Identification of Li-ion Battery Parameters Using Neural Networks

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Abstract

There is an increase in the demand for Li-ion batteries particularly in Electric Vehicles (EVs). Identifying the Li-ion battery parameters will help in estimating the state of charge (SOC) accurately. In this paper, Li-ion battery is represented with one RC equivalent circuit. The charging/discharging behaviour of the generic battery in MATLAB-SIMULINK is used to get the relation between open circuit voltage and SOC. The circuit parameters are determined using neural network. The performance of the identified parameters is verified with the generic battery in MATLAB.

Index Terms

Battery parameters, neural network, one RC circuit, state of charge

I. Introduction

Battery is energy storing device through chemical processes. The demand of batteries is increasing due to several factors. The shift of automobiles towards electric vehicles, rising price of fossil fuels, global push for renewable energy and recent research and development in field of battery technologies are major factors for increasing demand of batteries.

Li-ion battery is gaining popularity over other types of batteries in recent times due to their high energy density, lower self-discharge rate, and longer life span. [1] Li-ion batteries are used in aerospace [2], power grids [3], Electric vehicles [4] and many more.

There are various forms of battery models out of which in electrical models the open circuit voltage and state of charge curve is utilized to determine the equivalent circuit parameters. Estimating battery parameters is crucial for the battery management system. Battery can be damaged due to overheating [5], overcharging or over discharging [6]. The battery health will degrade with ageing this is due to the frequent charging/discharging. State of Health [7] can be identified using internal resistance and capacitance. Internal resistance helps in identifying safety hazard like overheating whereas capacitance helps in identifying charge and discharge rate of the batteries.

For an accurate SOC estimation, the battery parameters need to be identified.. There are several methods for estimating battery parameters like least squares technique [8], Kalman Filter [9] and many more. In this paper, one RC equivalent circuit is considered and the circuit parameters are identified using Neural Network which helps in solving complex and non-linear model, and predicting various parameters with high accuracy. Pulse test is performed on the generic battery model and the discharging pattern is utilized to get the V_{oc}-SOC relation. An effort is made to find the best fit circuit parameters with minimum error between the actual voltage and estimated voltage. The main contribution in this work is that the time-domain expression is used to verify the circuit parameters generated by Neural network model. This will enhance the battery terminal voltage close to the actual voltage.

II. Battery modelling

Battery modelling is complex because of nonlinear, dynamic [10], temperature-dependent [11], and aging-related behaviour of batteries [12]. The correlation between the State of Charge (SOC) and the Open Circuit Voltage (OCV) is crucial for understanding and monitoring battery performance. The SOC-OCV relationship in Li-ion batteries is nonlinear [13]. There are different types of battery models depending upon their needs like the first-order RC model, the second-order RC model [14], the Rint Model [15], Dual Polarization model, the hysteresis model [16] and many more. In this paper, the Li-ion battery is represented with first-order RC model which is shown below. It contains a voltage source (E), Ohmic resistance (R_o), polarization resistance (R_1), polarization capacitance (C_1), terminal voltage (V) and load current(I). The generic battery model in MATLAB-SIMULINK is used to get the charging and discharging profiles. The battery specifications are nominal voltage is 12 V and nominal capacity is 5 Ahr. Initially the pulse test is carried out to get the charging/discharging profiles. V_{oc}-SOC curve is plotted and is divided into several segments [17]. Each segment is represented as a linear equation (1)

$$V_{oc} = a_i + b_i SOC \tag{1}$$

For each segment curve fitting is used to determine the constants a_i and b_i, here i represents the segment. The curve is divided into 10 segments considering the change of SOC is 10%. The a_i and b_i values are shown in below Table I. SOC is calculated using Coulomb counting method. The open circuit voltage is then calculated using (2).

The data required to train the neural network is generated from the time-domain equation. SOC is used as an input to the Neural network and the This is obtained from the state-space model for the one RC circuit [18].

$$v(t) = I_{ch} R_1 \left(1 - e^{\frac{-t}{R_1 C_1}} \right) + (I_{ch} a_i \eta_i) \frac{t}{C_q} + R_o I_{ch} + b_i \tag{2}$$

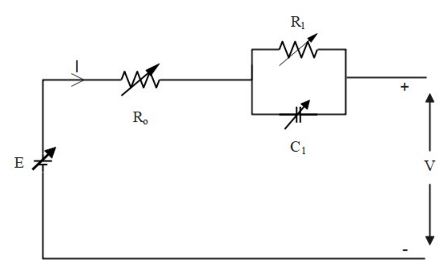
where, I_{ch} is the charging/discharging current, η_i is the Coulombic efficiency of the battery, C_q is the battery capacity

TABLE I
a_i AND b_i VALUES FOR DIFFERENT SEGMENTS

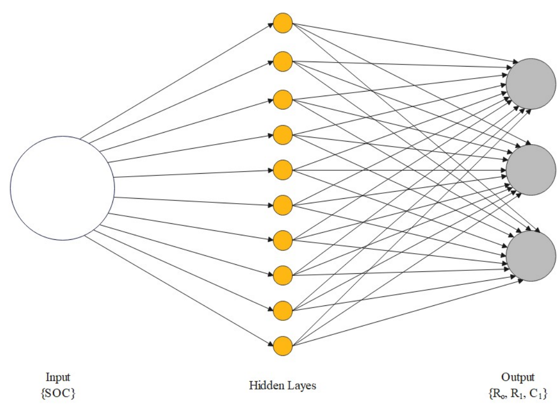
Segment(i)	1	2	3	4	5	6	7	8	9	10
a_i	0.0789	0.0020	0.0024	0.0032	0.0032	0.0067	0.0111	0.0220	0.0644	0.7622
b_i	5.485	12.59	12.53	12.56	12.34	12.17	11.85	5.38	0.0762	5.38

The step by step process opted for the battery parameter identification:

1) Assume that the battery is fully charged, SOC is 100%
2) Perform the pulse test, discharge the battery at 1C-rate for 80s then a resting period of 40s
3) Get the open circuit voltage and SOC
4) Plot V_{oc}-SOC curve and divide into segments (i), obtain the linear relationship and determine a_i and b_i
5) Using time-domain expression get the required data sets for Neural network and train it
6) Use SOC as input and get the best fit for the terminal voltage



(a)



(b)

Fig. 1. (a) Single order RC model of Li-ion batteries (b) Neural Network

III. The Levenberg-Marquardt algorithm (LMA)

This paper employs the Levenberg-Marquardt algorithm. LMA uses hybrid approach between the Gauss-Newton algorithm and the Gradient Descent algorithm. It is an optimization technique. It is extensively utilized for estimating non-linear parameters, including fitting models to data in diverse areas such as machine learning, computer vision, and more. It tends to have better convergence properties for non-linear least squares problems. When close to the minimum, LMA behaves like Gauss-Newton, providing fast convergence. Far from the minimum, it behaves like Gradient Descent, ensuring stability. [19] [20]

$$x_k = -(J^T * J + \lambda * I)^{-1} * J^T * Y \tag{3}$$

where x_k represent search direction, J=Y' denotes the Jacobian, $\lambda > 0$ is a parameter and I is the identity matrix of order n.Y denotes the system of absolute value equations.

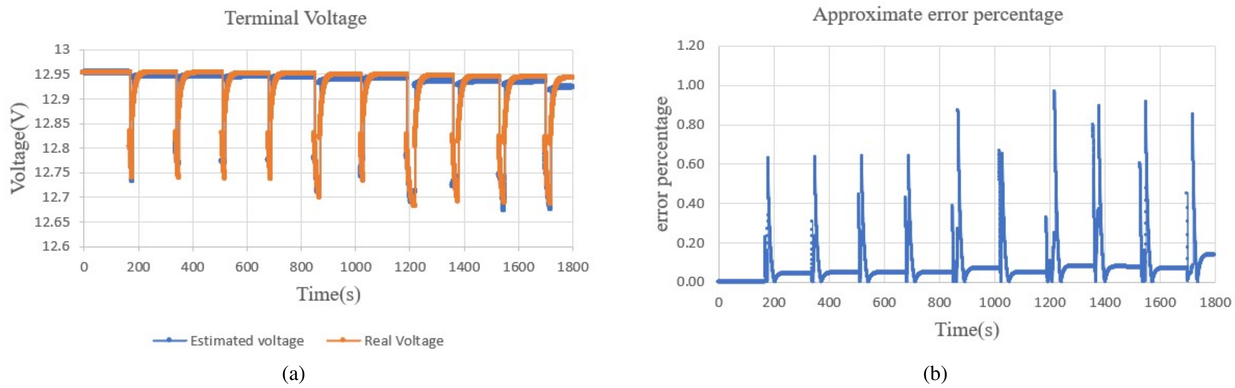


Fig. 2. (a) Terminal Voltage (b) Approximate Error Percentage

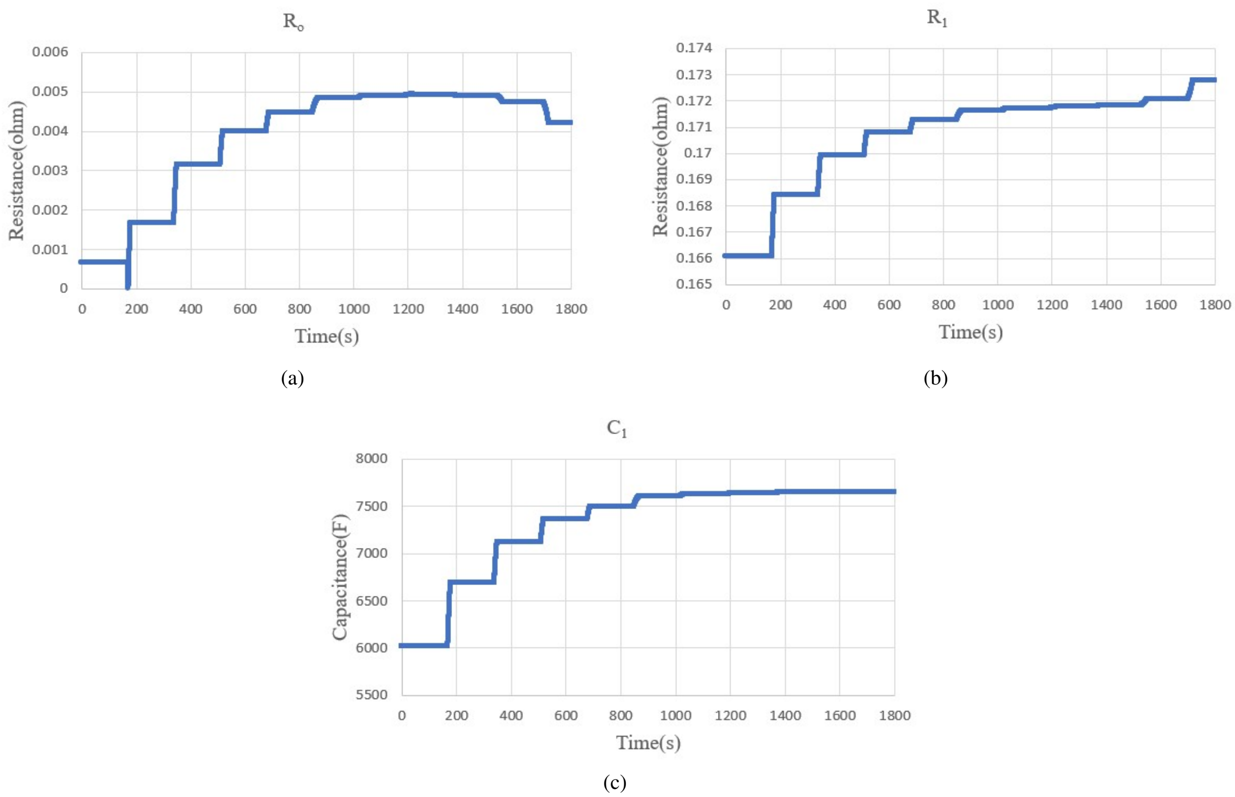


Fig. 3. Variation of (a) R_o (b) R_1 (c) C_1

IV. Simulation Results

The simulation studies are first performed on the generic battery model. The required constants a_i and b_i are obtained from the V_{oc}-SOC relation. Neural network model is trained with the data obtained from the time domain expression. The best fitted results are obtained from the Neural network. The comparison of the generic battery voltage and the equivalent circuit voltage is shown in Fig.2(a). It is observed that the estimated voltage is very close to the actual voltage of the generic battery model. The approximate error percentage is shown in Fig. 3(a). The error lies between 0 to 1% which is acceptable. The variation of R_o, R_1 and C_1 shown in Fig. 3 varies with the amount of charge left in the battery. During the initial period there is a variation in the parameters this is because in the discharging process it has been observed that the battery voltage dips by 1 to 1.5 V. Whereas once the SOC reaches to 95% the battery voltage is steady up to 35% so the battery parameters are also having steady values during this period from 800s to 1000s. The results are shown up to 20% SOC. Beyond this there is a sudden dip in this voltage which is too far from the nominal voltage.

V. Conclusion

In this paper, the battery parameters on single order RC model using neural network are estimated. State-of-charge and the time-domain equation are used to identify the Li-ion battery parameters. The proposed method is verified with the generic battery model available in MATLAB-Simulink. The results shows that the error between real and estimated voltage lies between 0 to 1%. The root mean square error (RMSE) of the model is 0.0184. Therefore, the Li-ion battery can be represented as one RC circuit whose dynamics are close to the generic battery model. The method can be implemented on real-time. However, this paper does not take account of temperature while calculating the parameter.

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