International Journal For Technological Research In Engineering
Volume 7, Issue 8, April-2020 *ISSN (Online): 2347 - 4718*

MACHINE LEARNING BASED STATE OF HEALTH ESTIMATION OF LITHIUM ION BATTERIES

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Abstract: ***Today's automotive industry is undergoing significant changes in technology thanks to economic, political and environmental pressures. The shift from conventional internal combustion vehicles to electric vehicles brings with it a new host of technical challenges. The most prominent challenge in electric vehicles is modelling and predicting the states of the Lithium Ion batteries that power them. There is a constant risk of batteries having an early End of Life and hence turning into scrap. Therefore, to prevent the same, two major parameters are identified which can be assessed in order to prevent the early degradation of batteries. The parameters are State of Charge (SOC) and State of Health (SOH). The existing methods in order to predict the above two parameters include the Coulomb Counting Method (CCM), OCV (Open Circuit Voltage Method) and Fuzzy Logic Method. These methods show promise for small and predictable datasets but when the data becomes non-linear and the variability of the current and voltage parameters increase, these methods do not provide satisfactory results. Therefore, this paper proposes a State of Charge and State of Health estimation method based on Kalman Filter. Employing a Kalman Filter for the state estimation of the battery pack not only allows for enhanced accuracy of the estimation but allows the battery modelling engineers to develop a lithium ion battery that would last longer.***
Keywords:State of Charge (SOC), State of Health (SOH), Coulomb Counting Method (CCM), Open Circuit Voltage (OCV) & Fuzzy Logic Method, Kalman Filter

I. INTRODUCTION

A battery management system is the key component which assures the smooth functioning of battery packs.One of the key functions of the battery management system is to protect the battery from damage due to external factors.A battery management system (BMS) protects the overall system and provides optimal performance management of energy storage. In addition to on-line monitoring of the terminal voltage of every single cell, a BMS is required to predict and provide each cell's State of Charge (SOC) and state of health (SOH), which are the most important indicators for adapting each cell's optimized loading timely for extending the whole pack life.

In simple terms, the battery SOC can be employed in a figurative sense as a replacement for the fuel gauge used in conventional vehicles. Similarly, the SOH can be likened to the odometer.[1] Overcharging and over-discharging are two of the major problems that are faced by battery packs and aBMSwhich is successfully able to predict these critical parameters will eventually ensure the longevity of the same. For proper functioning Electric vehicles, there needs to be a robust online estimation of SOC and SOH parameters. Unfortunately, as there is a fuel indicator for fuel vehicles, there is no concrete technique for direct measurement of the states. Instead, it is estimated by the measured theoretical battery variables, such as the time-varying voltage and the charging/discharging current. Data-driven methods can be divided into direct measurement and model-based methods. Direct measurement methods include the Coulomb counting method (CCM), Open Circuit Voltage (OCV) method, and the impedance method[3].

The CCM is performed through measuring the discharging current over time and then making a Current-Time (I-t) integration to obtain an estimated SOC value.[4] The disadvantages of CCM are that it relies on the accuracy of the current sensor and it can accumulate errors due to its open-loop nature. The OCV method is relatively accurate but needs a sufficient rest time. The accuracy reduces in case of a flat OCV-SOC curve. [7,8] In the model-based approach, one measures the battery's online data and applies these signals as model inputs to calculate the SOC (output).

Electrical and electrochemical models are the widely used battery models. All the parameters work well on fresh cells but give erroneous results on aged cells. Therefore, all battery researchers are delving into Adaptive methods for prediction. Therefore, by dynamically combining two crucial parameters, that are, Open circuit voltage (OCV) & Coulomb Counting Method (CCM), a significantly more accurate estimation can be achieved. In order to achieve this, a Kalman filter is employed.

II. METHODOLOGY

In order to determine the state of charge (SOC), it is to be linked with two major parameters, namely, Open circuit voltage (OCV) & Current.

For relating both the parameters, the process flow is as follows.

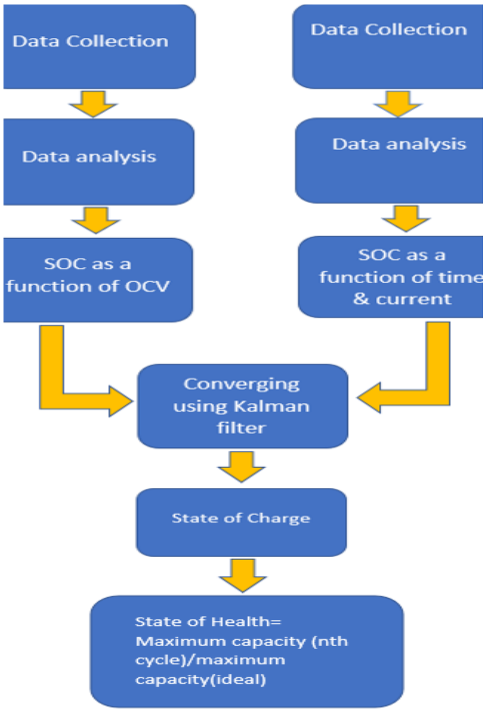

Fig 1. Process flow

As observed in the process flow, there will be two separate branches of measurement, namely, SOC as a function of OCV & SOC as a function of time & current. Both process flows follow the common data processing techniques, that is, Data collection, analysis and Output.

SOC as a function of OCV: The process explanation is as follows:

1)Data Collection: The data is collected on the cell's open circuit voltage as it goes from hundred percent to zero percent. A quasi-discharge technique is employed to speed up the process. In this technique, the battery is drained at C/20 where C is the cell capacity. Based on the Ohm's law calculations, the circuit schematic to achieve data collection.

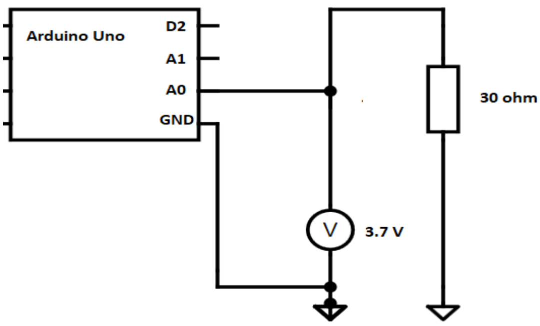

Fig 2. OCV measurement circuit schematic

The OCV measurement values are collected from the Serial monitor and python is used to convert the data points into .csv file.

2)Data analysis: The obtained data points are normalized from 0 to 100 percent scale and from those data points, a polynomial function is fit to get the state of charge as a function of open circuit voltage. The polynomial fit is determined by performing a chi square analysis using a python script.

SoC (OCV) =
268.4970355259198 * OCV^8 + -6879.270367122276 * OCV^7 + 76716.49575172913 * OCV^6 - 486365.6733759814 * OCV^51917287.1707991716 * OCV^4 -4812471.06572991 * OCV^3 7511312.300797121 * OCV^2 -6665390.783393391 * OCV 2574719.229612701

SOC as a function of current and time:

1)Data Collection: The Lithium ion cells are placed in series with 1-ohm resistor and a 60-ohm test load. The voltage drop is measured by the Arduino across the power resistor. Using ohm's law concept, the precise value of R is obtained. This value of R is sent to the Python via the serial monitor.

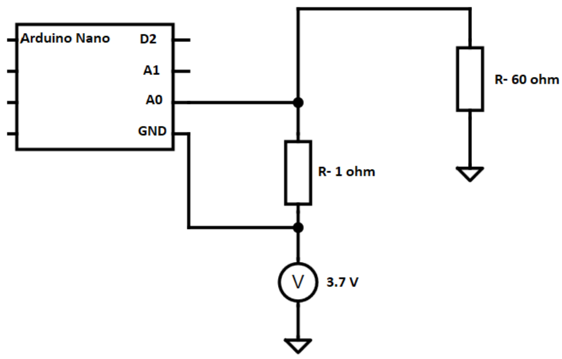

Fig 3. Current measurement circuit schematic

2)Data analysis: An 18650 cell is used rated 3Ah for which the total number coulombs are calculated. The State of charge used is obtained by coulombs used over total coulombs. After adding and subtracting the state of charge used with the initial state of charge, we obtain the State of charge as a function of time and current. The total formulae obtained is as follows:

$$Total\ coulombs = 3Ah \times \frac{60min}{hr} \times \frac{60s}{min} (1)$$
$$= 10{,}800\ coulombs$$

$$Coulombs\ used = I \times \Delta t = \frac{C}{s} \times S (2)$$
$$SoC\ used(\%) = \frac{coulombs\ used}{total\ coulombs} \times 100$$
$$= \frac{I \times \Delta t}{10{,}800} \times 100\ (3)$$

$$\mathrm{SoC}(t, I) = \mathrm{SoC}_0 - \mathrm{SoC}\ Used = \mathrm{SoC}_0 - \frac{1 \times \Delta t}{10{,}800} \times 100 (4)$$

Based on the above steps, the system diagram for the Kalman filter is shown as follows.

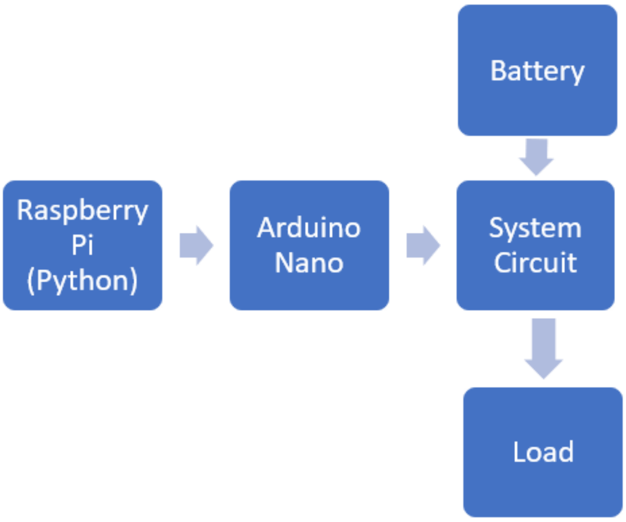

Fig 4. System diagram

Kalman filter circuit: The Kalman filter circuit is designed to operate in two states, namely, Current measurement state and OCV measurement state.

1)Current Measurement: In this condition, the relay is at off position. The battery which is connected to the load discharges through the 1-ohm power resistor. The voltage drop that occurs across R is measured by the Arduino Nano. The measured voltage drop is used to determine the current and this value of current is sent to Python.

2)OCV Measurement: In this condition, the relay is at high. The battery in this case is disconnected from the load. Due to this, the OCV measurement is taken. The voltage drop across R1 is measured and this value is sent to python.

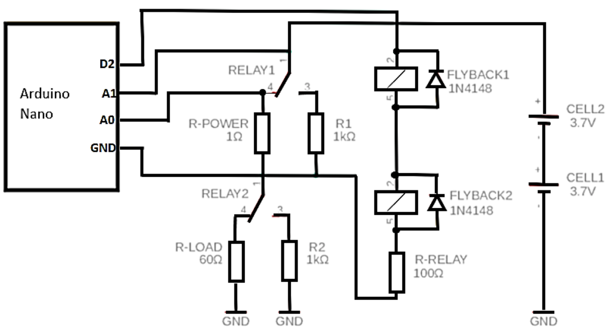

Fig 6. Current and OCV measurement

III. CALCULATIONS

Kalman filter Algorithm:

The Kalman filter process includes four steps, namely, initialization, prediction, measurement, updation and repetition. The four processes and their respective equations are given as follows.

Initialization: Thestate estimate and the estimate variance matrix are initialized by using measured OCV and current values. The Last estimate equation and estimate variance matrix equations are devised as follows.

$$\text{Last state estimate:} \hat{x}_{t-1} = \begin{bmatrix} (\text{initial SoC } (\backslash\%)) \\ (\text{initial current I}) \end{bmatrix} \quad (5)$$

$$Estimate\ Variance\ Matrix : \vec{P}_{t-1} = \begin{bmatrix} \sigma^2_{\text{estimate}} & 0 \\ 0 & \sigma^2_{\text{estimate}} \end{bmatrix} \quad (6)$$

Prediction: The updationof the transformation matrix occurs in a time interval over which the current is measured. The prediction process occurs for each iteration. The transformation matrix is:

$$Transformation\ Matrix : \vec{F}_t = \begin{bmatrix} 1 & -\frac{\Delta t}{10{,}800} \times 100 \\ 0 & 1 \end{bmatrix} (7)$$

In order to obtain the new state estimate and variance, the last state is multiplied with the state transformation matrix. The new current measurement which is obtained from Arduino is utilized to update the second component of the state estimate matrix. The equations for new state estimates and new estimate variance are as follows.

$$New\ state\ estimate: \hat{x}_{t|t-1} = \vec{F}_t \begin{bmatrix} (SoC(\%)) \\ (I) \end{bmatrix} (8)$$

$$New\ estimate\ variance: \vec{P}_{t|t-1} = \vec{F}_t \begin{bmatrix} \sigma^2_{\text{estimate}} & 0 \\ 0 & \sigma^2_{\text{estimate}} \end{bmatrix} \vec{F}_t^T \ (9)$$

Measurement: For the observation matrix, the raw sensor data is used without any manipulation. The raw data can be represented in the form of an identity matrix in our case.

$$Observation\ Matrix: \vec{H} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} (10)$$

The state measurement is obtained by measuring the OCV.

$$State\ measurement: \hat{y}_t = \vec{H} \begin{bmatrix} \text{SoC}(OCV \text{ reading}) \\ I \end{bmatrix} \quad (11)$$

The observation noise matrix is set lower than the estimation variance matrix.

$$Observation\ Noise\ Matrix : \vec{R} = \begin{bmatrix} \sigma^2_{\text{measurement}} & 0 \\ 0 & \sigma^2_{\text{measurement}} \end{bmatrix} (12)$$

Updation: The Kalman gain is calculated at first. For calculating the Kalman gain, the primary step is the calculation of the residual vector, that is, the difference between measured and estimated state).

$$Residual\ Variance\ matrix: \vec{S}_t = \langle \vec{H} | \vec{P}_{t|t-1} | \vec{H}^T \rangle + \vec{R} (13)$$

The Kalman gain calculated is as follows.

$$Kalman\ gain: \vec{K}_t = \vec{P}_{t|t-1} \vec{H}^T \vec{S}_t^{-1} \text{--}(14)$$

To adjust the new best estimate, the residual vector is multiplied with the Kalman gain and added to the state estimate.

$$New\ best\ estimate: \hat{x}_{t|t} = \hat{x}_{t|t-1} + \vec{K}_t \hat{z}_t \text{--}(15)$$

The estimated variance matrix is updated using the Kalman gain.

$$New\ estimate\ variance\ matrix: \vec{P}_{t|t} = (\vec{\|} - \vec{K}_t) \vec{P}_{t|t-1} (16)$$

Repetition: In this step, the new estimate is set as the last estimate and the new estimate variance matrix is set as the last estimate variance matrix.

$Last\ state\ estimate: \hat{x}_{t-1} = \hat{x}_t (17) Last\ estimate\ variance\ matrix: \vec{P}_{t-1} = \vec{P}_{t|t} (18)$

IV. RESULT AND DISCUSSION

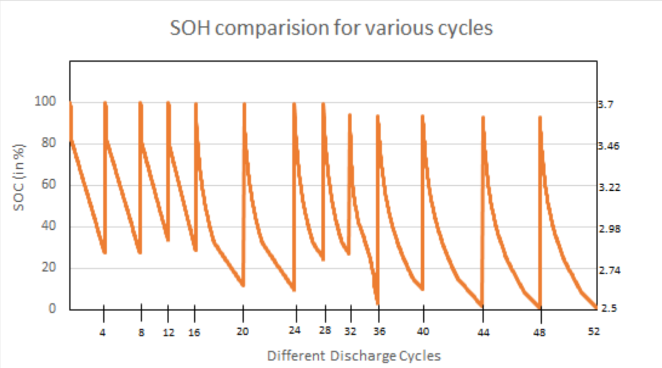

Figure 7: SOH comparison for various cycles

As charge depends upon two parameters, namely, current and time, two conditions arise. These conditions depend upon the load of the battery.

For constant load condition, the formula for charge is as follows.

Qm= I*Δt (19)

Here, I is the current obtained

Δt is the discharge time interval.

As observed above, in constant load conditions, there is no change in current observed due to external factors.

For variable load conditions, there arises a problem. Due to environment changes, the fluctuations in current is observed. To avoid this, an element of integration is introduced in the equation.

Qm= ∫ I *δt (20)

Here, δ is the time interval.

The formula for state of health is as follows:

$SOH = Qm(instantaneous\ value\ of\ cycle)/Qm(ideal)$ (21)

Qm: The maximum charge of the battery in coulombs.

ACKNOWLEDGMENT

We would like to acknowledge the battery testing laboratory in our college for providing us with the battery's charge and discharge data and also allowing to use their facility for testing our model.

V. CONCLUSION

The State of Charge of the 18650-lithium ion battery is calculated using Open Circuit Voltage and Coulomb Counting Method. By using Kalman Filter both these values are converged to their actual values. The State of Health devised comes out to be the ratio of maximum capacity of nth cycle to the maximum capacity of ideal cycle. This model can be used to fine tune electric vehicles so that the batteries can be utilized to their full potential.

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