Estimation of SOH in a Li-ion Battery using Capacity Fade

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Abstract - *This paper presents online estimation of SOH, Capacity fade and Capacity for Li-ion batteries used in Electric Vehicles. Battery capacity estimation is done separately for driving and charging mode. The driving mode algorithm is developed based on electrical equivalent circuit model. The model developed is simulated using MATLAB/Simulink and the simulations are done considering the changes in the number of cycles, temperature and charge – discharge profiles.*

Key Words: Li-ion battery; state of health; capacity; capacity fade; U-D RLS algorithm

1. INTRODUCTION

Use of conventional Internal combustion engine vehicle leads to ecological imbalance & non renewable energy sources are going to exhaust in upcoming years. Improved fuel economy is the urgent need in today's autonomy. So, the advancement in the electrochemical batteries is of great concern. Despite the concern focus has shifted from lead acid batteries to Li-ion batteries. Reason being is Lead acid batteries have high self-discharge, short operating life, low power density, low energy density etc. Even still Li-ion batteries suffers from the disadvantage of performance degradation, low reliability due to ageing process and low thermal stability [7]. So, the primary focus in the design of batteries is to minimize power loss, capacity loss and to extend the life of battery.

To achieve long operating life & optimized performance require the in-depth knowledge about the state of health (SOH) and state of charge (SOC). There are two main losses are observed in Li-ion batteries. They are power fade and capacity fade. Power fade is due to uneven growth of internal resistance in the battery. And capacity fade is due to the adverse variation in the temperature, repeated usage over time. This capacity fade estimation provides information about vehicle range. As the fade or the loss increases, the range of electric vehicle decreases. This fade management is challenging aspect in battery management system [1].

Conventional methods of estimating battery capacity are inaccurate and most methods work only for specific temperature, charge-discharge profile etc. So, such methods are highly undesirable.

There are various estimation models available in the literature. Most of them either inaccurate or impractical for real time vehicle scenarios [4]. Other methods depend on so called ageing models. These ageing tests will take years to complete the estimation [5] and they are not suitable for dynamic applications. However, direct estimation of capacity is very difficult.

The electrical behavior of Li-ion batteries is modeled using equivalent diagrams [6]. Typically, capacitor or voltage source is used to represent OCV. Battery internal resistance is represented by a resistor and Battery different chemical effects such as diffusion, double layer are represented by R-C pairs. Increasing the R-C pairs, increases the complexity but the accuracy of the results increases. These electrical parameters experience a change with SOC, SOH and temperature

2. LI-ION BATTERY EQUIVALENT CIRCUIT MODEL

Equivalent circuits are the theoretical circuits which are most commonly used in different types of batteries. In this paper, a second order equivalent circuit model is used. This Equivalent circuit model (ECM) is used to describe the electrical behavior the LI-ion battery.

The second order ECM gives more accurate results compared to first order ECM. The order of the model can be found by hybrid pulse power characterization test (HPPC) [3].The circuit diagram of the second order ECM is as shown in Fig. 1. The two-RC-pair ECM captures two main chemical process. The R1-C1 pair account for double layer effect and R2-C2 account for diffusion effect. In Fig. 1, Voc is the open circuit voltage (OCV). And it defined as the voltage difference between the two terminals of a battery in the absence of load connection. Vt is the terminal voltage is the voltage resulted from the OCV and drop across total impedance of the circuit. V1 is the voltage drop across R1-C1 pair and V2 is the voltage drop across the R2-C2 pair.

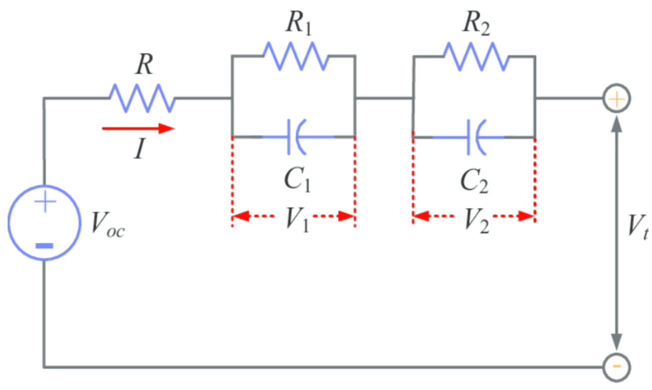

Fig -1: The equivalent circuit diagram of Li-ion battery

SOH is a figure of merit condition of a battery compared to its ideal conditions. Capacity fade is the loss in the capacity of the battery. And capacity is the number of charges a battery can deliver at the rated voltage. But SOC is the ratio of remaining charges in the battery to the nominal capacity of the battery. With decrease in capacity, battery stores less charge at the same SOC level and it is known that SOC is a monotonic function of OCV, i.e. SOC neither increases nor decreases completely with variation in OCV but varies monotonically with OCV. And the old battery has fewer remaining charges compared to a new battery. This implied that with less capacity, terminal voltage of a battery increases faster at the same SOC level. This information further implied that battery capacity correlates with change of OCV divided by charge accumulation, i.e. $\Delta Voc/\Delta Q$,

where

$$\Delta Q = \int_{t=t0}^{t=tf} I(t)dt$$

This fact is used further to develop capacity estimation algorithm.

By applying KVL to ECM, we get battery terminal voltage as

$Vt(k) = Voc(k) + I(k)R + V1(k) + V2(k)$ (1)

3. ESTIMATION OF CAPACITY

3.1Driving Mode

Battery enters into driving mode when the vehicle is moving and battery is discharging. In this mode battery current varies as the power requirement for the vehicle changes. So, battery current is taken as one the input to the system. As the discharging current varies offers rich signal excitation to estimate battery capacity.

We have equations in discrete time domain, given by

$$\begin{bmatrix} V1(k) \\ V2(k) \end{bmatrix} = A \begin{bmatrix} V1(k-1) \\ V2(k-1) \end{bmatrix} + B\, I\,(k\text{-}1)$$

$$Vt(k) - Voc(k) = C \begin{bmatrix} V1(k) \\ V2(k) \end{bmatrix} + D\, I\,(k) \quad (2)$$

where $A = \mathrm{diag}\,(a_1, a_2)$, $B = [b_1\ b_2]^T$, $C = [1\ 1]$ and

$D = R$, and

$$a_1 = \exp\,[-\Delta t/(R_1 C_1)]$$
$$b_1 = R_1\,[1-(\exp -\Delta t/(R_1\, C_1))]$$
$$a_2 = \exp\,[-\Delta t/(R_2\, C_2)]$$
$$b_2 = R_2\,[1-\exp(-\Delta t/(R_2 C_2))] \quad (3)$$

Where Δt is the sampling period. The equations (2) & (3) shows that Voc is not a constant but varying signal. So, to capture variation of OCV, it is no more modeled as constant. The transfer function can be written as follows

$$Vt(Z) - Voc(Z) = C(Z\,I - A)^{-1} + D\, I\,(Z)$$

$$= \left(\frac{b1(z-a2)+b2(z-a1)}{(z-a1)(z-a2)} + R\right) I(Z) \quad (4)$$

Where I is the identity 2×2 matrix.

After Z-transformation the above equation becomes as

$Vt(k) = (a1 + a2)Vt(k-1) - a1a2Vt(k-2) + R^*I(k) + [b1+b2-(a1 + a2)R]^*I(k-1) + (a1a2R-b1a2 - b2a1\ I(k-2) + Voc(k)-(a1 + a2)^*Voc(k-1)+a1a2Voc(k-2)$ (5)

As per coulomb counting method, the definition of battery capacity can be modified as

$C = \Delta Q/\Delta SOC$ (6)

Where C is battery capacity in AH, ΔQ is total charge accumulation over the period and ΔSOC is the change in SOC

Further the equation (6) can be modified by substituting ΔQ as

$$\Delta Q = \Delta Voc/h$$

And Equation (6) changes to $C = \Delta Voc/(\Delta SOC * h)$ (7)

It can be observed from (7) that the battery capacity C is inversely proportional to h and change in SOC and also directly proportional to change in OCV.

The ratio $\Delta Voc/\Delta SOC$ defines the slope of the curve OCV versus SOC. This OCV versus SOC curve can be obtained via experiments. A lookup table having the values of $\Delta Voc/\Delta SOC$ is established. And the new parameter h is calculated as follows.

As h depends on change in OCV which is given by

$$\Delta Voc(k) = Voc(k) - Voc(k-1)$$

Similarly, terminal voltage equation changes to

$\Delta Vt(k) = Vt(k) - Vt(k-1)$

Further (5) changes to

$\Delta Vt(k) = (a1 + a2)\ \Delta Vt(k-1) - a1a2\Delta Vt(k-2) + R\Delta I(k)$

$+(b1+b2-(a1+a2)R)\Delta I(k-1)+(a1a2R-a2b1-a1b2)$

$*\Delta I(k-2) + \Delta Voc(k) - (a1 + a2)\Delta Voc(k-1) + (a1a2)$

$*\Delta Voc\ (k-2)$ (8)

And new parameter changes to

h = $\Delta Voc(k)/\Delta Q(k) = \Delta Voc(k)/(I(k-1)\Delta t)$ (9)

Substituting equation (9) in equation (8), we get

$\Delta Vt(k) = [1 - (a1+a2) + a1*a2]*h*I(k-1)*\Delta t$

$+ (a1+a2)*\Delta Vt(k-1) - a1*a2\Delta Vt(k-2) + R*\Delta I(k) + [b1+b2$

$- (a1+a2)*R + (a1+a2-a1a2)h\Delta t]\Delta I(k-1) + (a1a2R - a2b1$

$- a1b2 - a1a2h\Delta t)\ \Delta I(k-2)$ (10)

The above equation can be written in simplified form as

$\Delta Vt(k) = \theta^T\phi(k)$ (11)

Where $\phi(k) = [I(k-1)\ \Delta t, \Delta Vt(k-1), \Delta Vt(k-2),$

$\Delta I(k), \Delta I(k-1), \Delta I(k-2)]^T$ (12)

$\Delta I(k) = I(k) - I(k-1)$ & $\theta = [\theta1, \theta2, \dots, \theta6]^T$

But the elements of θ are as follows

$\theta1 = [1 - (a1+a2) + a1*a2]h$

$\theta2 = a1+a2$

$\theta3 = -a1*a2$

$\theta4 = R$

$\theta5 = b1 + b2 - (a1+a2)R + [(a1+a2) - a1*a2]h\Delta t$

$\theta6 = a1*a2*R - a2*b1 - a1*b2 - a1*a2*h\Delta t$ (13)

From equation (13) h can be inferred as

$h = \theta_1 / (1 - \theta_2 - \theta_3)$

Now the task is to find θ and in turn h from the measured terminal voltage and battery current to estimate battery capacity.

Recursive least square (RLS) algorithms are robust algorithms which are successfully applied in many industries. Here, we have used U-D RLS algorithm [7]. The objective this RLS algorithm is to modify or correct previous estimate with some correlation. It will just provide next preceding estimate. This method is successfully applied in many industries due to computational efficiency, high estimation accuracy, stability and robustness.

In the U-D RLS algorithm P is defined as the Positive definite covariance matrix, $P = UDU^T$, where U is the upper triangular matrix in which upper triangular elements should be greater than zero and D is the diagonal matrix where diagonal elements are equal to one. The elements P are needs to be updated through the multiplication of U & D matrices.

This algorithm uses only measured terminal voltage, battery current and previous estimate of θ. The parameter θ vary with the small operation change. So, as to compensate this forgetting factor λ *is* introduced.

The one stage algorithm has the following steps

Step 1:

Read current $I(k)$ and voltage $V(k)$ where k = 1,2.

Initialize Nonvolatile memory (NVM) with the previous estimate of θ and set initial value for forgetting factor such that $0 < \lambda \leq 1$.

Step 2:

Update $\phi(k)$, using the input values.

where $\phi(k) = [I(k-1)\Delta t, \Delta V(k-1), \Delta V(k-2), \Delta I(k), \Delta I(k-1), \Delta I(k-2)]$T

Step 3:

Introduce two new vectors k and l as

$k = [k_1,\dots,k_n]^T = [U(k-1)]^T*[\phi(k)]$

$l = [l_1,\dots,l_n]^T = [D(k-1)]*k$

and initialize $\alpha 0 = \lambda$.

Step 4:

For $j = 1,2, \dots, 6$, follow Step 4.1-4.2

Step 4.1: Compute the following:

$\alpha_j = \alpha_{j-1} + f_j g_j$

$D(k)_{jj} = (\alpha_{j-1} D(k-1)_{jj})/(\alpha_j \lambda)$

$b_j = l_j$

$c_j = -k_j / \alpha_{j-1}$

Step 4.2: For $i = 1,2, \dots, j-1$, go to Step 4.2.1 (if j=1, skip Step 4.2.1).

Step 4.2.1: Calculate the following:

$U(k)_{ij} = U(k-1)_{ij} + b_i c_j$

$b_i = b_i + U(k-1)_{ij}\, b_j$

Step 5:

Compute G(k) = $[b_1,\ldots,b_n]'/\alpha_n$.

Step 6:

Compute the error estimation as

$\epsilon(k)= \Delta V\mathrm{t}(k) - \theta^{\mathrm{T}}(k-1)*\phi((k)$

Step 7:

Update θ to minimize the estimation error ϵ by

$\theta(k) = \theta(k-1) + L(k)*\ \epsilon(k)$.

Step 8:

Compute the parameter h

where $h = \theta_1 / (1 - \theta_2 - \theta_3)$

Step 9:

Now evaluate capacity C $= \Delta Voc/(\Delta SOC * h)$.

Step 10:

Determine the capacity estimate validity If it is valid, save θ to NVM for next operation. Otherwise, save only $V(k)$ and $I(k)$ for next operation and Go to Step 2 and continue the algorithm.

3.2 Charging mode

Battery enters into charging mode when vehicle needs charging. In this mode current remains constant throughout period and can be considered as DC current. In this mode RLS algorithm cannot be used because there is a lack of signal excitation for parameter convergence.

The voltage across R1-C1 is V1 and voltage across R2-C2 is V2, these RC pairs saturate after initial period in charging mode and the voltages V1(k) and V2(k) are neglected. And the equation (1) modified as follows

$Voc(k) = V\mathrm{t}(k) - I(k)*R$

The battery capacity in the charging mode is calculated as follows

$$\mathrm{C(k)}=\left(\sum_{i=1}^{k-1} \mathrm{I(i)}\right)/(\mathrm{SOC(k)} - \mathrm{SOC(1)})\ \Delta t$$

Where SOC(k) is the SOC at the k th iteration

SOC(1) is the previous SOC

3.3 Combined charging and driving mode

In this mode both charging and driving mode are combined. Here the definition of number of cycles plays a very important role. It is defined as the one complete charge and one complete discharge. Cycle definition varies with the requirement and may not be the same as defined above.

4. ESTIMATION OF CAPACITY FADE

The loss in the capacity is due to various factors such as temperature variation, repeated usage over time and due to formation of solid electrolyte interface (SEI). Such a capacity fade estimation is challenging. Here we have estimated capacity fade by the following formula

Capacity fade = Cnominal-C(k)

Where Cnominal is the nominal capacity given by the manufacturer in the datasheet.

4.1 Estimation of SOH

SOH is an index which measure the health condition of a battery. It represents the health status of the battery. It is estimated by the following formula

SOH=1 – capacity fade/(Cnominal-Ceol)

Where Ceol is the capacity at the end of life

i.e. Ceol=0.8Cnominal.

5. RESULTS AND DISCUSSION

In this paper, MATLAB/Simulink software used to simulate the circuit. Fig.2 shows the complete simulation of the proposed system.

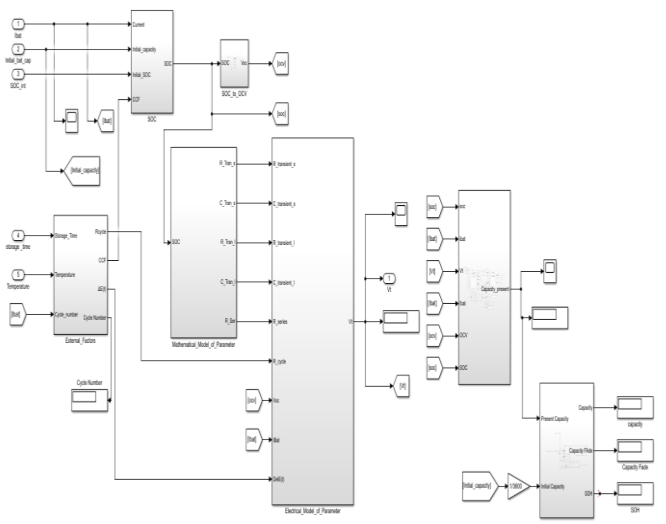

Fig -2: Overall proposed system model.

Here, input the system such as SOC, Ibat, Vt and OCV is given from the 1st model and the 2nd model forms the main part of the proposed system which estimates capacity, capacity fade and SOH.

Fig-3 shows the input to the proposed system. Reader can refer [2] for the complete detailed analysis of the input system. This 1stmodel provides inputs such as Ibat, Vt, SOC and OCV.

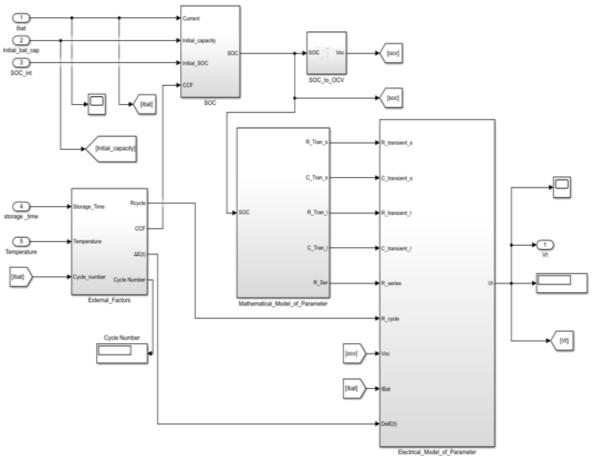

Fig -3: 1st model (input model)

Fig.4 shows the 2nd model which gives detailed information about the proposed system [1]. This model includes all capacity estimation algorithm, capacity fade and SOH.

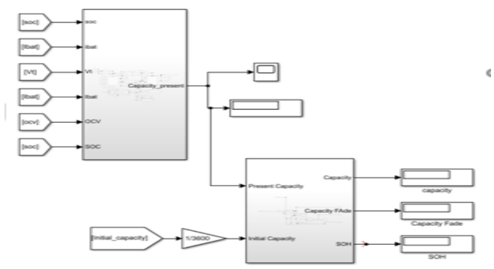

Fig - 4 2nd model (output model)

Fig.5 shows the Simulink model of capacity estimation algorithm for driving mode. Algorithm is implemented in Simulink scope but not in programming scope.

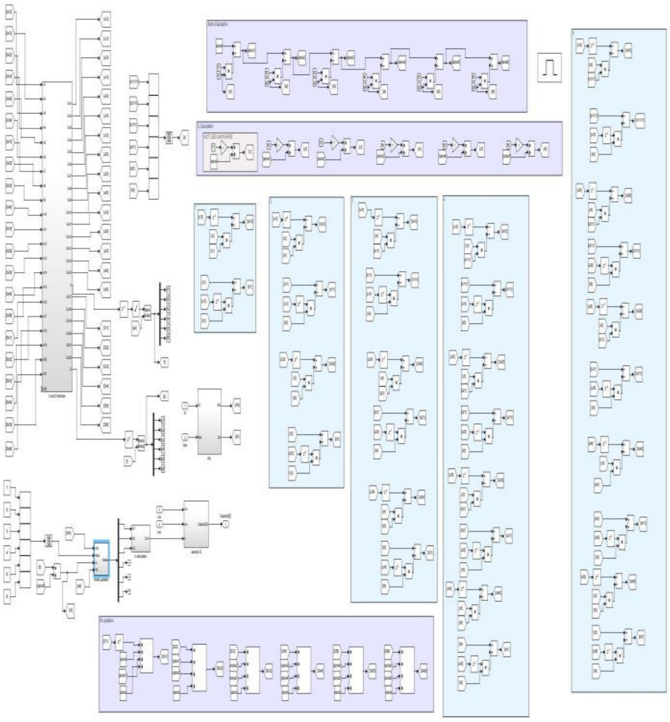

Fig-5 Driving mode capacity estimation algorithm implementation in simulink.

Fig.6 shows the Simulink model of combined capacity estimation algorithm. This figure shows the merging of both driving mode and charging mode.

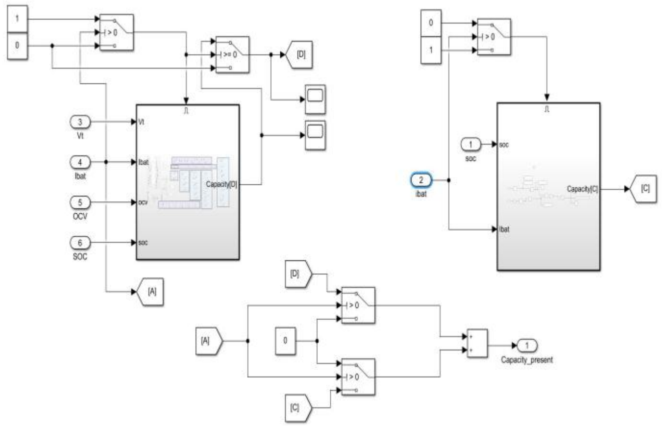

Fig – 6 combined driving and charging mode.

Fig.7 shows the simulation result of capacity, capacity fade and SOH for the input of 850mAh, 298k,0.8A pulse current for 50% duty ratio for 4505 cycles. We found that capacity faded from 850mAh to 722mAh and SOH reduced to 84.97%.

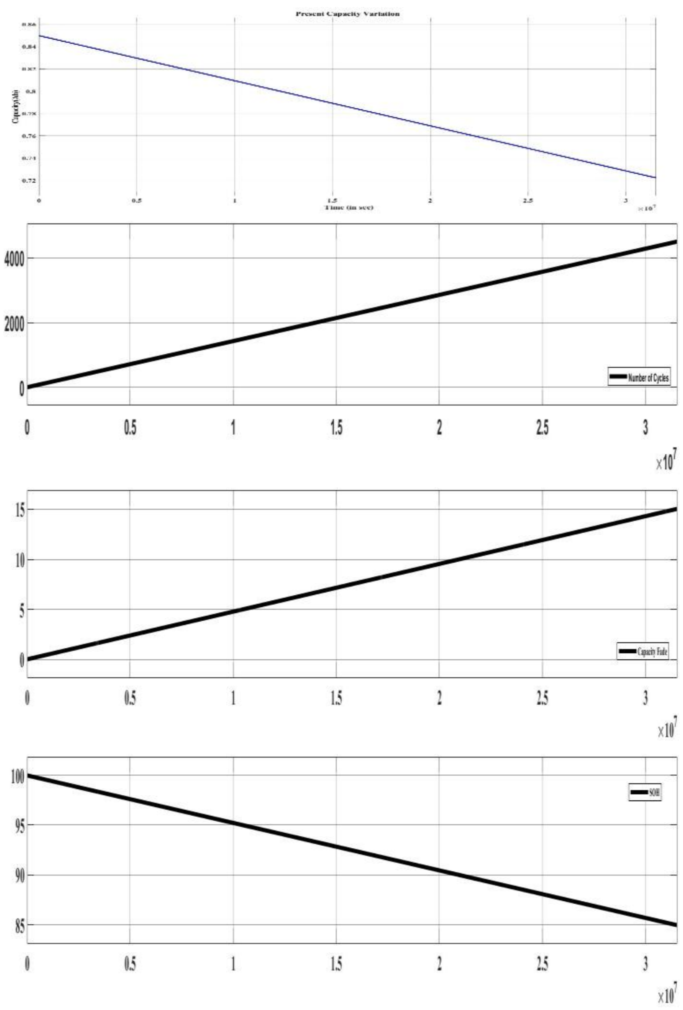

Fig-7 Simulation results of capacity, capacity fade and SOH

6. CONCLUSION

The proposed system estimates SOH, capacity fade and SOH considering the significant effects of temperature and charge-discharge profile. Onboard algorithm developed for both driving and charge mode and the developed algorithm are simulated in MATLAB/Simulink and the results show that developed model can be applied in real time vehicle operation.

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