Estimation of Equivalent Circuit Model Parameters for a Generic Battery Using Least-Square Method

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Abstract— **A generic battery represents a generalized battery model. This battery does not use the parameters of the battery, and only works with the maximum charging point, breakpoint, and nominal point. In this paper, two widely used electrical equivalent circuit models (ECMs), i.e., 1-RC and 2-RC are constructed to represent the generic battery model to analyze battery characteristics easily. So, ECM can be used as a generalized battery model, and it is the widely used modeling technique for State-of-Charge (SOC), State-of-Health (SOH) estimation, etc. of the battery. ECM and generic battery models are charged/discharged using the same current profile. The parameters of the ECM are estimated using the simulated current and voltage profile of the generic battery by the least-square method. This paper shows a detailed calculation for the ECM parameters estimation, and ECM can replace the generic battery. The comparison of estimated SOC with generic battery SOC for the same testing condition has been done to validate the modeling of the battery. Furthermore, A lithium-iron-phosphate (LFP) battery voltage profile is compared with ECM and generic battery voltage profile to validate the estimated parameters of the ECM.**

Keywords—equivalent circuit model, generic battery, least-square method, lithium-iron phosphate, state-of-charge, coulomb counting method

I. INTRODUCTION

Electric vehicles (EVs) are a clean alternative to conventional internal combustion engines for reducing pollutants in the transportation sector [1]. When an energy storage system (ESS) uses electrochemical storage, such as batteries, a precise model of the system voltage and capacity is crucial for assessing the capacity of the system to carry out the different tasks necessary for electric vehicle (EV) applications [2]. In general, as more detailed physiochemical phenomena are included in a battery model, its simulation results can be expected to be more reliable, but at the cost of increased computational effort. The following categories apply to battery models based on their modeling methodology [3]: Equivalent Circuit (EC) [4, 5], Empirical or Semi-Empirical Dynamic Models, and Electrochemical Multiphysics. This paper represents a MATLAB generic battery model by resistors and capacitors and a dc voltage source. With the increasing number of resistors and capacitors, accuracy increases but complexity also increases. So, to balance the trade-off between accuracy and complexity; first-order (1-RC) and second-order (2-RC) represent the generic battery model. The parameters of the ECM are estimated to analyze the dynamic behavior of the battery. In literature [3, 6], many methods have been discussed to estimate the parameters of the battery, e.g., Least-Square estimation, Recursive Least-Square [11], Particle Swarm Optimization [12], Artificial neural network [13], etc. Here, the least-square estimation method [15, 16] has been used to estimate the parameters of the generic battery, as it is easier to implement, and the computational cost is lesser than other methods. These methods are mainly used for online parameter estimation of the battery. The parameters of the battery depend on SOC, and it cannot be measured directly. So, the SOC of the battery is also estimated. The literature suggests many methods for calculating SOC [7, 8, 14]. Some algorithms for SOC estimation are the Coulomb counting method, Kalman filter, Fuzzy logic, enhanced coulomb counting method, etc. Here Coulomb counting method is used for SOC estimation of the ECM.In this work, a LFP (SAMSUNG 18650 26J) battery has been tested to validate the ECMs. However, the physical battery may not be available in the laboratory. In that case, a generic battery can act as a physical battery and be tested in the same condition as the physical battery.

II. MODELING OF GENERIC BATTEY

1-RC and 2-RC models can represent the generic battery. Higher accuracy for estimating the parameters is required for appropriately modeling the battery [9]. ECMs consist of ohmic resistance, polarization resistance, polarization capacitance, and open-circuit voltage (OCV). The association between the electrolyte resistance and the resistance of the cell components results in ohmic resistance. The transient response is analyzed using polarization resistance and capacitance during charging and discharging.

Open-circuit voltage is the no-load terminal voltage of the battery. However, during no-load , OCV slowly increases to the terminal voltage due to the relaxation of the polarization losses. The OCV of the battery can be calculated in two ways. Firstly, After estimating the RC parameters, OCV can be directly calculated experimentally by subtracting the impedance drop from the terminal voltage using the load current at that moment. Secondly, by measuring the terminal voltage experimentally in no-load conditions. But, the battery should get sufficient relaxation time in that case. The relaxation is the phase following the discharge period when there is no current, and the battery voltage reaches equilibrium. OCV is more accurately estimated by the measured battery voltage when the relaxation time is more (multiple hours). Therefore, the least-square estimation method is used to estimate the battery parameters. The modeling and its parameter estimation procedure is discussed below.

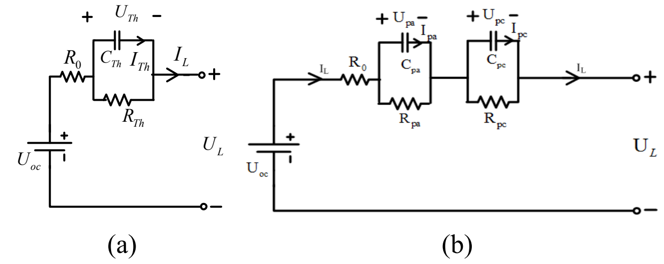


Fig.1 ECM of lithium-ion battery (a) 1-RC model (b) 2-RC model

A. Modeling and Parameter estimation of 1-RC model

1-RC model consists of one internal resistance (R_0), one RC parallel circuit (R_{Th}, C_{Th}), and open-circuit voltage (U_{oc}). The ohmic resistance is due to the association of the resistance of electrolytes and the cell components. The capacitance is used to analyze the transient response during discharging and charging. 1-RC model is shown in Fig. 1(a). The 1-RC model can be represented by the following equations:

$$\begin{aligned} \dot{U}_{Th} &= -\frac{U_{Th}}{R_{Th}C_{Th}} + \frac{I_L}{C_{Th}} \\ U_L &= U_{oc} - U_{Th} - I_L R_0 \end{aligned} \tag{1}$$

Let I_L is the load current, U_{Th} is polarized voltage, U_L is load voltage, and the direction of the arrow represents the positive direction of current in the circuit. Impedance voltage drop while charging:

$$E_L = U_{OC} - U_L \tag{2}$$

The impedance transfer function can be expressed as:

$$G(s) = \frac{E_L(s)}{I_L(s)} = -\frac{U_{oc}(s) - U_L(s)}{I_L(s)} = -\left(R_0 + \frac{R_{Th}}{1 + R_{Th}C_{Th}s}\right) \tag{3}$$

Assuming $\tau_1 = R_{Th}C_{Th}$ and using bilinear transformation rule, $s = \frac{2}{T}\cdot\frac{1-z^{-1}}{1+z^{-1}}$ where T is sample time.

The discrete transfer function

$$G(z) = -\frac{\left(\frac{2R_0\tau_1 + (R_0 + R_{Th})T}{2\tau_1 + T} + \frac{\left[(R_0 + R_{Th})T - 2R_0\tau_1\right]z^{-1}}{2\tau_1 + T}\right)}{\left(1 + \frac{T - 2\tau_1}{2\tau_1 + T}\cdot z^{-1}\right)}$$

The transfer function can be represented as

$$G(z) = \frac{a_2 + a_3 \cdot z^{-1}}{1 - a_1 \cdot z^{-1}} \tag{4}$$

After comparing (3) and (4)

$$a_1 = -\frac{T - 2\tau_1}{2\tau_1 + T}, a_2 = -\frac{2R_0\tau_1 + (R_0 + R_{Th})T}{2\tau_1 + T},$$

$$a_3 = -\frac{\left[(R_0 + R_{Th})T - 2R_0\tau_1\right]}{2\tau_1 + T}$$

These parameters (a_1, a_2, a_3) are estimated by the least square method. After that, inverse bilinear transform is used in (4) to set the relation between continuous and discrete parameters.

$$G(s) = \frac{\frac{2(a_2 + a_3)}{T - a_1 \cdot T} + \frac{a_2 - a_3}{1 - a_1}\cdot s}{s + \frac{2(1 + a_1)}{T(1 - a_1)}} \tag{5}$$

Based on (3) and (5), the parameters can be written as

$$R_0 = \frac{a_3 - a_2}{1 - a_1}, \tau_1 = \frac{T(1 - a_1)}{2(1 + a_1)},$$

$$R_{Th} = \frac{2(a_2 - a_1 a_3)}{1 - a_1^2}, C_{Th} = \frac{T(1 - a_1)^2}{4(a_2 - a_1.a_3)}$$

These are the estimated parameters of the first-order equivalent circuit model.

By equating (1) and (5), the system can be determined by the discrete time-domain difference equation

$$E_L(k) = a_1 E_L(k-1) + a_2 I_L(k) + a_3 I_L(k-1) \tag{6}$$

Equation (2) can be expressed as $E_L(k) = U_{oc}(k) - U_L(k)$

Open-circuit voltage (OCV) depends on the SOC of the battery. The SOC of the battery are changing very slowly with time. So for a small change of time, changes in SOC and is small.

$$\frac{U_{oc}(k) - U_{oc}(k-1)}{T} = 0 \Rightarrow U_{oc}(k) = U_{oc}(k-1) \tag{7}$$

Equation (6) can be written as

$$U_L(k) = (1 - a_1)U_{oc}(k) + a_1 U_L(k-1) + a_2 I_L(k) + a_3 I_L(k-1) \tag{8}$$

The parameter vector and observation data matrix are as follows:

$$\theta = \left[(1 - a_1)U_{oc}(k) \quad a_1 \quad a_2 \quad a_3\right]^T,$$

$$\psi = \begin{bmatrix} 1 & U_L(k-1) & I_L(k) & I_L(k-1) \\ 1 & U_L(k-2) & I_L(k-1) & I_L(k-2) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & U_L(k-m-1) & I_L(k-m) & I_L(k-m-1) \end{bmatrix}$$

The present measurement moment is denoted by k, while observation periods are represented by m, ψ is the known data matrix that has been measured. θ is the parameter vector that is to be estimated. Equation (7) can be expressed in matrix form:

$U_L(k) = \psi\theta + \xi$, where ξ is the error vector.

The cost function of the least-square method is given by

$$J = \sum_{i=0}^{m}\left[\xi(k-i)\right]^2 = \xi^T\xi \tag{10}$$

The parameter vector of the battery model using the least square algorithm can be solved as follows:

$$\theta = \left(\psi^T\psi\right)^{-1}\psi^T U_L \tag{11}$$

Where $U_L = \left[U_L(1) \quad U_L(2) \quad \cdots \quad U_L(k-1)\right]$ (12)

B. Modeling and Parameter estimation of 2-RC model

2-RC model consists of ohimc resistance, and two parallel polarized RC elements, as shown in Fig.1b. Polarization can be noticed based on the characteristics of a generic battery. Polarization can be classified into two types. Activation polarization occurs due to the charge transfer rate of the battery. Concentration polarization occurs due to the diffusion voltage. The following equations can represent the 2-RC model:

$$\dot{U}_{pa} = -\frac{U_{pa}}{R_{pa}C_{pa}} + \frac{I_L}{C_{pa}}$$
$$\dot{U}_{pc} = -\frac{U_{pc}}{R_{pc}C_{pc}} + \frac{I_L}{C_{pc}} \quad (13)$$
$$U_L = U_{oc} - U_{pa} - U_{pc} - I_L R_0$$

I_L is the load current and $E_L = U_{oc} - U_L$ is the impedance voltage drop, the Impedance transfer function can be expressed as

$$G(s) = -\frac{\left(R_0 s^2 + \frac{R_0(\tau_1+\tau_2)+R_{pa}\cdot\tau_1}{\tau_1\cdot\tau_2} + \frac{R_0+R_{pa}+R_{pc}}{\tau_1\cdot\tau_2}\right)}{\left(s^2 + \frac{\tau_1+\tau_2}{\tau_1\cdot\tau_2}\cdot s + \frac{1}{\tau_1\cdot\tau_2}\right)} \quad (14)$$

Assume $\tau_1 = R_{pa}C_{pa}$, $\tau_2 = R_{pc}C_{pc}$

By using the bilinear transformation rule, $G(s)$ can be discretized, and it is written in the form as

$$G(z) = \frac{b_0 + b_1\cdot z^{-1} + b_2\cdot z^{-2}}{1 + a_1\cdot z^{-1} + a_2\cdot z^{-2}} \quad (15)$$

b_0, b_1, b_2, a_1, a_2 are the coefficients that have to be estimated by the least square method. The discrete transfer function may be rewritten in the following way:

$$G(s) = \frac{\frac{b_0-b_1+b_2}{1-a_1+a_2}\cdot s^2 + \frac{4(b_0-b_1)}{T(1-a_1+a_2)}\cdot s + \frac{4(b_0+b_1+b_2)}{T^2(1-a_1+a_2)}}{s^2 + \frac{4(1-a_2)}{T(1-a_1+a_2)}\cdot s + \frac{4(1+a_1+a_2)}{T^2(1-a_1+a_2)}} \quad (16)$$

by comparing equations (15) and (16)

$$R_0 = \frac{b_0-b_1+b_2}{1-a_1+a_2}, \tau_1\cdot\tau_2 = \frac{4(b_0+b_1+b_2)}{T^2(1-a_1+a_2)}$$

$$R_0(\tau_1+\tau_2) + R_{pa}\cdot\tau_2 + R_{pc}\cdot\tau_1 = \frac{4(b_0-b_2)}{T(1+a_1+a_2)}$$

$$\tau_1+\tau_2 = \frac{4(1-a_2)}{T(1-a_1+a_2)}, R_0+R_{pa}+R_{pc} = \frac{(b_0+b_1+b_2)}{(1+a_1+a_2)}$$

Like 1-RC model, the 2-RC model can be represented by

$$U_L(k) = (1+a_1+a_2)U_{oc}(k) - (1+a_1)U_L(k-1)$$
$$-b_0 I_L(k) - b_1 I_L(k-1) - b_2 I_L(k-2) \quad (17)$$

TABLE I. ESTIMATED PARAMETERS OF THE 1-RC MODEL

$SOC(\%)$	$R_0(\Omega)$	$R_{Th}(\Omega)$	$C_{Th}(kF)$	$\tau_{Th}(\text{sec.})$
0	0.0548	0.01411	3.5527	50.128597
5	0.0546	0.00971	3.9194	38.0574
10	0.0546	0.00834	5.484	45.73656
15	0.0545	0.00859	4.96975	42.6901
20	0.0544	0.00834	6.023	50.23182
30	0.0544	0.007149	4.367	31.3507
40	0.0542	0.007179	4.491	32.24089
50	0.0543	0.007425	5.0793	37.71380
60	0.0542	0.0093956	3.5824	33.6588
70	0.0541	0.00852	4.2834	36.495
80	0.0543	0.009576	3.6153	34.62011
90	0.0542	0.0082753	4.049	33.5066
100	0.0542	0.00845	4.9183	41.5596

TABLE II. ESTIMATED PARAMETERS OF THE 2-RC MODEL

SOC	$R_0(\Omega)$	$R_{pa}(\Omega)$	$C_{pa}(kF)$	$R_{pc}(\Omega)$	$C_{pc}(kF)$
0	0.0548	0.1023	0.1065	0.0624	0.7335
5	0.0546	0.0019	2.6196	0.0225	1.6388
10	0.0546	0.0015	3.1039	0.0314	1.8805
15	0.0544	0.0015	4.5947	0.0278	2.6298
20	0.0543	0.0025	6.6683	0.0081	8.9462
30	0.0545	0.0014	3.4103	0.0321	1.9682
40	0.0542	0.0088	3.0103	0.0303	1.3515
50	0.0544	0.0016	8.8669	0.0169	3.6949
60	0.0543	0.0017	3.8478	0.0306	1.6574
70	0.0541	0.0018	3.3032	0.0359	1.5037
80	0.0542	0.0017	2.5372	0.0359	1.1816
90	0.0543	0.0017	2.7589	0.0524	2.0901
100	0.0543	0.0015	6.3915	0.0247	3.4061

θ is an unknown parameter matrix and ψ is a known parameter matrix

$$\theta = \left[(1+a_1+a_2)U_{oc}(k) \quad (1+a_1) \quad b_0 \quad b_1 \quad b_2\right]^T$$

$$\psi = \begin{bmatrix} 1 & -U_L(k-1) & -I_L(k) & -I_L(k-1) & -I_L(k-2) \\ 1 & -U_L(k-2) & -I_L(k-1) & -I_L(k-2) & -I_L(k-3) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & -U_L(k-m-1) & -I_L(k-m) & -I_L(k-m-1) & -I_L(k-m-2) \end{bmatrix}$$

According to the least square algorithm, the parameter vector of the battery model can be solved as:

$$\theta = \left(\psi^T\psi\right)^{-1}\psi^T U_L \quad (18)$$

$$U_L = \left[U_L(2) \quad U_L(3) \quad \cdots \quad U_L(k)\right] \quad (19)$$

The output sequence is Y, and the number of sample data is m. The polarized resistances and capacitances of the battery varies with SOC due to the redox reaction (oxidation and reduction) occurs in the battery.

III. SOC Estimation of The Model

The battery SOC is an important aspect. Accurate SOC prevents the battery from over-discharge, overcharge. It also indicates the estimated driving range of a vehicle. SOC can be represented as the ratio of remaining capacity $Q(t)$ to its maximum capacity, $Q_{\max}$, which denotes the maximum accumulated charge in the battery. It is used to protect the battery from over-charging and over-discharging the battery. Otherwise, the battery may be permanently damaged. SOC can be represented as

$$SOC(t)=\frac{Q(t)}{Q_{\max}} \Rightarrow SOC(t)=SOC(0)\pm\frac{\int_{t_0}^{t_0+\tau} i(\tau)\cdot d\tau}{Q_{\max}} \tag{20}$$

Where, $SOC(t)$ = State-of-charge in percentage, $SOC(0)$ = Initial SOC, $i(\tau)$ = Charging/discharging current, τ = Timespan for charging/discharging, $(-I)$ denotes the charging current and (I) denotes the discharging current.

Fig. 3 shows the block diagram for SOC estimation of 2-RC model using coulomb counting method. The load current of ECM is measured by current sensor and the sensor data is used to estimate the SOC of the ECM in MATLAB/Simulink platform. Similarly, SOC is estimated for 1-RC model.

IV. Experimental Set-up and Results

Lithium-iron-phosphate (LFP) batteries are chosen as they have a higher energy density, longer life, and are cheaper than other lithium-ion batteries. The capacity and nominal voltage rating of SAMSUNG 18650 26J battery are 2600mAh, 3.66V. The maximum and minimum cut-off voltages are 4.2V and 2.8V. The battery has been tested in Arbin Instrument (Model: LBT21084UC SN:213343) which is shown in Fig. 2a. The system connects to the host computer through an Ethernet cable to receive control signals, and it uploads real-time test data. The host computer manages and controls the cycler. The testing system can measure the voltage range of -5V to +5V and current of 1A.

Fig. 4a shows the experimental set-up for battery testing. A pulse test has been done to test the battery and the simulations.

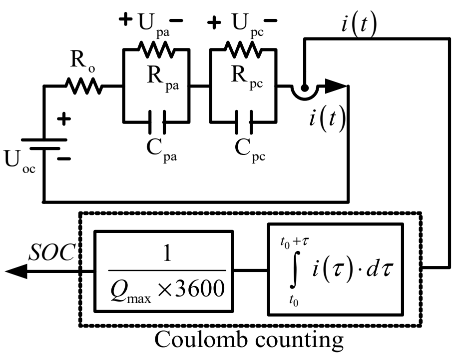
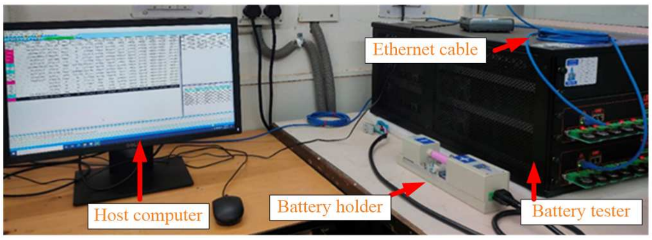
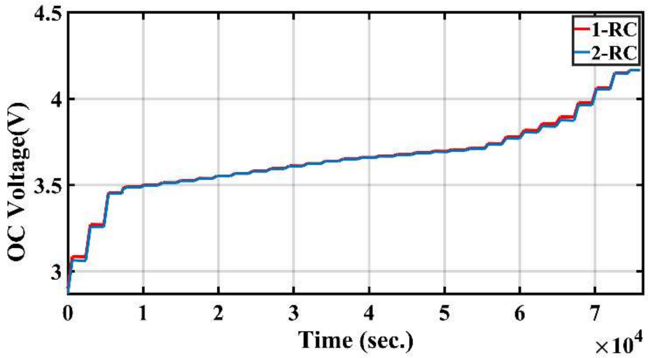


Fig. 3 Block diagram for SOC estimation of 2-RC model



(a)



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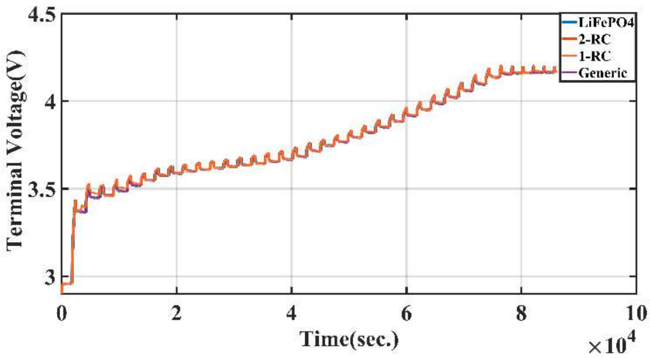

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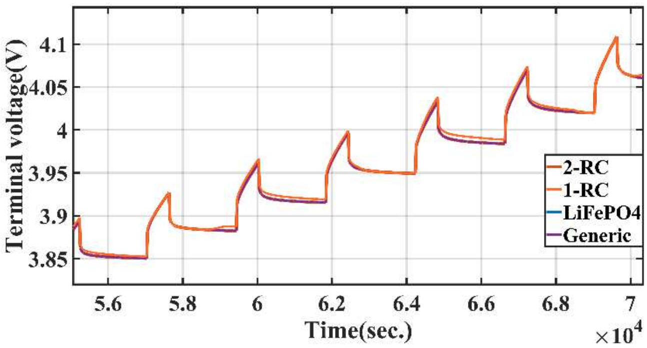

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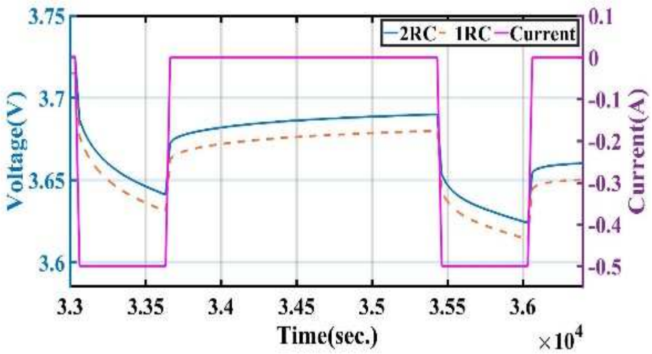

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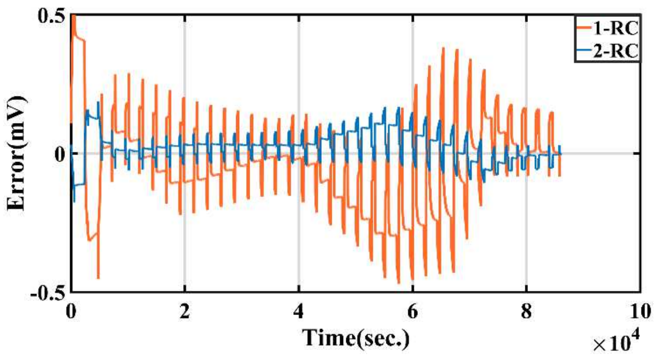
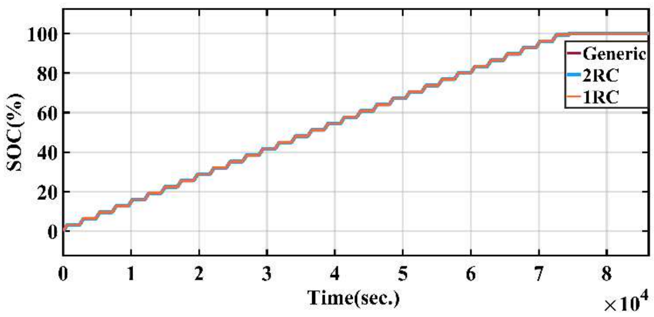


(f)



(g)

Fig. 4(a) Experimental set-up for battery parameter estimation (b) OCV of 1-RC and 2-RC model (c) Terminal voltage comparison of physical battery, generic battery and ECMs (d) Zoomed view of the terminal voltage comparison of ECMS, physical battery, and generic battery (e) Discharging pulse current and terminal voltage profile (zoomed) (f) Comparison of error between ECMS and the generic battery (g) Estimated SOC profiles of ECMs and generic battery

Positive pulsed current (PPC) and Negative pulsed current (NPC) are used for battery charging and discharging, respectively. The programmed pulse current is 0.52A and zero at relaxation time. The pulse duration is 10 minutes, and the relaxation timespan is 30 minutes. So, the pattern repeats after 40 minutes. 64460 samples are taken for battery testing and used for the parameter estimation of the battery. Since the variance in cell capacity is essentially constant over 10 seconds, it was assumed that SOC is constant throughout that time. In Fig. 4, all the results are shown during the charging time. The generic battery has been created by using LFP battery specifications. The least-square method has estimated the parameters using the experimental current and terminal voltage data. After that, the estimated parameters have been used to design ECMs (1-RC and 2-RC). Resistances, capacitances, and OCV values for different SOC level were estimated for a half cycle. Fig. 4b shows the estimated OCV curve for 1-RC and 2-RC models.

The ECMs are validated by comparing the terminal voltages of physical SAMSUNG battery, generic, and ECMs, shown in Fig. 4c, 4d. The error curve is described as the terminal voltage difference between ECMs and generic battery which is shown in Fig. 4g. It can be observed that the error for 1-RC model varies from -0.45mV to $+0.5\text{mV}$, whereas for 2-RC model error is from -0.1mV to $+0.2\text{mV}$. Therefore, the 2-RC model can describe the battery with better accuracy. The estimated SOC of ECM has been compared with generic battery SOC, which is shown in Fig. 4h. It can be observed that SOC of ECMs and SOC of generic battery are approximately superimposed. Therefore, the terminal voltage and SOC data validate the ECMs, as ECMs can accurately describe the characteristics of the battery.

V. Conclusion

The widely used generic MATLAB model capacity does not express as a function of temperature, self-discharge, discharge current, and cycle number [5]. 1-RC and 2-RC models have designed to replace the generic battery. The ECM parameters have been estimated by the least-square method. It has been observed that the 2-RC model can better describe the generic battery model. Suppose the physical battery is not available in the Research Centre, and the battery parameters are required for further research. In that case, a generic battery can be used as the physical battery with the same specifications as the physical battery. The parameters of that physical battery can be estimated by the approach which has been described in this paper. SOC of the ECM has been estimated by the Coulomb Counting method and verified by the estimated SOC of the generic battery. It has shown that ECMs can accurately describe the characteristics of the generic battery.

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