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Estimate Equivalent Circuit Internal Resistance Battery LiFePO4

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***Abstract*—This research investigates the internal resistance and capacitance characteristics of Lithium Iron Phosphate (LiFePO4) batteries utilizing an equivalent circuit model based on resistor-capacitor (RC) networks. The growing integration of batteries in diverse applications, including electric vehicles and renewable energy systems, necessitates robust battery health monitoring strategies. This work employs current and voltage data acquired during battery discharge, subsequently analyzed using MATLAB 2023b software to determine the pertinent RC parameters. A third-order Equivalent Circuit Model (ECM) of RC, comprising three RC pairs, is implemented to enhance the precision of parameter estimation. The results demonstrate a strong correlation between the number of RC pairs and the accuracy of dynamic battery response representation. A higher-order model generally yields more precise estimations of battery performance. However, increasing model complexity can lead to overfitting, potentially diminishing the model's ability to accurately reflect actual battery behavior. This study contributes significantly to the understanding of LiFePO4 battery internal characteristic modeling and underscores the importance of balancing model fidelity with computational complexity.**

Keywords—LiFePO4 Battery, Internal Resistance, RC Equivalent Circuit Modeling, Parameter Estimation.

I. Introduction

Batteries are essential components in modern energy storage systems due to their increasing use in everyday devices [1], [2]. Applications range from electric vehicles and portable electronics to renewable energy systems. Accurate monitoring of internal resistance is crucial for optimal performance and impacts battery health and lifespan [3], [4].

Measuring this internal resistance poses a significant challenge in battery data management, hindering efficient calculation[5]. This study focuses on methods for estimating battery internal resistance. Previous research has explored first-order Equivalent Circuit Model (ECM) batteries [6] and second-order Equivalent Circuit Model (ECM) [7], [8]. Using Matlab 2023b, this study simulates a 3 RC series circuit to estimate the internal RC parameters of a 48V, 100 Ah, 15-cell Lithium Iron Phosphate (LiFePO4) battery, utilizing voltage and current data measured during discharge.

This research aims to develop and test an RC parameter estimation model specifically for LiFePO4 batteries. By leveraging current, voltage, and battery measurements, this method aims to provide accurate RC parameter estimates for various battery types. Furthermore, it seeks to address the challenges of estimating the internal RC parameters of LiFePO4 batteries, which exhibit non-linear behavior and are influenced by diverse environmental factors.

II. Research Methodology

A. Battery equivalent circuit model

To understand how a battery works inside, need a representative model, called an equivalent circuit model. This model is crucial for accurately identifying the battery's characteristics. This accuracy is highly significant for various applications from estimating the State of Charge (SoC) to optimizing charging strategies.

The model's complexity directly relates to how accurately it represents the battery. This complexity is usually measured by how many series RC circuits are in the model. These RC circuits represent the battery's internal polarization. Polarization refers to the voltage drop caused by internal chemical reactions during charging or discharging. The more RC circuits you use, the more accurately you can represent how polarization affects battery performance. So, adding more RC circuits makes the model more sensitive to those polarization dynamics.

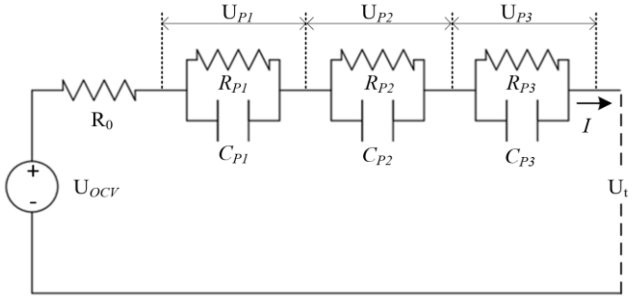

Figure 1. Third-order ECM RC pair of battery LiFePO4.

This research uses a third-order RC equivalent circuit model. This means it uses three parameters to represent the battery's dynamic behavior. They chose third-order because it strikes a good balance between model complexity and the desired accuracy. A third-order model is accurate enough to represent the tested battery's characteristics while still being computationally efficient.

$$\begin{cases} U_{OCV} = I \, . R_0 - U_{P1} + U_{P2} + U_{P3} + U_t \\ I = \dfrac{U_{P1}}{R_{P1}} + C_{P1}\dfrac{dU_{P1}}{dt} \\ I = \dfrac{U_{P2}}{R_{P2}} + C_{P2}\dfrac{dU_{P2}}{dt} \\ I = \dfrac{U_{P3}}{R_{P3}} + C_{P3}\dfrac{dU_{P3}}{dt} \end{cases} \quad (1)$$

This third-order RC model shown in Figure (1) has a circuit made up of R_{P1}, R_{P2}, R_{P3}, C_{P1}, C_{P2}, and C_{P3}. R_0 is the internal resistance, U_t is the terminal voltage, U_{OCV} is the battery's open circuit voltage, I is the battery current, and U_{P1}, U_{P2}, and U_{P3} are the output voltages of each RC series, which act as voltage sources. The basic equation for this equivalent circuit is shown in equation (1).

B. Battery profile

This study employs empirical measurements acquired from a Battery Management System (BMS) for a Lithium Iron Phosphate (LiFePO4) battery. Comprehensive specifications for the LiFePO4 battery are detailed in Table 1, which provides a thorough overview of its key operational parameters. The BMS serves as the primary data acquisition system, meticulously recording performance indicators of the LiFePO4 battery. The measurements constitute the empirical basis of this research, enabling a rigorous analysis of battery behavior under diverse operational conditions. Leveraging this high-resolution BMS data, the study aims to elucidate the performance characteristics and operational nuances of the LiFePO4 battery. This comprehensive analysis will contribute significantly to advancements in LiFePO4 battery technology.

Table 1. LiFePO4 Battery Specifications

Specifications	**Value**
Nominal Capacity (kWh)	2.4
Deep of Discharge (%)	90
Charge Voltage (Volt)	53.2 - 54
Discharge Voltage (Volt)	45 - 53
Nominal Voltage (Volt)	48
Charge / Discharge Current (A)	MAX 50 (1C)

The measurements were taken while the battery was discharging from SoC 100% to 0%. You can see the results in Figure 2.

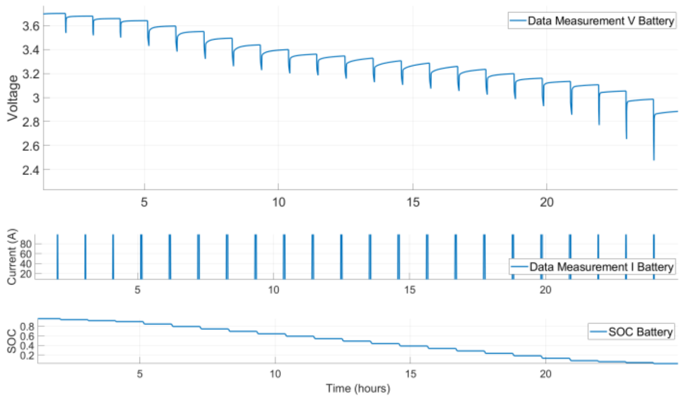

Figure 2. Data Voltage, Current, and SoC measurement Battery LiFePO4 related to time (hours).

C. Estimate Equivalent Circuit LiFePO4

In Estimating the internal RC parameters of a LiFePO4 battery, it's important to understand the relationship between predictors and estimated variables related to battery State of Health (SoH) [7]. This research uses MATLAB version 2023b. There are three steps in estimating RC parameters: the first step is loading and preprocessing the data. Battery measurement data is fed into the simulation to initialize the identification process.

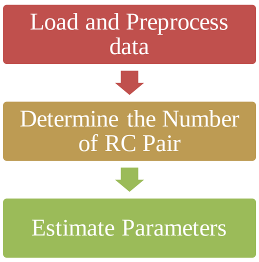

Figure 3. Data Voltage and Current measurement Battery LiFePO4 related to SoC Battery.

In the Determine the number of RC Pairs step, the relaxation time is compared at the beginning, middle, and end of the pulse. This method calculates the ratio of τ values. τ (Tau) represents the time constant related to resistance and capacitance [9]. The third time constant is represented as.

$$\tau_1 = R_1 C_1 \tag{2}$$

$$\tau_2 = R_2 C_2 \tag{3}$$

$$\tau_3 = R_3 C_3 \tag{4}$$

Parameter estimation step, in this step the Open Circuit voltage value, Internal Resistance, R_x, and τ_x will be identified and optimized with the SDO Optimizer Option.

III. Results and Discussion

Determining the appropriate number of RC pairs is crucial for this research as it constitutes a fundamental assumption regarding the battery's equivalent circuit model. An incorrect determination can introduce significant errors in the simulation. The initial phase presents the measured data, illustrated in Figure 1, which will be employed for the identification of the RC pairs. This phase fundamentally demonstrates the relationship between the battery's state of charge, voltage, and current.

A comparison of the voltage to the time constant pulse at the beginning of the pulse, the middle of the pulse and the end of the pulse of the input voltage pulse to the SoC is carried out. From the comparison of the time constant, the identification value of the Em (Open Circuit Voltage) and R_0 (Internal Resistance) is obtained. Based on previous research [10] the relationship between internal resistance and SoC is that the internal resistance value will increase as the SoC decreases in the battery. the relationship between internal resistance and SoC can be seen in the equation (5).

$$R_0 = a \, . SOC^b \, (1 - SOC)^c \tag{5}$$

where SoC represents the battery charge level, ranging from 0 (empty battery) to 1 (fully charged battery), parameters $a > 0$, while b and $c \leq 0$.

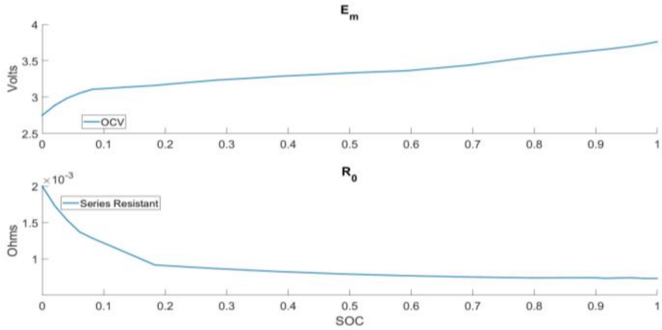

Figure 4. E_m and R_0 Battery LiFePO4 identification

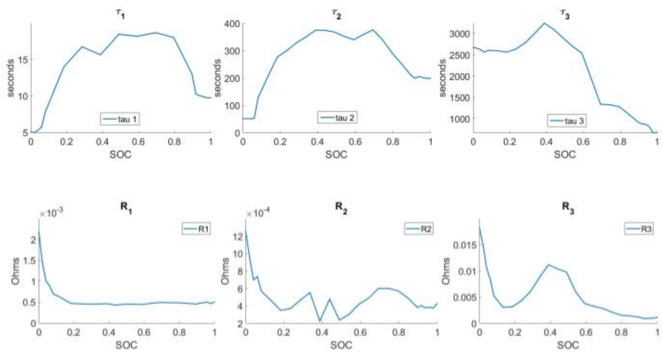

Figure 5. R_x and τ_x Battery LiFePO4 identification

The time constant values τ_1, τ_2, and τ_3 are identified through adjustments to the relaxation time of the pulse using an exponential fit. While the determination of R_1, R_2, and R_3 is identified using a linear fit system. The values of R and τ represent the dynamic response of the battery [8].

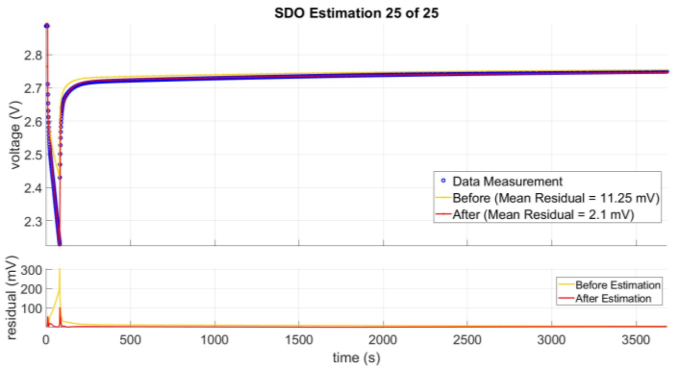

Figure 6. Data Voltage and Current measurement Battery LiFePO4 related to SoC Battery.

To determine the optimization value of determining the final value of Em, R_0, R_1, R_2, R_3, τ_1, τ_2, and τ_3. SDO Optimize is done using the Least-Squares Nonlinear (Isqnonlin) method.

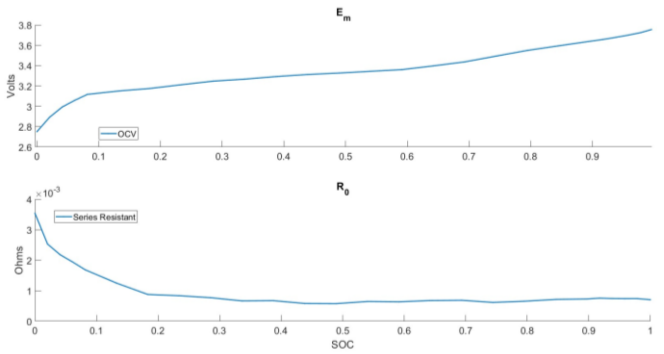

Figure 7. E_m and R_0 Battery LiFePO4 Estimate related to SoC Battery after SDO Optimization.

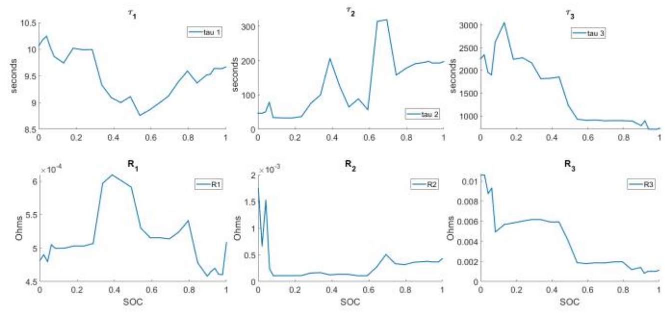

Figure 8. R_x and τ_x Battery LiFePO4 Estimate related to SoC after SDO Optimization.

IV. Conclusion

This research shows how important it is to figure out the right number of RC pairs when modeling a battery because it really affects how the battery responds. The more RC pairs you use, the more dynamic the battery estimation becomes. However, if there are too many RC series it will result in overfit which will eliminate the ability of the simulation to estimate a battery. This study shows that the resistance and capacitance values of LiFePO4 batteries using third order ECM can be seen in the Table (2).

Table 2. Internal Resistance Estimation Result

SoC (%)	R_1 (mΩ)	R_2 (mΩ)	R_3 (mΩ)	C_1 (F)	C_2 (F)	C_3 (F)
0	0.48	1.74	10.63	20.98	26.98	212.23
10	0.50	0.11	5.69	19.48	300.09	536.71
20	0.50	0.11	6.02	19.98	335.36	378.61
30	0.60	0.17	6.17	15.55	586.35	294.78
40	0.60	0.14	5.92	15.00	908.71	313.43
50	0.53	0.11	1.88	16.53	805.09	492.72
60	0.52	0.27	1.86	17.29	1165.07	489.02
70	0.52	0.33	1.95	18.04	478.45	459.92
80	0.48	0.36	1.19	19.52	530.44	744.66
90	0.47	0.37	1.01	20.51	521.73	702.55
100	0.46	0.37	1.01	20.93	521.73	699.74

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