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Optimization by Means of Genetic Algorithm of the Equivalent Electrical Circuit Model of Different Order for Li-ion Battery Pack

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***Abstract*—**The purpose of this article is to optimize the Equivalent Electric Circuit Model (EECM) of different orders to obtain greater precision in the modeling of Li-ion battery packs. Optimization includes considering circuits based on 1RC, 2RC and 3RC networks, with a dependent voltage source and a series resistor. The parameters are obtained experimentally using tests in the time domain and in the frequency domain. Due to the high non-linearity of the behavior of the battery pack, Genetic Algorithm (GA) was used to solve and optimize the parameters of each EECM considered (1RC, 2RC and 3RC). The objective of the estimation is to minimize the mean square error between the measured impedance in the real battery pack and those generated by the simulation of different proposed circuit models. The results have been verified by comparing the Nyquist graphs of the estimation of the complex impedance of the pack. As a result of the optimization, the 2RC and 3RC circuit alternatives are considered as viable to represent the battery behavior. These battery pack models are experimentally validated using a hardware-in-the-loop (HIL) simulation platform that reproduces the well-known New York City cycle (NYCC) and Federal Test Procedure (FTP) driving cycles for electric vehicles. The results show that using GA optimization allows obtaining EECs with 2RC or 3RC networks, with high precision to represent the dynamic behavior of a battery pack in vehicular applications.

***Keywords*—**Li-ion battery packs modeling optimized, EECM, GA, electric vehicle applications.

I. Introduction

Li-ION batteries have a higher energy density, higher discharge rate, smaller size and weight, among other advantages compared to other energy storage solutions currently available in the market [1]. That is the reason that in recent years, Li-ion batteries have emerged as a solution for storing energy, particularly in electric mobility transportation. The Li-ion battery is very difficult to control because of great complexity in the electrochemical reactions that govern its behavior. Therefore, system manufacturers that use this type of batteries in their applications require finding a model under different operating conditions to somehow control the performance of the battery and monitor its state in the short and long term [2].

Different techniques have been used to model a Li-ion battery in the literature, which can be classified into three main techniques: physical models, electrochemical ones and other alternative techniques for modeling [3], [4]. Of these latest techniques, EECMs are the most used since they are simple and practical, allowing a complex electrochemical process to be replaced by a simple electrical circuit. In addition, the EECM allows representing the behavior in stable and dynamic state of the battery. The battery model can be characterized for different secondary conditions, such as the temperature, state-of-charge (SoC), aging, loss of capacity, current, etc. [5]-[7]. In this way, a more complex model is obtained what improve the accuracy.

A simple EECM, which represents the battery behavior, consists of a circuit with zero time constant, containing a voltage dependent source in series with a resistor [8]. The voltage source corresponds to the battery open circuit voltage (OCV) and it is usually higher when the battery is fully charged and it is smaller when the battery is discharged. Thus, the OCV has a high dependence on SoC and lower degree of dependence with the temperature [5]. To determine the OCV values, time domain tests are frequently used [9]. The series resistance can represent the voltage drop of the battery when it is under load. This situation implies that the power is dissipated in the form of heat through the resistance; therefore, the energy efficiency is not perfect. This simple model is useful for applications that do not interest the dynamic behavior of the battery, because they only required knowing the static behavior of the system.

More complex EECMs have been used in the literature, containing one or more additional time constants, provided by the inclusion of additional RC networks. This RC component describes the transient response during charge/discharge of the battery [10], [11]. In [12], EECM with two RC networks was proposed. The first RC network modelled the battery resistance, load transfer and double layer effect. The second RC network was used to capture the diffusion effect of the battery that occurs at a very high time scale, about tens or hundreds of seconds. This model was used to estimate the SoC of a Li-ion cell; the results show that the model has an important role in the accuracy of the estimation of the battery

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states.

Modeling in the frequency domain has been widely used to identify and find an equivalent circuit model for a battery. Electrochemical impedance spectroscopy (EIS) is a technique that allows finding the impedance spectrum based on the frequency of a li-ion cell or battery [9], [13]. From the EIS test, it has been shown that a Li-ion battery has fractional properties, which at a low frequency (> 1 Hz) produces a straight line in the Nyquist graph. This behavior is represented in the circuit by a non-linear element known as a constant phase element (CPE). A particular case of a CPE is known as Warburg impedance when the straight line forms an angle of 45° [14]. This element has been used in the literature to model the diffusion of lithium ions in the electrodes of a Li-ion battery. Warburg impedance presence in the circuit implies that differential equations of the model are difficult to solve, which increases the complexity of simulating the circuit. To find an approximation of this element, *n*-RC circuits connected in series can be used. The decision of the number of RC component depends on the required accuracy and the available computation speed [6], [15]. However, a large number of RC circuits mean a greater computational load in the simulations of a battery, therefore different algorithms have been proposed to identify and optimize the parameters of an EECM, containing from 3RC to 8RC. The complexity of the model and the processing time increase with the amount of RC circuits used, which implies that some authors have to reduce the model to one or two 2RC networks, reducing the accuracy of the battery model. In [16], a Bayesian Network (BN) is proposed to determine the parameters of an EECM. The values proposed by this BN are compared with the parameters obtained by an impedance analyzer using a circuit with 2RC, 3RC and 8RC. The results show that using the adjustment with BN provides an error of 3.5% and 4.6% for the circuit of 2RC and 3RC components, respectively. On the other hand, the lowest error obtained with the impedance analyzer was 3.3% for a circuit with 8RC components. Therefore, the adjustment with BN achieves greater precision with few RC circuits. As a conclusion, a good parameter identification algorithm of an EECM can achieve high model accuracy with a smaller number of circuit elements.

This paper proposes a technique based on GA to identify the parameters of an EECM associated with different frequencies and that represents the electrical behavior of a lithium-ion battery pack. Experimental tests are developed in the time domain, to obtain the OCV-SoC ratio, and also in the frequency domain by means of EIS tests, from which the battery frequency spectrum at different SoC is obtained. From these experimental tests, the impedance spectrum is obtained the parameters of the impedance of the EECM are obtained by means of GA minimizing the mean square error between the measured and estimated impedance. To compare GA accuracy when using low and high order EECM models, three circuits with an incremental number of RC networks (from 1RC, 2RC to 3RC components) are tested. Each EECM is experimentally validated using a HIL platform that reproduces the NYCC and FTP urban driving cycles of an electric vehicle. The results show that it is possible to obtain an EECM with 2RC or 3RC with high precision to represent the dynamic behavior of a battery packs in vehicular applications using GA.

II. Experimental Tests

This section presents the experimental tests developed to obtain the model of a commercial Li-ion battery pack composed of four parallel cell strings and a battery management system (BMS) which controls cell voltage, temperature and current of each serial connection, cell balance function, protection functions and charging and discharging process. A schematic battery pack layout is shown in Fig. 1 and Table I shows the main electrical characteristics.

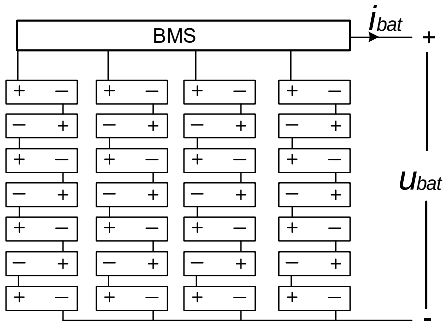

Fig. 1 Schematic battery layout

TABLE I
Battery Packs Characteristics.

Cell reference	MP176065int
Pack rated voltage	25.9 V
Pack maximum voltage	29.4 V (4.2 V/cell)
Pack minimum cut-off voltage	20.3 V (2.9 V/cell)
Pack Capacity	50 Ah
Pack maximum current	50 A
Range of temperature (charge)	-20°C to 60°C
Range of temperature (discharge)	-30°C to 55°C

Frequency domain tests are preformed to evaluate the complex impedance by EIS. To determine the OCV-SoC ratio, time domain tests are carried out.

A. Frequency Domain Tests

EIS is a technique that allows electrochemical systems to be characterized, such as batteries, supercapacitors, etc. This technique consists of an experimental test in the frequency domain that allows modeling electrochemical systems by calculating the impedance in a given frequency range (from about mile-Hertz to Megahertz). Therefore, it is a useful tool to investigate the chemical reactions that occur inside a Li-ion battery pack [17]. In an EIS test, the current and voltage are measured at each test frequency and the impedance at each point is calculated. The resulting current has the same frequency as the applied voltage but different in magnitude and phase, in this way the impedance of this dipole can be determined with the ratio between the applied voltage and the injected current [18]. Once the spectrum is obtained, an equivalent circuit can be found to represent the behavior of a

Li-ion battery.

In this work, the typical EIS test has been modified to test the Li-ion battery pack. To do so, the frequency sweep signal generated by a commercial impedance analyzer is amplified using the experimental structure proposed in [19]. The impedance of the battery pack is measured for a frequency range from 1 mHz to 5 kHz and it has been evaluated under five different SoCs (20%, 40%, 60%, 80% and 90%). Fig. 2 shows the results obtained from the EIS tests, plotted in a Nyquist graph at different SoCs. These plots show that variations of SoC affect the impedance of the battery at low and medium-low frequencies. Above medium frequencies, battery impedance parameters are not affected by changes in SoC.

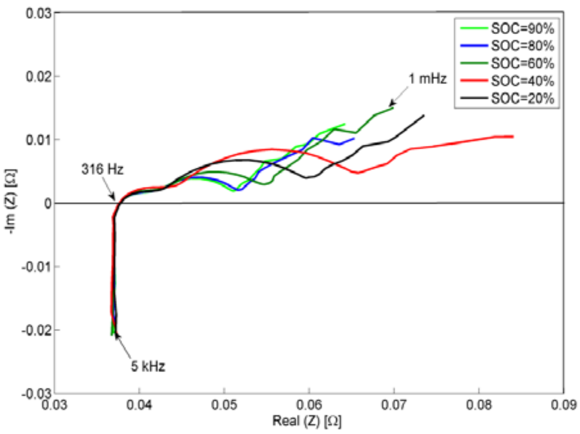

Fig. 2 Impedance spectrum at different SoC

Four different zones can be identified from the impedance spectrum plot of Fig. 2, where each zone is related with different electrochemical processes that occur inside the battery pack and can be represented with one or more elements in an electric equivalent circuit. The low frequency zone can be related the diffusion process on state solid of lithium ion in the electrodes of the battery and can be represented in a circuit with a CPE or *n*-RC components. The medium-low and medium frequency zones are associated with the slow migration of lithium ions through the different SEI layers that cover the active mass and can be represented in a circuit with 1RC or 2RC components. The high frequency zone can be related at inductive reactance effect attributed to the porosity of the electrodes and the conductors connected between the instrument and the battery. This zone can be represented in a circuit with an inductance. Finally, the intersection with x-axis can be associated with electrolyte of the battery and can be represented with a resistance in the circuit [20]-[22].

B. Time Domain Tests

The OCV-SoC characteristic is obtained by means of the voltage and current analysis of experimental time domain tests [23], [24]. These experimental tests consist of applying a series of current pulses to charge or discharge the battery over the entire SoC range.

The procedure to obtain the relationship OCV-SoC beginning with the battery pack charging at 100%, which is when the battery voltage reaches 29.4 V (pack maximum voltage). Next, the battery is discharged in pulses of 10 A (constant current) during 30 min followed by 90 min of relaxation time. The OCV correspond the voltage measured at the end of each relaxation period. After the discharge has concluded, the battery pack is charged again in pulses of 10 A (current constant) during 30 min each, followed by 90 min relaxation time. The upper voltage level in the charging process is imposed at 29.4 V. In both charging/discharging process it is not possible to reach 100% and 0% of SoC because the BMS limits the current to protect the battery pack. For this situation the maximum voltage and minimum cut-off voltage is considered as 100% and 0% of the SoC, respectively. Results of the discharge and charge tests do not have a representative deviation because Li-ion cells have low hysteresis. For this reason, average values have been used to calculate the OCV-SoC relationship. Fig. 3 shows the experimental average OCV and the OCV adjusted with a polynomial of order five of (1):

$$OCV(SOC) = -27.58 \cdot SOC^5 + 50.00 \cdot SOC^4 + 3.476 \cdot SOC^3 + \\ -50.00 \cdot SOC^2 + 33.01 \cdot SOC + 20.52 \qquad (1)$$

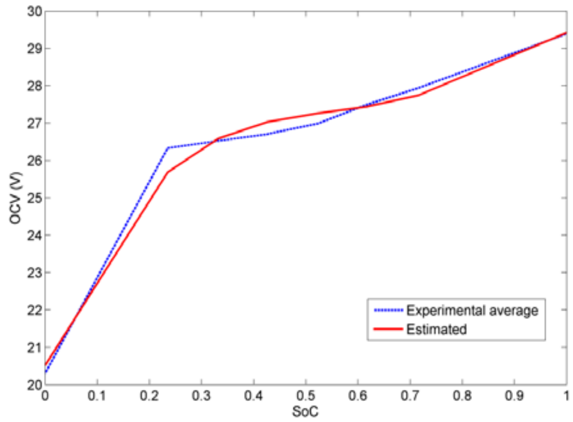

Fig. 3 OCV-SoC curve.

III. Battery Pack Model

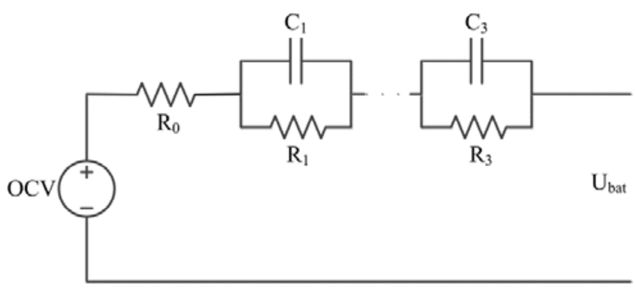

Fig. 4 EEC model

In this section, the experimental data obtained from both frequency and time domain tests in Section II are used to model battery pack. The electrical dynamics are represented by an EECM consisting of a dependent voltage source, a resistance and a network of different order composed of a capacitor in parallel with a resistance (RC network). To evaluate the accuracy of this battery modeling, three EEC alternatives with 1RC, 2RC and 3RC components are considered, respectively. The topology of the EECM is shown in Fig. 4.

The general expression of the input impedance of the electrical circuit in Fig. 4 can be defined by (2):

$$Z = R_0 + \frac{R_1\left(\frac{1}{j\omega C_1}\right)}{R_1 + \left(\frac{1}{j\omega C_1}\right)} + \ldots + \frac{R_n\left(\frac{1}{j\omega C_n}\right)}{R_n + \left(\frac{1}{j\omega C_n}\right)} \tag{2}$$

In addition, (3) shows the general expression the output voltage ratio of the circuit of Fig. 4:

$$U_{bat}(t) = OCV(SOC) - R_0 i - v_1(t) - \ldots - v_n(t) \tag{3}$$

where n is the order of the ECCM, $v_n(t)$ is the voltage in the resistance n of the RC networks, $i(t)$ is the current of the circuit in a clockwise direction.

A. GA Models

In this work, a methodology that allows optimizing of the parameters of the EECM is used. Considering the problem of determining the parameters of an electric circuit, where the circuit topology is known but not the value of their parameters. Further, it is possible obtained experimentally the input impedance of the circuit at different frequency (frequency domain tests). Then, the optimization model shown in (4) can be raised to solve this problem:

$$\min \Sigma_k \left(Z_k^{med} - Z_k^{cal}(v)\right)^2 \quad \text{s.t.} \quad v^{min} \le v \le v^{max} \tag{4}$$

where Z_k^{med} is the sample k of the magnitude of the measured impedance in the experiment, Z_k^{cal} is the calculated impedance for the sample k. The design variables were $v = [R_s, R_1, C_1, R_2, C_2, R_3, C_3]$. The EECM parameters obtained through (4) are calculated for the different values of SoC.

In many applications, different algorithms have been implemented to optimize non-linear process models. Considering the high non-linearity presented by this type of adjustment, the evolutionary technique GA was selected among different methodologies, since it was the test that produced the smallest adjustment error [5]. Fig. 5 shows a comparison in the impedance spectrum setting for SoC = 90%. The root mean square relative error (RMSE) of the EECM with 1RC, 2RC and 3RC components were: 6.26%, 1.07% and 1.05%, respectively. Therefore, the EECM with 2RC and 3RC components has greater precision to represent the frequency response of the battery pack.

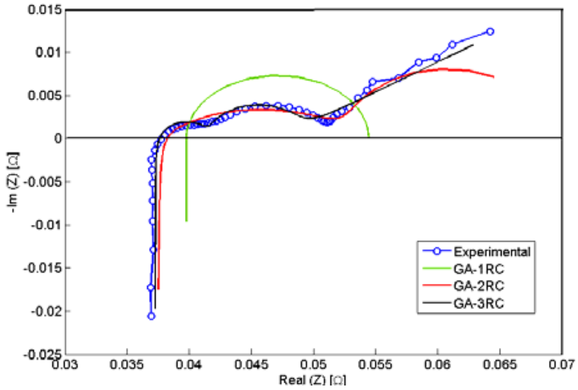

Fig. 5 Accuracy of impedance estimation at 90% SoC

IV. Experimental Model Validation

The resulting battery pack model accuracy has been tested by means of two different experimental tests. Both EECMs with 2RC and 3RC networks were experimentally validated using a HIL platform that reproduces the NYCC and FTP urban driving cycles of an electric vehicle. The HIL platform proposed in [25] was used for these experimental tests. This platform consists of an electronic load and a power source to simulate the dynamic behavior of an electric vehicle, which are controlled by mean of a dSpace® system in synchronization to simulate the vehicle power demand during acceleration and braking. The current profiles associated to each driving cycle were used as the input of the proposed battery pack model implemented in a MATLAB®/Simulink environment.

During the HIL simulation, the data of the current and voltage of the battery pack at each driving cycle are recorded. To determine the accuracy of each model, the voltage response of the battery pack model has been compared with the real voltage measurements at battery pack terminals. Figs. 6 and 7 show the current profiles of each driving cycle.

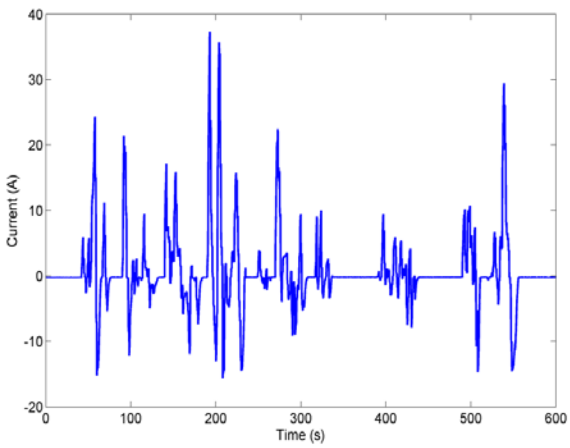

Fig. 6 NYCC current profile

Figs. 8 and 9 show the comparison of the measured pack voltage and the simulated voltage for each model (with 2RC and 3RC components). Results show that both models with

2RC and 3RC networks present high accuracy to reproduce the voltage response of the battery pack. The RMSE of the voltage response were: 0.21% and 0.25% for the NYCC driving cycle, respectively. For the FTP driving cycle, the RMSE were 0.61% and 0.61%, respectively. The RMSE in this case of FTP can be produced because the faster acceleration/breaking cycle in comparison of the NYCC.

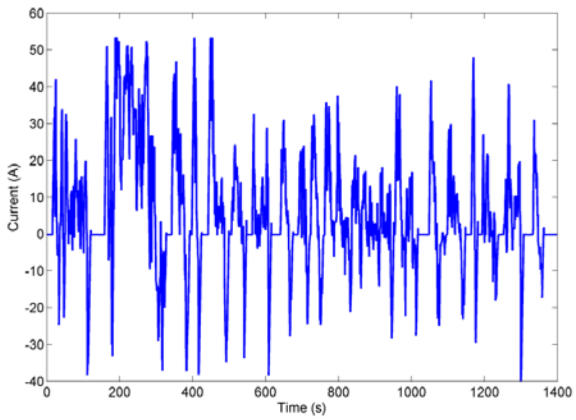

Fig. 7 FTP current profile

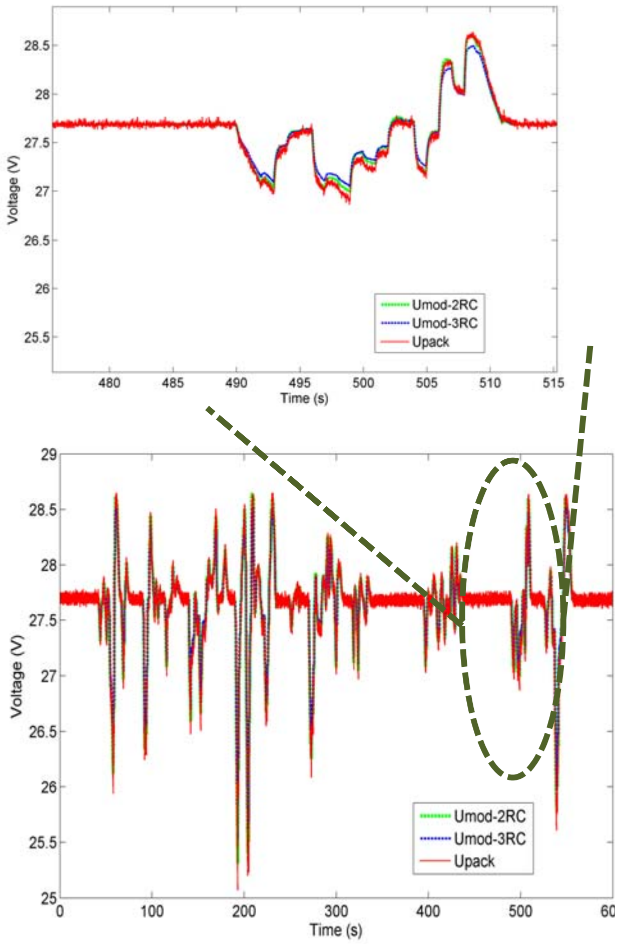

Fig. 8 Simulation NYCC cycle

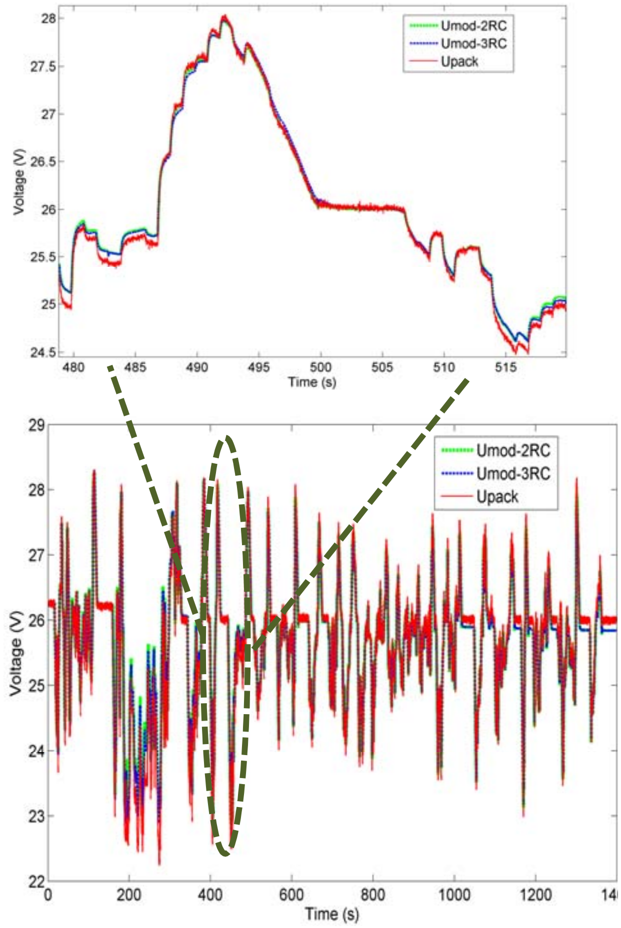

Fig. 9 Simulation FTP cycle

V. Conclusion

In this research, different EECMs for the battery pack are optimized. The proposed EECM consists of a dependent voltage source, a resistance and RC networks of different order. The voltage source, representing the OCV-SoC relationship, is performed in the time domain by means of pulsed current tests. The modeling of the internal impedance is performed in the domain frequency, by impedance spectroscopy technique. The accuracy of different EECMs with 1RC, 2RC and 3RC networks is analyzed to represent the behavior of the real battery pack. The parameters of each EEC model considered in this work are optimized by means of a GA, which solves the optimization problem that minimizes the mean square error between the measured impedance in the experimental battery pack and the impedance simulated by each circuit. Results show that the EECMs with 2RC and 3RC components have greater precision to represent the frequency response of the battery pack comparted to the EECM with a single RC network. Therefore, these two EECMs are used to represent the behavior of the battery pack.

Both EECMs with 2RC and 3RC networks are experimentally validated using a HIL simulation platform that reproduces the well-known NYCC and FTP urban driving cycles for electric vehicles. Results show that maximum error of the voltage response of each EECM is less than 0.7% for each cycle analyzed.

As main conclusion, in this research work a low-order EECMs are obtained to represent with high accuracy the dynamic behavior of a real battery pack.

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