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Estimation of Internal Resistance of Lithium Ion Battery

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***Abstract** - Due to environmental pollution and fossil fuel declination, internal combustion engine vehicles are slowly going down. Electric vehicle is now gaining popularity in personal and public transportation because of its' zero emission of toxic gases. Battery pack is used to provide power to electric vehicle. To monitor the health of battery cells internal resistance calculation is essential. It provides not only the health information of the battery but also used for SoC and SoH calculation. To calculate the available power at the battery terminal we need accurate value of the internal resistance. Internal resistance can be found by calculating the ratio of change in voltage and change in current. This type of internal resistance calculation produces high inaccuracy. So in this research we have utilized moving average method to calculate the internal resistance of a lithium ion cell which provides good accuracy and reliable value..*

Keywords – Battery equivalent circuit model, OCV, SOC, SOH, SOP

I. INTRODUCTION

In recent years declination of conventional fuels and increasing pollution will lead the automotive industries to reduce the use of conventional fuel vehicles and to give more importance on implementation and use of electrical vehicles for transportation. Electric vehicles uses electricity as a source of power for acceleration as well as auxiliary components which does not emits the pollutant gasses like conventional fuel vehicles. Battery packs are the main power house of electrical vehicles, which consists of number of cells connected together to form a battery pack. because of their advantages like high specific energy density, high energy density and more cyclic life, lithium-ion batteries are most commonly used for power storage in electric vehicles.

The Battery management system (BMS) is one of the most important core component of such vehicles, which ensures a safe, reliable and efficient operation of battery pack. The main function of BMS is state estimation, state monitoring, thermal management of battery and balancing of battery. Accurate estimation of various battery states like SOC (state of charge), SOP (state of power) and SOH (state of health) is most important in battery management to guarantee the high efficient working of battery.

Ageing level of battery can be described by SOH. As the battery ages, the internal resistance of the battery increases. Due to the increase in internal resistance the available power at the terminal of the battery decreases. So for safe and reliable operation of battery, monitoring the internal resistance becomes a very important task for the BMS. In recent days there are many research going on to estimate in internal resistance like kalman filter technique, neural network and fuzzy logic, this techniques needs large memory allocation and computational time.in this research we are estimating the internal resistance by moving average method and we are estimating SOH based on the resistance estimation.

A.Internal Resistance Estimation

1) Battery model:

There are different battery models which are classified in to five categories namely empirical model (EM), Electro Chemical Model (ECM), Electrical Equivalent Circuit Model (EECM), Electro Chemical Impedance Model (ECIM) and Data Driven Model (DDM). Because of its low complexity and computational requirements and high compatibility for embedded system applications equivalent electric circuit model is best suited for SOH estimation.

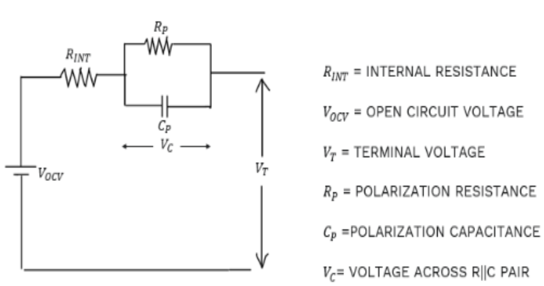

Fig 1. Electrical Equivalent Circuit Model (EECM)

2) Resistance Estimation:

From equivalent circuit model fig 1, the terminal voltage equation can be written as,

$V_T = V_{OCV} - i\,R_O - V_{C1} - V_{C2}$......................................1

As it is seen from the equation terminal voltage of the battery depends on OCV and the voltage drop across the internal resistance and each RC pair branches. As the number of RC branches increases, the model behaves exactly like a battery. But that will increase algorithm complexity. For simplicity we will use 2 RC pair and validate our result.

Internal resistance of battery has a huge effect on terminal voltage. We can estimate the battery resistance by considering the The ratio of change in voltage and change in current.

From equation 1 we can write,

$\Delta V_T = \Delta V_{OCV} - \Delta i\,R_O - \Delta V_{C1} - \Delta V_{C2}$.....................2

Where, ΔV_T= change in terminal voltage

ΔV_{OCV}= change in open circuit voltage

Δi = change in current

ΔV_{C1},ΔV_{C2} = change in polarization branch voltage

In battery management system ECUs are used for monitoring the battery pack. The internal resistance algorithm is used inside the ECU which takes inputs from the battery by sampling. The sampling time of the ECU is 100ms. During this time interval OCV will not change. Hence ΔV_{OCV} can be neglected. This does not affect the change in terminal voltage equation. RC pair in the circuit model represents the polarization effect of the battery, The time constants for the RC pair of the battery is very high, Sampling time of the ECU is too small when compared to the RC pair time constant. So the voltage across the RC pairs do not change during the sampling time So we can neglect the voltage drop across RC pairs After all this assumption the change in terminal voltage equation is written as,

$\Delta V_T = \Delta i . R_O$...3

Here for discharging case, current is taken +ve and for charging case current is –ve. As it can be seen from equation 3 the internal resistance simply becomes R0= $\Delta V_T / \Delta i$. Using this formula the internal resistance value is calculated.

If we see closely the resistance value depends on the change in current value. If Δi is small then from the equation it is noted that the resistance value becomes large which is not the true value. Error in that case will be too much. Similarly if the Δi is large then it will produce true value of the resistance. In[5] they have shown that for change in current equal to C/3 where C is the rated capacity of the battery the noise in that resistance measurement is large. But when the change in current is equal to 1C then the value of the resistance is accurate. So to reduce the noise we need to filter the values. This can be done by using a moving average filter.

The proposed block diagram of Estimation of state of health of battery by internal resistance estimation is shown in bellow figure.

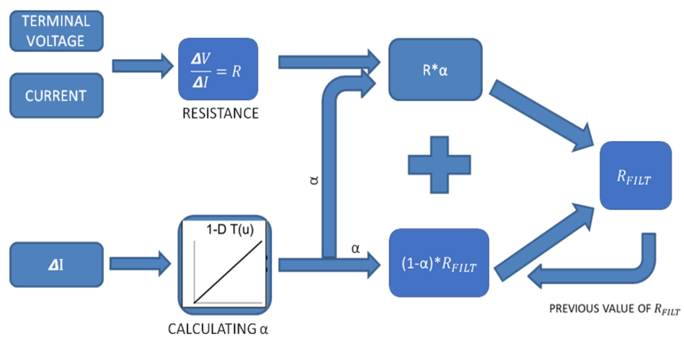

Fig 2.proposed block diagram

II. MOVING AVERAGE METHOD

To reduce the noise produced in the estimation moving average filtering method is used in this article. The basic equation of the moving average is,

$$X_{Filt_K} = X_{Filt_{K-1}}(1-\alpha) + X_K.\alpha$$

where ,

α = filter coefficient ,

X_{Filt_K}= filtered value at time instant k ,

$X_{Filt_{K-1}}$ = filtered value at time instant k-1 or previous value of X_{Filt_K}

X_K = measurement value at the time instant k.

The value of α depends on the change in current a small change in current can produce large noise in the measurement to reduce that noise we can give less weightage to the measurement value and higher weightage to previous filtered value. Similarly for large current variation like 1C we can give higher weightage to the measurement value and less weightage to the previous filtered value.

Generally the limit for the α is 1 i.e the α varies from 0 to 1. Now to determine the α value we first need to determine the maximum and minimum current variations limit. Above the maximum current variation, α value will be 1 and for below minimum current variation α value will be 0. For any current variation which is within the current variation limit α value will be between 0 to 1.The change in α value is almost linear. From minimum current variation to maximum current variation, α value will increase linearly as is in figure 3.

To calculate the internal resistance this method requires an initial value due to the use of previous filtered value in the equation $X_{Filt_{K-1}}$. This value can be set by initial measurement of internal resistance or we can set the value as per the specification of the battery. This will influence the result depending upon the α used.

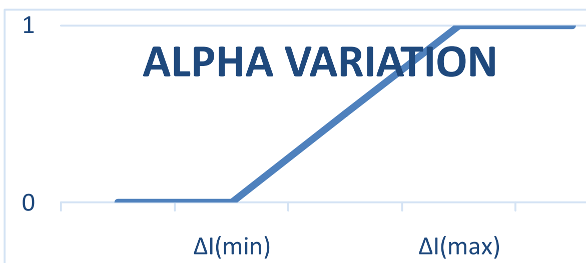

Fig 3. ALPHA variation

III. RESULTS

Results are validated using battery ECM model and MATLAB software; we need battery parameters and OCV data to get exact battery behaviour. In ref [6] NCR18650PF battery produced by Panasonic Company with a capacity of 2750 mAh and nominal voltage of 3.6 volts is considered as the test battery.

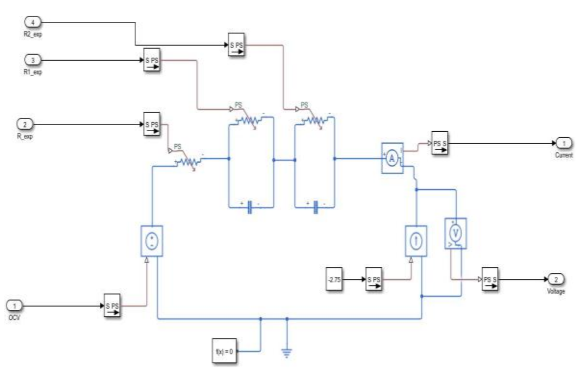

Fig.4 Test system

Equations for the OCV and for the various parameters are as follows

$$V_{OCV} = -0.2564.SOC^5 - 0.2185.SOC^4 + 1.816.SOC^3 - 1.715.SOC^2 + 1.244.SOC + 3.303$$

Open circuit voltage of a battery depends on SOC and temperature. Dependency on the temperature has a minimal effect on open circuit voltage. So temperature effect has been neglected. Open circuit voltage cannot be found directly. It is found only by doing experiments on the battery. Below figure 5 shows the variation of OCV with respect to SOC.

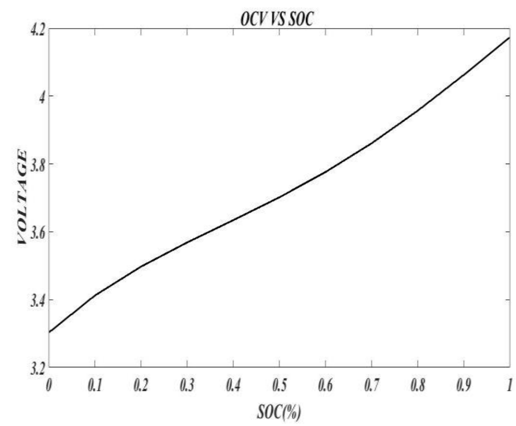

Fig.5 Variation of OCV

2 RC pair is used in the battery model. The values of polarization resistances and internal resistance for various SoC values are as follows

Table 1: Internal resistance values of numerous SOC

SOC(%)	R_0(mΩ)	R_{P1}(mΩ)	R_{P2}(mΩ)
90	33.76	14.10	9.47
80	31.69	17.88	12.78
70	31.00	16.34	9.21
60	30.45	15.21	7.25
50	30.36	13.49	8.29
40	30.69	12.52	12.69
30	31.75	12.39	13.72
20	34.46	13.30	8.82
10	47.36	18.13	15.78
0	88.93	20.12	34.39

Using the above data MATLAB simscape model is developed which behaves exactly like the NCR18650PF battery. But in the lower SoC region it produces error as stated in the literature. So the lower SoC region of the battery is avoided while using our algorithm. So we can use our algorithm to check the variation of internal resistance with SoC. Here the capacitance value of the RC pairs are kept constant at 17111 F. Also the experiments are done at room temperature (25°C). So this is valid for only on that temperature.

Internal resistance does not depend only on SOC of the battery but also depends on the temperature. In [12] they have showed how the resistance is changing with temperature. We will incorporate the change of internal resistance due to temperature in our model also. Generally as the temperature decreases resistance increases and as the temperature increases the resistance decreases. Taking all those variables in consideration we have made the simscape model in MATLAB.

Fig.5 shows the battery model of the NCR18650PF battery. Here SOC is calculated using coulomb counting. Then this SOC value is used to calculate OCV and resistance values.

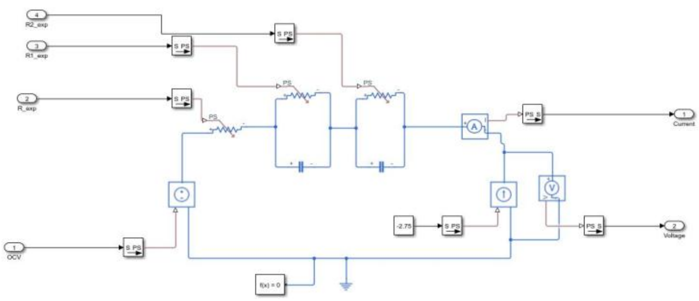

Fig.6 Battery model of NCR18650PF

The output voltage from this battery model for constant current of 2.75A is shown below

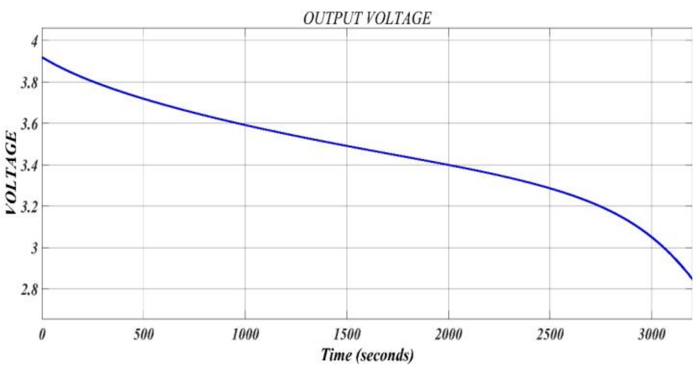

Fig.7 SOC curve

A. CASE STUDY:-

Two cases have been analysed for validation of the proposed algorithm which all detailed in this chapter.

1) Case 1:

In the first case study we will be calculating error in the measurement of the internal resistance when battery is discharged with constant current of 1C or 2.75A with a resting time of 10 minute. Here the temperature is kept constant at 25°C. Constant current is provided to the battery for 1 minute which gives the duty ratio of 9.09%. Current and corresponding voltage values are collected and their waveforms are shown in fig 8 and 9. True value of the resistance is calculated from table 1. The error in the estimation is also shown in the figure 10.

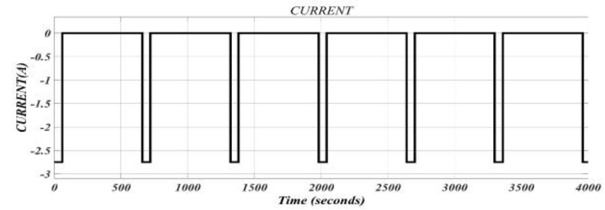

Fig.8 Current values

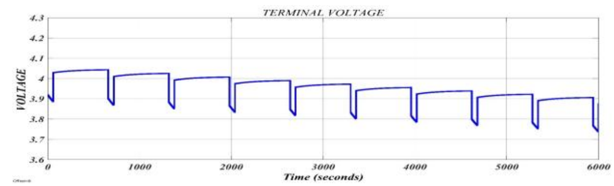

Fig.9 Voltage values

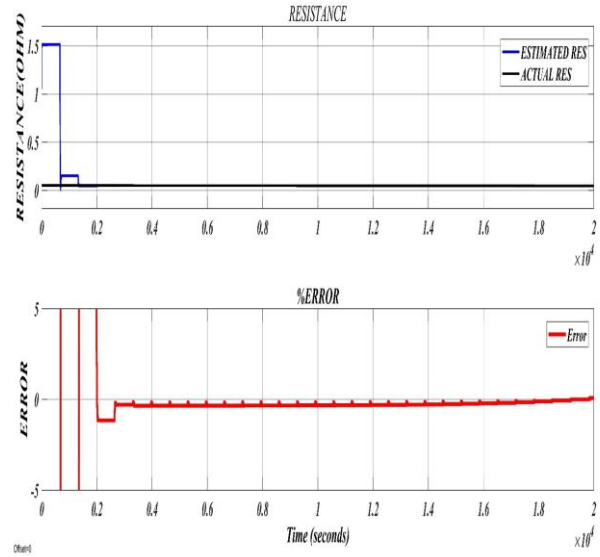

Fig.10 Estimation of error

As it is seen from the result that the algorithm can detect the resistance accurately. But it requires some time to converge in case of constant current discharge pulse. Also the error limit is within ±5% which shows that the algorithm as a good accuracy. As our battery model provides wrong data during the lower SoC level, the error value slightly increases in that region. Although it does not violate the ±5% limit.

2) Case 2:

In this case a battery test current which provided by the Centre for Advanced Life Cycle Engineering (CALCE) battery group has been utilized. Here the battery temperature is also varying with time. Current profile and voltage profile of the battery are shown in fig 11 and 12. The temperature variation and the % error in resistance estimation are shown in the figure 13 and 14 respectively.

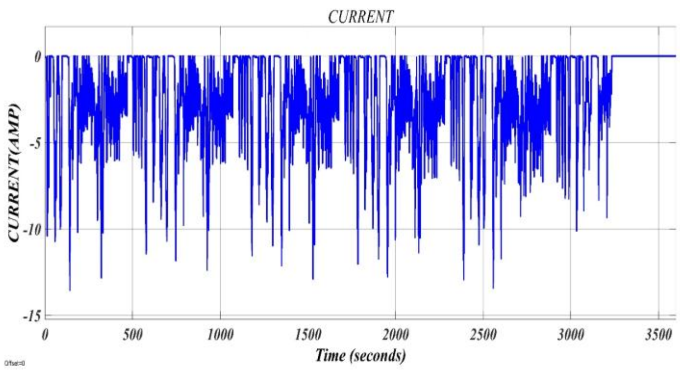

Fig.11 Current profile

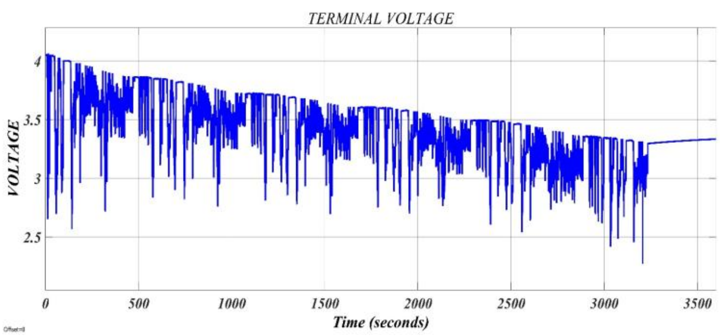

Fig.12 Voltage profile

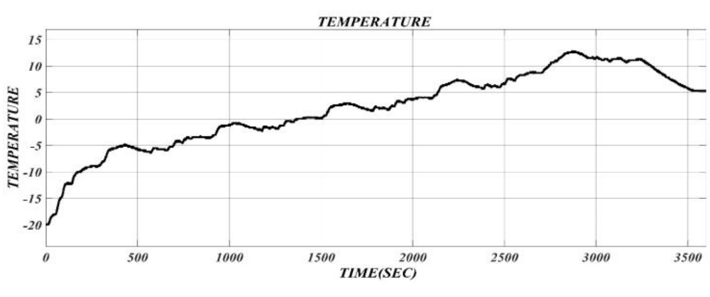

Fig.13 Variation of temperature

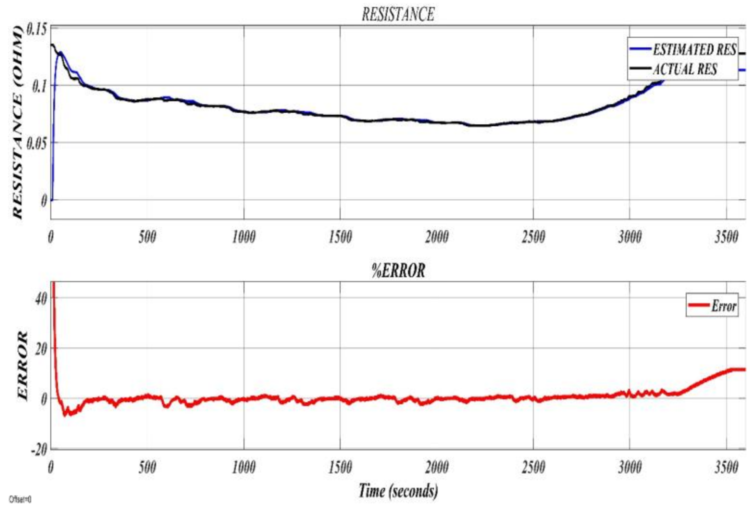

Fig.14 Percentage error estimation in resistance

As it is seen from the above graphs, our algorithm works accurately. Initially it requires some time to converge. Convergence time in this case is lower than the previous case. Although the error in the lowest part of SOC is increased significantly from the previous case which is due to the error in the battery model.

IV. CONCLUSION AND FUTURE SCOPE

In the research we have used 2 RC pair model for internal resistance estimation of lithium ion battery which produces exact battery behaviour. As it is noticed from the previous project outcomes, the moving average method to find the internal resistance of the battery works perfectly for various current and temperature data. In both the cases initial error is high. But after convergence it produces less than ±5% error which is acceptable. Although it is working perfectly it has some limitation. This method cannot be used for constant current charge or discharge case. In that case change in current will be zero which will produce wrong internal resistance data. This method provides a simple but effective way to estimate the battery internal resistance which can be used to calculate State of Health (SoH) or State of Power (SoP) of a battery. As this method needs a significant current variation, it can be used in the mild hybrid vehicle where current variations are rapid.

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