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Review Article

Classification of Equivalent Circuit Models for Lithium-ion Batteries

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Abstract *- Equivalent Circuit Models (ECMs) are the simplest models used to define the behavior of a Lithium-Ion Battery (LIB). Since their inception, many variations have been developed with the objective of improving the accuracy requirement of measuring and predicting the State of Charge (SoC) and State of Health (SoH) of a lithium-ion cell. This improvement has been fueled by the need for Electric Vehicles (EVs) to mimic the behavior of Internal Combustion Engines (ICEs) by supporting a longer drive before recharging. Despite the many variations of ECMs that are available in the literature, each one can be linked to six core models which are often adjusted by including a new parameter to reduce the modelling error. These core models are a formulation of Ordinary Differential Equations (ODEs) with an input equation as the SoC and an output equation as the terminal voltage (v) of the battery. The input equation is often similar for all the six core models. This review paper will summarize these core models and organize them in a table format, which can be used as a reference for researchers in this field. A treatment of the Root Mean Square Error (RMSE) analysis of two improved models from the core models will also be provided to demonstrate the effect of including a new parameter in the model. The analysis will be based on a Nickel Manganese Cobalt Oxide (NMC) negative electrode battery chemistry.*

Keywords *- Equivalent Circuit Models, Lithium-Ion Battery, Modelling error, Ordinary Differential Equations, State of Charge.*

1. Introduction

Equivalent Circuit Models (ECMs) are the earliest and most common models to be used in modelling the behaviour of Lithium-ion Batteries (LIBs) [1]. They are also considered the simplest to implement as they are represented by simple Ordinary Differential Equations (ODEs). Researchers have laboured to make gradual improvements in the accuracy measurement of State of Charge (SoC) as this affects the capacity and life of the battery cell. It relates to the amount of available charge in the battery cell and has no units. A full battery cell will indicate an SoC of 100 percent, while an empty battery cell will indicate an SoC of 0 percent. A less accurate model will lead to incorrect readings of the SoC and, thus, incorrect use of the battery cell. Incorrect use of the battery cell degrades the life of the battery cell considerably [2].

The increased demand for electric vehicles has further emphasized the importance of accurate prediction of the SoC. Due to environmental conservation needs, Battery Electric Vehicles (BEVs) are more preferred to Internal Combustion Engines (ICEs) [3]. This has increased the need for bulk battery storage systems. The resources to produce batteries are scarce. They must be managed properly. Proper modelling of batteries ensures their proper management and utilization. Accurate models will lead to more capacity being available for utilization in the battery cell and, thus lesser number of cells needed to support the same drive train. This has thus pushed for the development of accurate ECMs [4]. The accuracy of an ECM is determined by its modelling error. This is the deviation of the predicted circuit behaviour by the model from the results obtained through experimentation. The higher the deviation, the lower the accuracy. An observable example of such is shown in Figure 1, where if a battery is left to rest after the load is removed, it indicates a higher terminal voltage reading [5].

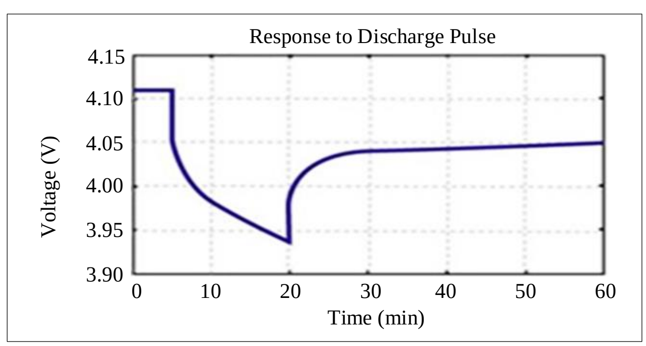

Fig. 1 Diffusion voltage curve (extract from [5])

The Earlier ECMs did not include this behaviour and as such, led to huge modelling errors. The Root Mean Square Error (RMSE) method is one of the measurements for the modelling error.

All ECMs are developed from six-core models. They are all represented using Ordinary Differential Equations (ODEs). They contain an input equation of the State of Charge (SoC) and an output equation of the terminal voltage of a battery cell. The input equation is similar for all the models. Its parameters are dependent on the cell chemistry and external factors such as temperature [6].

The variations are often a result of a very small improvement, mostly determined by environmental influences on the battery cell. Each of the six core models has its strength levels, and some of them are currently obsolete. However, they are often referred to while developing models from principle as they provide insights into the basic principles of operation of the cell. This will be well discussed in the sections that will follow.

The battery cell chemistries also play an important role in defining ECMs. Different cell chemistries have different behaviors under no-load conditions. The graph below demonstrates this concept by showing the differences in the terminal voltage reading under no-load also the Open Circuit Voltage (OCV) over a range of SoC for different negative electrode cell chemistries [7].

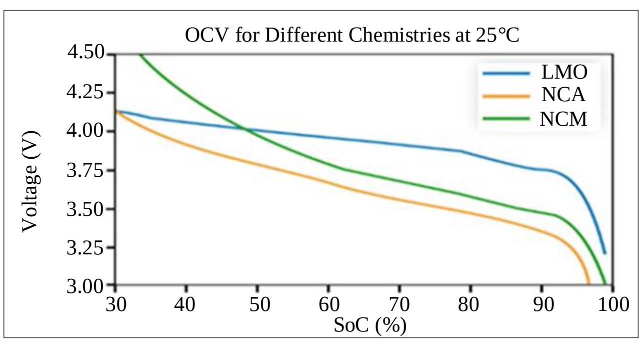

Fig. 2 OCV vs SoC at different cell chemistries

Thus, it can never be assumed that there is a proportional relationship between the OCV and SoC. Cell chemistry must be taken into account while developing the models. For this review paper, the Nickel Manganese Cobalt Oxide (NMC) cell chemistry will be the chemistry under consideration in the analysis section of the paper.

2. The Core Equivalent Circuit Models

Variants of Equivalent Circuit Models are developed from six-core models. This is often based on small improvements such as the behaviour of the model around a changing temperature environment, user behaviours and the enhancement in the measurement of one or more parameters in the model. The core models address the main observable behaviours of a model, such as voltage drops, history in the usage of the battery and internal behaviours of the chemical components in the battery. These main behaviours are well described in the sections that follow with graphical representations of the experimental proof of their existence.

The state of charge input equation recurs in each of the models. A section dedicated to SoC will be provided and the remaining sections describing the models will show the output equation only.

2.1. The State of Charge Input Equation

The State of Charge equation is derived from recognizing that the terminal voltage of a charged cell in loaded conditions is not always higher than that of an empty cell [8]. In unloaded conditions, the relationship is proportional. The behaviour of a cell being charged or discharged can be quantified, and its value at any time is defined as the State of Charge (SoC) [9]. This relationship is often defined mathematically by the ordinary differential equation as

$$\frac{dz}{dx} = (sgn)\eta(t)i(t)/Q \qquad (1)$$

in dot notation as,

$$\dot{z(t)} = (sgn)\eta(t)i(t)/Q \qquad (2)$$

The change in SoC over time is represented by $\dot{z(t)}, \eta(t)$ is the coulombic efficiency of the electrode material, $i(t)$ is the resultant current due to charge movement in the cell, and Q is the amount of charge, Q, in the cell. The value on the right of the equation is a signed quantity represented by (sgn). This value is negative during charging periods and positive when discharging the cell. This is the instantaneous relationship of SoC. The continuous relationship over some time interval is obtained by integrating the instantaneous equation. This will give,

$$z(t) = z(t_0) - \frac{1}{Q}\int_{t_0}^{t} \eta(\tau)i(\tau)d\tau \qquad (3)$$

$z(t_0)$ is the initial value of the SoC at time t = 0. The integral term describes the change of the change of SoC from the initial time to some other time t when the measurements are taken. The sign is negative for discharging and positive for charging periods. For measurements at sampled points in time, it is important to discretize the equation. This is often important for implementation in digital systems such as microcontrollers.

Time, t_0 at a discrete time can be represented k, time, t as the next time sample represented by $k + 1$, the integral as the change in time, Δt and $t = \tau$. The discrete equation is thus written as;

$$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k] \tag{4}$$

This is the final equation for the SoC, and it will be constant for all six core models. As such, a reference to this equation will be provided in the sections that follow [10].

2.2. The Combined Model

The input equation is Equation (4). The output equation, which represents the terminal voltage, is defined in three different forms. This includes the Shepherd model as in (5), the Unnewehr Universal model as in (6) and the Nerst model as in (7).

$$y_k = E_0 - Ri_k - \frac{K_i}{z_k} \tag{5}$$

$$y_k = E_0 - Ri_k - K_i z_k \tag{6}$$

$$y_k = E_0 - Ri_k + K_2 \ln(z_k) + K_3 \ln(1 - z_k) \tag{7}$$

y_k is the terminal voltage, R, cell internal resistance, K_i, polarization resistance. The output equation is a combination of these three models and is given as

$$y_k = K_0 - Ri_k - \frac{K_1}{z_k} - K_2 z_k - K_3 \ln(z_k) + K_4 \ln(1 - z_k) \tag{8}$$

The RMSE of the combined model is estimated at 34.7 mV for a multi-rate pulse test, which is a significant deviation from the observable value [11].

2.3. The Simple Model

The simple model is the first step to more accurate models for ECMs. The models that follow will improve on this by adding parameters that represent significant observations in battery behaviour. It relates the Open Circuit Voltage (OCV) to the SoC. It also includes the effects of diffusion voltages due to the internal resistance of the battery cell in the model. This effect of diffusion voltage is often indicated as an equivalent series resistance when modelled in a circuit as

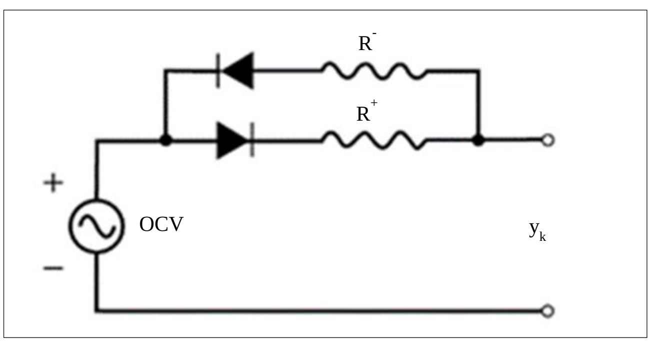

Fig. 3 Circuit representation of the simple model [10]

The output equation is thus given as,

$$y_k = OCV(z_k) - R_0 i_k \tag{9}$$

Figure 3 shows this relationship clearly by applying Kirchoff's Voltage Law (KVL) in the circuit. This states that the terminal voltage y_k in discrete form is a result of the voltage under no-load conditions and the voltage drop due to the internal resistance of the cell. The SoC, z_k is a function of the OCV.

The RMSE of the simple model for a multi-rate pulse test is estimated at 36.2 mV. This is slightly poorer than the combined model's accuracy. Later improvements to this model will show a great reduction in this modelling error and eventually make the combined model obsolete [12].

2.4. The n-Hysteresis Model

This is the immediate improvement to the simple model. It observes that aside from diffusion voltages, the cell terminal voltage is dependent on the history of use of the battery. When you charge a cell from 0 percent to 100 percent SoC, then you begin discharging it slowly. It will rest at a value that is slightly lower than the initial value measured at the same terminal voltage. Similarly, suppose you discharge a battery from 100 percent to some percentage close to 0 and begin charging it at a slow rate to some value. In that cas this value will be slightly higher than the previously indicated value at the same terminal voltage [13]. This is best demonstrated in Figure 4 below as,

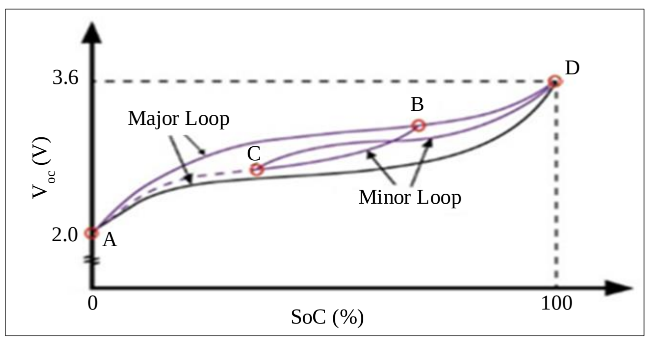

Fig. 4 Charge discharge profile demonstrating hysteresis [13]

This effect is defined as hysteresis and has a considerable contribution to the measured terminal voltage of a cell. Hysteresis is a complex parameter to measure and often the defining factor for accuracy for modern ECMs. It is given by h_k and is dependent on whether a cell is being charged or discharged. The maximum of this value is used to estimate the voltage drop due to hysteresis. The terminal voltage equation now becomes as

$$y_k = OCV(z_k) - R_0 i_k - s_k M(z_k) \tag{10}$$

s_k is the sign of the hysteresis voltage due to charging or discharging a cell, M indicates the maximum polarization due to hysteresis, and the parameter is fully dependent on the SoC, z_k.

Modelling hysteresis as a circuit element is often represented by a resistor-capacitor pair in series with the ESR of the cell. This is indicated by the circuit below as

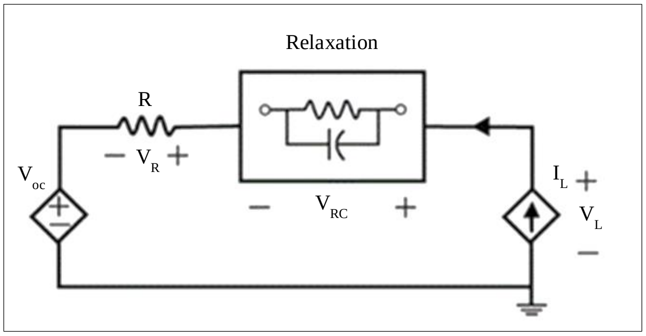

Fig. 5 Circuit representation indicating hysteresis [13]

For higher accuracy, several of the resistor-capacitor pairs are often lumped together. This leads to several states of the model of n-state hysteresis models. n represents the number of resistor-capacitor (R-C) pairs used in the model. The one-state hysteresis model as an example is thus given as

$$y_k = OCV(z_k) - R_0 i_k + h_k \tag{11}$$

2.5. The Enhanced Self-Correcting Model

This model includes the consideration of pulsed current effects on the cell. In pulsed situations, the time constant varies over the utilization period of the cell. The graph of terminal voltage vs time will be a decaying pseudo-square curve on the discharge period, for example, in Figure 6 as,

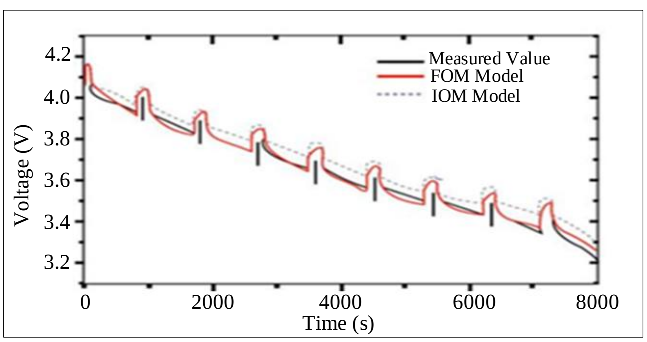

Fig. 6 Discharge pulses over time [14]

The enhanced self-correcting model models these pulsed events using a low pass filter. This is applied to the current, i_k and the SoC, z_k. The terminal voltage equation becomes as

$$y_k = OCV(z_k) + filt(z_k) + filt(i_k) - R_0 i_k \tag{12}$$

To show the effect of hysteresis effect, the equation can be written as

$$y_k = OCV(z_k) + h_k + filt(i_k) - R_0 i_k \tag{13}$$

In this case, $h_k$is a function of the filtered values of both SoC and the applied current. OCV is a function of the SoC only, and the final two terms in a function of current only. Like the n-state hysteresis model, the filter is represented electrically by a tuned resistor-capacitor pair. The more the number of such pairs in a series the more accurate the model becomes. This can be represented as

$$y_k = OCV(z_k) - R_0 i_k + h_k + g_1 f_1 k + g_2 f_2 k + \cdots + g_n f_n k \tag{14}$$

The factor $g_n f_n k$ indicates the number of filters used in the circuit [14].

2.6. The n-Order RC Model

The n-order RC Model summarizes the effects of hysteresis and pulsed events as a cluster of series R-C networks. The internal resistance is maintained as in the simple circuit, and the OCV is still a function of SoC. The resultant circuit (Figure 7) is as,

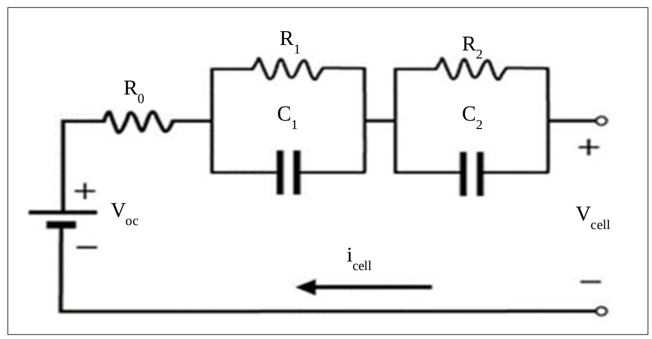

Fig. 7 Circuit representation of the n-order RC model

The Thevenin method is applied to this circuit while looking at the circuit from the terminal voltage side. The output equation becomes as

$$y_k = OCV(z_k) - R_0 i_k - U_{ik} \tag{15}$$

U_{ik} is the voltage constant of the RC network and is given as

$$U_{i,k} = \frac{Q_0}{C} \tag{16}$$

Q is the initial charge capacity in coulombs, and C is the capacitance in the RC network in Faradays.

The n-order RC model is also often called the Thevenin model, the transmission line model, the single-cell model, the Rint model or the dual-polarization model [15].

2.7. The n-Order RC Model with n-State Hysteresis

This model is a combination of the n-state RC model and the n-state hysteresis model. The first-order RC model with n-state hysteresis, for example, is represented as,

$$y_k = OCV(z_k) - R_0 i_k - U_{1k} + h_k \quad (17)$$

The general form of this model is as

$$y_k = OCV(z_k) - R_0 i_k - U_{ik} + h_k \quad (18)$$

3. Modelling Errors

This section provides some data on the modelling errors from the literature on the six core models and an improved two-order RC (2RC) model. The tables are not for direct comparison as the tests were done under different conditions over different timespans. It can, however provide a face view of the improvements done over time and the need to continue developing newer models.

The section also introduced four different types of tests which will be discussed in brief for the sake of understanding and interpreting the tables. The 2RC model is based on the Nickel Manganese Cobalt (NMC) Oxide cell chemistry, while the six core models are based on the Nickel-Metal hydride (N-MH) cell chemistry [16].

3.1. Dynamic Discharge Pulse Test (DDP)

This test involves applying a discharge pulse to the battery and measuring the response of the battery to this stimulus in real time. The discharge pulse is considered the input parameter, and the response is the output parameter.

The two parameters are often viewed as first and second-order parameters, respectively and are often fed into an Artificial Intelligence (AI) system to provide predictions for the model. Such AI systems include, for example, Artificial Neural Networks (ANN), Fuzzy Logic etc. It is the first test shown in Table 1 for the 2RC model [17].

3.2. Worldwide Harmonized Light Duty Test Cycle (WLTC)

This is a real-time test that involves working with the application system under test. It begins with a fully charged cell with all systems of a lightweight vehicle, for example, turned OFF. Different operating conditions, such as start-stop, acceleration-deceleration, and changes in the speed of the vehicle, are observed over time, and a simulation of the operating cycle is generated. The lightweight vehicle, in this case, is often placed in a controlled environment called a test rig and various environmental conditions, such as temperature, can be adjusted with ease to provide the desired output. Some of the results are shown in the second 2RC test in Table 1 [18].

3.3. Multi-Rate Pulse Test

This test is also called the Hybrid Pulse Power Characterization (HPPC) test. It is used to determine the performance characteristics of a battery cell in real-time and at certain SoC and temperature points. Charge and discharge pulses are applied accordingly under desired SoC points and the output profile of certain parameters of the battery, such as voltage and current response, is recorded. The computation of the modelling error from the output profile is easily calculated. Column 2 of Table 2 provides some tests of this test for the six core models [19].

3.4. Multicycle UDDS Test

These are real-time tests done under the United States Environmental Protection Agency that ensure sustainable driving in the city for light-duty vehicles. UDDS stands for Urban Dynamometer Driving Schedule and relates an electric vehicle's performance over a defined range to that of an ICE. Table 2 shows the modelling error results of this test for the six core models under different temperature conditions [20].

Table 1. Root Mean Square Errors (RMSE) for the second-order RC model at different temperature conditions

	15°C	**25°C**	**35°C**	**45°C**
DDP	0.35	0.22	0.19	0.37
WLTC	N/A	0.13	0.11	N/A

Table 2. Root Mean Square Errors (RMSE) for the core models at different temperature conditions

	Multi-Rate Pulse Test (mV)	**Multicycle UDDS Test (mV)**		
		-30°C	**0°C**	**25°C**
Combined Model	34.7	50.1	24.1	23.3
Simple Model	36.2	165.8	26.9	22.4
The Zero-State Hysteresis Model	21.5	62.2	24.6	22.3
The One-State Hysteresis Model	21.5	48.7	14.1	14
ESC Model	13.8	39	14.5	14

4. ECMs Classifications Summary

This section summarizes the six core models in a table format. The column to the right shows the full set of Ordinary Differential Equations (ODEs) that describe each of the models. It can now be easily seen that the input equation is similar for all the models, and only the output equation changes.

The input equation provides the next state of the State of Charge (SoC) from the input current and battery cell characteristics, and the output equation gives the resulting terminal voltage for both load and unloaded conditions. The simplicity and accuracy of the models can also be seen from one model to the next.

The combined model has more parameters in its output equation, which will require more time to identify. It also has no consideration of many of the commonly observable behaviours of a battery cell. This makes it the most complex and least accurate model of the six. An improvement is observed from the simple model, then the hysteresis model and finally to the model that includes both characteristics.

The first two models are not often commonly used as they do not contain parameters representing the most common behaviours of the battery. The remaining four can be interchangeably used as any of them can provide the accuracy required for SoC measurement. They are also easily implementable in simple microcontrollers.

Table 3. Summary of the classifications of Equivalent Circuit Models (ECMs)

Model Name	Model Equations
The Combined Model	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = K_0 - Ri_k - \frac{K_1}{z_k} - K_2 z_k - K_3\ln(z_k) + K_4\ln(1-z_k)$
The Simple Model	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = OCV(z_k) - R_0 i_k$
The n-Hysteresis Model	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = OCV(z_k) - R_0 i_k - s_k M(z_k)$
The Enhanced Self-Correcting Model	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = OCV(z_k) - R_0 i_k + h_k + g_1 f_1 k + g_2 f_2 k + \cdots + g_n f_n k$
The n-Order RC Model	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = OCV(z_k) - R_0 i_k - U_{ik}$
The n-Order RC Model with n-State Hysteresis	$z[k+1] = z[k] - \frac{\Delta t}{Q}\eta[k]i[k]$ $y_k = OCV(z_k) - R_0 i_k - U_{ik} + h_k$

Improvements in these models do not often contain much and sometimes it is as simple as improving the parameter identification process. This table serves as a quick reference for any researcher to learn the basic ECMs and plan for the development of newer models from any of choice.

5. Conclusion

Equivalent Circuit Models (ECMs) are powerful models used to estimate the State of Charge (SoC) of a battery cell. Six foundational ECMs model the main behaviours of a battery. Newer models improve one or more parameters in these models to enhance the accuracy of the measurement of SoC. This is also often dependent on the cell chemistry of the negative electrode. That means that as newer materials are introduced in the production of the negative electrode, the correct tuning is done to the affected parameters to get the proper model.

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