of Cyber-Physical systems (i.e. BMS) which monitor and maintain rechargeable batteries [1, 2]. As for determining SOC and SOH, a number of papers have been published which apply a Kalman Filter (KF) to rechargeable cells such as Liion or LiPo[3, 4, 5, 6]. This method has been shown capable of very accurate cell SOC estimation in real time.

However, an often-overlooked aspect of SOC estimation is that accurately estimating the SOC for an entire battery, even with a highly accurate cell model, cannot be done by simply considering the terminal voltage of that battery. This approach assumes that the constituent cells are always at the same SOC, and also have the same physical cell attributes, such as capacity or internal resistance. Research on model building has shown this is not the case [7, 8]. This approach is especially ineffective when one wants to accurately predict available power, as over- or under-estimates near the top or bottom of the SOC range could result in some cells being forced outside their safe operational ranges.

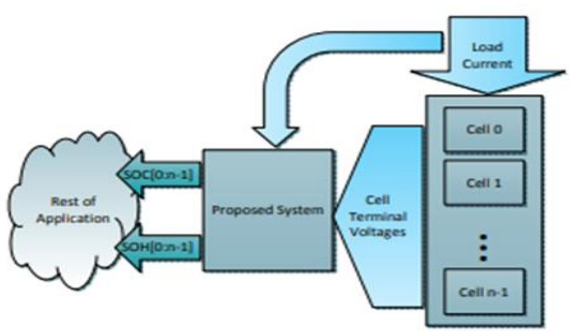

Fig. 1: System Overview. The system samples the voltage on each series connected cell, and the current which is loading the string, and produces real time SOC and SOH estimates for each cell.

The most straightforward method to estimate SOC/SOH for individual cells in a battery is to develop a model of an "average" cell, and deploy one or more KF which use this model to track the states of a set of cells. This allows research on single-cell methods to directly translate to a multi-cell approach. A black-box view of the proposed system context is shown in Fig. 1. The per-cell information can then be fed to battery protection logic, cell balancing logic, or summarized for instrumentation. The use of a KF rather than a bare model significantly increases the noise resistance and adaptability of the system.
In Section II we introduce our cell model, and validate simulation results with measurement data. In Section III we develop a framework for estimating both SOC and SOH (i.e. capacity) using a multiscale modification of the standard Unscented Kalman Filter (UKF). Note that this multi-scale approach is not application-specific; it can be used generally when a very slowly changing system parameter needs to be tracked. In Section IV we give a general analysis of our work, and finally conclude the paper in Section V.

battery model

Li-Ion Battery Equivalent Circuit

The accurate equivalent circuit of the Li-ion battery in [10] is used in this paper, where the equivalent circuit of the Li-ion battery is represented as in [11,13,17,21] and depicted in Figure 1, where R0 represents the internal resistance of the Li-ion battery, Rp1 and Cp1 indicate the activation polarization resistance and capacitance, respectively, and Rp2 and Cp2 are the concentration polarization resistance and capacitance, respectively

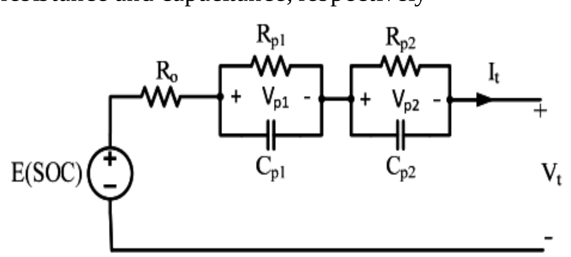

Figure 2. Equivalent circuit of Li-ion battery

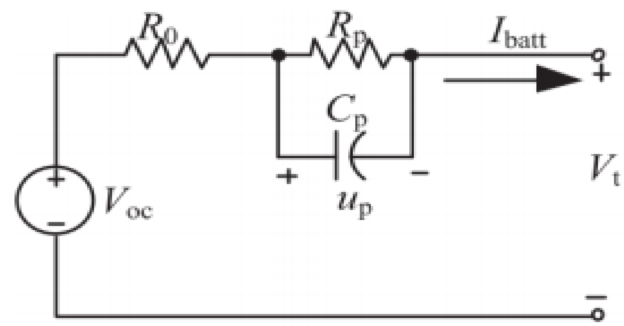

Figure 3. Thevenin battery model

Open circuit voltage Voc in Figure 1 is a battery voltage that measured when the battery is not connected to the load, up is the voltage of the parallel Rp and Cp. The resistance R0 is internal resistance of the battery while Rp, and Cp are the polarization resistance and capacitance, and Ibatt 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:

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

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

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

SOC AND SOH

(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 extende kalman filter method. This method can be formulated into:

$$SOC = SOC_0 - \frac{1}{C_{cap}} \int_0^t \eta\, I_{batt} dt, \quad (4$$

$$\dot{SOC} = -\frac{\eta\, I_{batt}}{C_{cap}} \quad (5$$

With kalman coefficient η is a constant value that defines charging and discharging process. SOC0 is the initial value of SOC just before Ibatt flow into or from the battery cell, and Ccap is the maximum ability of the new battery to store the current.

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]:

$$SOH_C = \frac{C_{act}}{C_{cap}}\ x\ 100\% \qquad (6$$

With SOHC is the value of SOH, Cact 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. 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 Ri are identical. When SOH value equal to 0%, the Ro will be twice of Ri value. SOH can be formulated into.

$$SOH_{R_i} = \left(1 + \frac{R_i - R_o}{R_i}\right)\ x\ 100\% \qquad (7$$

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

Extended Kalman Filter (EKF)

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.

$$x_{k+1} = Ax_k + BI_k + w_k \qquad (8$$

$$y_k = Cx_k + v_k \qquad (9$$

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

$$x(k) = \begin{bmatrix} SOC & u_p & R_0 & {}^{1}/_{C_{cap}} & {}^{1}/_{SOH} \end{bmatrix}^T \qquad (10)$$

$$A(k) = \begin{bmatrix} 1 & 0 & 0 & -\frac{\eta.\Delta t.I}{3600} & 0 \\ 0 & e^{-\frac{\Delta t}{R_p C_p}} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 2{,}2 & 0 \end{bmatrix}, \qquad (11)$$

$$B(k) = \begin{bmatrix} 0 \\ R_p.\left(1 - e^{-\frac{\Delta t}{R_p C_p}}\right) \\ 0 \\ 0 \\ 0 \end{bmatrix}, \qquad (12)$$

$$C(k) = \begin{bmatrix} \frac{f(soc)}{x_1} & -1 & -I(k) & 0 & 0 \end{bmatrix}, \qquad (13)$$

$$f(SOC) = a_1SOC^{12} + a_2SOC^{11} + a_3SOC^{10} + \cdots + a_{12}SOC^{1} + a_{13}. \qquad (14)$$

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

$$\hat{x}_0^+ = x_0 \qquad (15)$$
$$P_0^+ = P_{x_0},$$

Where Po 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:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \qquad (16)$$

error covariance:

$$Pk - = Ak{-}1Pk{-}1 + Ak{-}1\ T + Qk \qquad (17)$$

Step 2 : ``Kalman gain calculation:

Kalman gain:

$$K_k = P_k^- C_k^T [C_k P_{k-1}^- C_k^T + R_k]^{-1} \qquad (18)$$

Step 3 : update the measurement value:

state estimation measurement:

$$\hat{x}_k^+ = \hat{x}_k^- + K_k[y_t - C_k\hat{x}_{k-1}] \qquad (19)$$

Algorithm

This method is clarified and implemented in an algorithm, which is depicted in Figure 2.

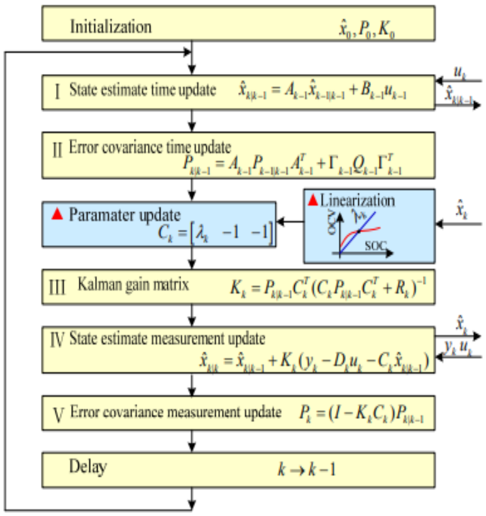

Figure 4. Algorithm flowchart of the Kalman filter.

EXPERIMENT SETUP

The experimental setup is a 12 V, 4 A, Li-ion pack, and the layout of the test bench is described as in Figure 5. This test bench consists of a programmable power supply and electronic load. The programmable power supply is a solar array simulator, which acts as a constant current source. This power supply is a 100 W module with maximum output voltage 12 V and maximum output current 1.5 A. The electronic load is working as a constant current load with the utmost current 1 A.

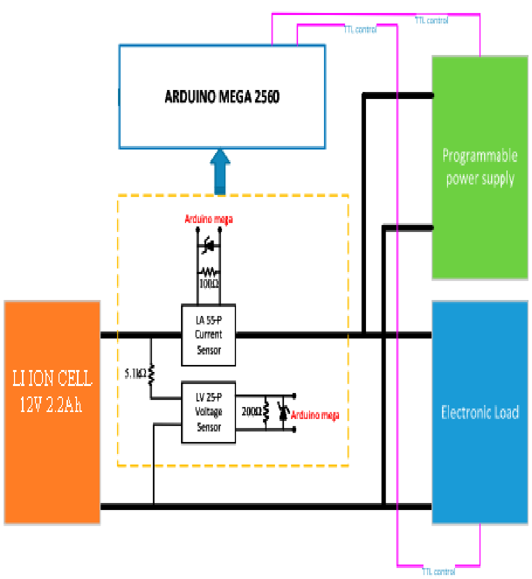

Figure 5. Experiment layout for testing the battery

Temperature Detection System:

The VCT detector IC detects the battery's VCT parameters and generates the voltage signal, Vbat, the current signal, VsenI , and the temperature signal, VsenT . The detected signals are couple to the 3-channel 10-bit ADC in the Arduino MCU module and converted into the digital signals, Dbat, DsenI , and DsenT , respectively. Referring to Fig. 2, the VCT detector IC is composed of the Wide Range Current Sensor, the OVP (Over voltage protector), and the OTP (Over temperature protector). By using the current division theory of the parallel resistors, the large battery current is converted to a sensed small current in the chip. Then, the sensed output signal, VsenI is obtained by the voltage drop of the sensed small current flowing through the resistor,

$$V_{senI} = \frac{R_{senI} \times R_{402}}{R_{401}} \cdot I_{bat} \qquad (20)$$

Fig. 3 shows the SOC algorithm. Firstly, the digital voltage signal, Dbat and the digital current signal, DsenI are read. Then, the SOCinit could be determined according to the battery voltage signal, Dbat by using the piecewise linear method. Thirdly, the DOD (Depth of Discharge) is obtained by the multiplication of the current signal, DsenI and the digital timing signal, Tcount, from the counter. Finally, the SOC is attained by subtracting DOD from SOCinit.

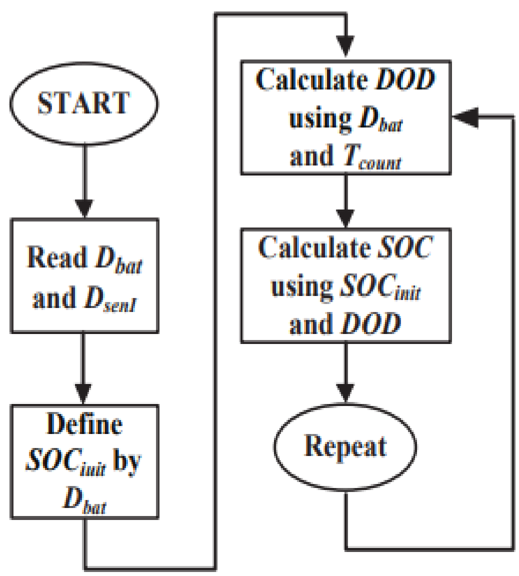

Fig 6:Temperature Detection

V. IMPLEMENTATION AND MEASUREMENT RESULTS

The model is simulated using Matlab with only current as an input (i.e., open-loop) to determine its accuracy. Although often simplified as constant, the Capacity of a cell changes very slowly with time. One cell cycle is defined as a complete discharge of a cell followed by a recharge, and is a common metric for describing its age. Our own measurements suggest a loss of around 0.1% per cycle. Although the rate is slow, a typical, modern Li-ion cell can be cycled more than 1000 times over its life. This will cause a measurable SOC divergence from the true value and decrease the accuracy of the filter.

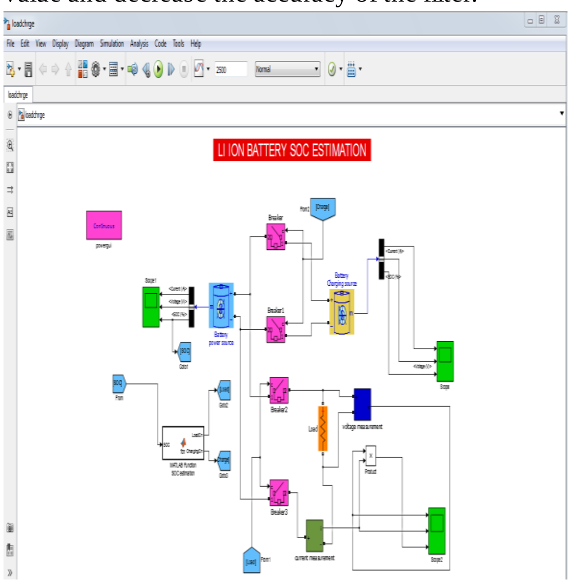

Fig 7:simulink model for soc estimation

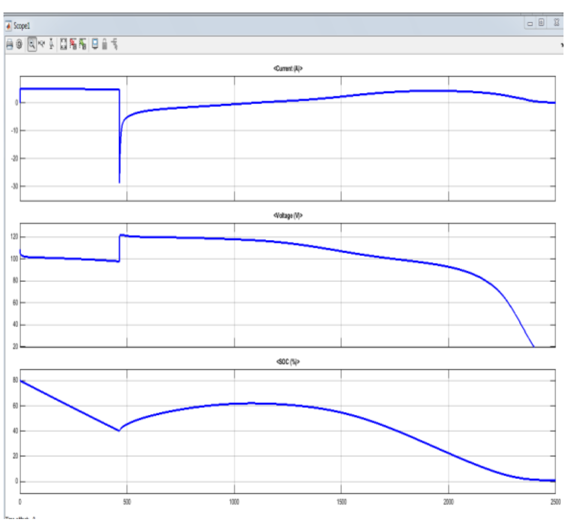

Fig8:Charging module SOC Estimation

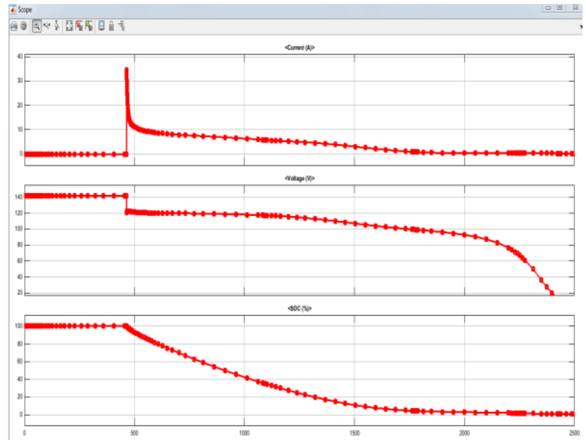

Fig9:battery model SOC estimation

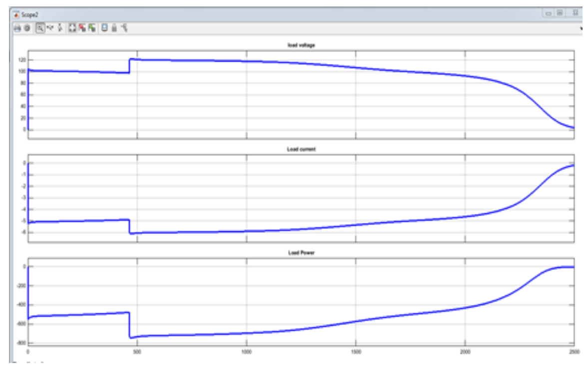

Fig11:Load variation

VI. CONCLUSION

In this paper we have demonstrated a new approach to estimating the the SOC and SOH of a battery using a Multi-scale EKF approach. Compared to the KF, the EKF eliminates the need to compute the recursive total derivative parameter estimation, which is challenging for the multi-scale case. The system's ability to track the state of different cells using the same general model was also demonstrated. The next step is an analysis of the supporting CPS architecture and the relationship between model sophistication and computational requirements By using the VCT Detector IC, the battery voltage, current, and temperature are detected. Besides, the SOC is calculated by the Arduino MCU module in the mini self-propelled vehicle. Based on the measurement results on silicon, the temperature detection error and the current detection errors are 2.08% and 0.35%, respectively.

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