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General Parameter Identification Procedure and Comparative Study of Li-ion Battery Models

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***Abstract*—Accurate and robust battery models are required for the proper design and operation of battery-powered systems. However, the parametric identification of these models requires extensive and sophisticated methods to achieve enough accuracy. This paper shows a general and straightforward procedure, based on Simulink and Simscape of Matlab®, to build and parameterize Li-ion battery models. The model parameters are identified with the Optimization Toolbox of Matlab®, by means of an iterative process to minimize the sum of the squared errors. In addition, this procedure is applied to a selection of five different models available in the literature for electric vehicle applications, obtaining a comparative study between them. Also, the performance of each battery model is evaluated through two current profiles from two driven profiles known as the Urban Driving Cycle (ECE-15 or UDC) and the Hybrid Pulse Power Characterization (HPPC). The experimental results obtained from a Li-ion polymer battery have been compared with the data provided by the models, confirming the effectiveness of the proposed procedure, and also, the application field of each model as a function of the required accuracy.**

***Index Terms*— ECE15, HPPC, Li-ion battery models, Matlab, Parameter estimation, Simscape, Simulink**.

I. INTRODUCTION

IN recent years, rechargeable batteries are playing an essential role as energy storage and as power sources for some electrical systems such as communications systems, renewable power systems, electric vehicles, electric buses, etc. [1], [2]. Lithium-ion batteries are being an essential technology in powertrain electrification of hybrid electric vehicles (HEV) and pure electric vehicles (EV), which allow reducing fuel consumption and decreasing greenhouse gas emissions [3]. This kind of battery presents some performances very suitable for transportation applications, such as high energy/power density ratio, slow self-discharge, high cycle life and lack of hysteresis effect in some of them [4].

In the state-of-the-art, numerous battery models have been reported for system-level modeling. Choosing between those models is a trade-off between model complexity, parameter estimation effort, and accuracy.

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In general, battery models can be classified into three categories: electrochemical, mathematical, and electrical. Electrochemical models consist of a set of partial differential-algebraic equations along with a wide range of limitations [5], [6]. The estimation of the electrochemical model is very accurate [7]. However, simulation with these models can be time-consuming, since it requires to solve a complex set of equations to identify the electrochemical properties [8]. Mathematical models are an alternative based on empirical formulas approaches [9],[10]. These models are empirical functions with parameters derived from datasheet or from static measurements and use a fewer number of equations. However, these models cannot represent the dynamic information correctly and provide inaccurate results in the order of 5%-20% error. Finally, circuit-based or electrical models are able to accurately exhibit the current-voltage characteristics of the batteries while maintaining simulation efficiency. The accuracy of these electrical models lies between electrochemical and mathematical models [11]. These models are based on resistors and capacitors connected to controlled voltages sources, and they can represent the fast dynamic of the battery with a high level of accuracy [12].

In the literature, several papers develop a comparative study among different models. So, [13] shows a systematic review of ten models, using nonlinear identification technique with the dual Extended Kalman Filter (dual-EKF). This paper concludes the RC model provides the best dynamic response and accuracy. In addition, [14] examines eleven electrical circuits models in which parameters are estimated with a genetic algorithm (GA), and it concludes that the higher and constant RC networks have better robustness considering parameter variations and sensor errors.

The main contribution of this paper is the proposal of a general and straightforward offline-procedure in order to estimate the battery model parameters. The identification method is based on the interface of MATLAB System Identification Toolbox, which uses numerical optimization to minimize the error between the measured and the estimated battery voltage. In order to verify the identification procedure, a comparative analysis of the most used battery models for electric vehicle applications is performed. The selected models can represent the most important battery effects that affect the control and battery.

The next sections are organized as follows: Section II describes the parameter estimation procedure for battery models using Simulink and Simscape. In Section III, the experimental setup is described. Section IV presents a description of different battery models and their main parameters. Section V shows the models of experimental validation using the ECE15 and HPPC dynamic driving cycle. Finally, in Section VI, the conclusions are presented.

II. Parameter Estimation Procedure

Battery models can be used in two ways: online and offline. Online models are used in real-time battery management systems for the state of charge (SOC) estimation, with tracking algorithms on different parameters [15],[16], [17]. On the other hand, an offline battery model is used for system-level design, to value the battery state of health or for simulation [18], [19]. The accuracy of these models greatly depends on carefully identified model parameters [20], [21].

However, from a practical point of view, this paper proposes to estimate and validate multiple parameters of the model at the same time, as it is made in the Optimization Toolbox of Matlab®. This parameter identification proposal can be used in both types of applications, offline and online, with some differences in the parameter estimation procedure. In this paper, this procedure is applied to offline modeling.

The identification of the model parameters p is performed by minimizing the cost function $F(p)$ (1), which is the minimum of the sum of the squared errors between the experimentally measured output voltage V_m and the model output voltage V_s, as shown in Fig. 1.

$$F(p) = \sum_{i=0}^{n} \left(V_m(t_i) - V_s(t_i, p)\right)^2 \qquad (1)$$

The optimization method used for parameter identification is known as Nonlinear Least Squares, described in [22]. This method is used since the quadratic cost function is easier to minimize than other cost functions, and it is sufficiently accurate for this type of application.

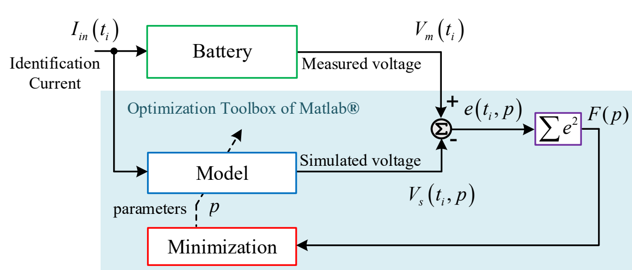


Fig. 1: Schematic diagram of the general parameter estimation.

Fig. 2 shows the battery model identification procedure to estimate the optimum parameter values once the identification current profile, model, and identification method have been chosen. Fig. 2a shows a general equivalent circuit model that represents many of the battery electric models available in the literature. Each model uses a different combination of elements, as it is shown in Section IV. *OCV* represents the open-circuit voltage; $V_v(SOC)$ represents a variable voltage depending on the state of charge (*SOC*); R_i and R_o are resistors, R_1C_1 to R_nC_n represent resistors and capacitors in parallel, and R_pC_p represent resistors and capacitors in series. This equivalent circuit model could be implemented in Simulink, Fig. 2b, or Simscape, Fig. 2c, where the identification current profile is the input signal, and the voltage and SOC are the outputs signals of the model.

In addition, the model could use different lookup tables, variable voltage sources, nonlinear resistors, and nonlinear capacitors to represent the nonlinear behavior of the battery [23].

Also, a detailed general identification procedure is depicted in Fig. 2d.

The procedure for using the tool includes several and straightforward steps:

A. Parameter Estimation

1) Build the equivalent circuit model. It can be a block diagram in Simulink or a circuit in Simscape.
2) Import experimental data for parameter estimation in the tool Parameter Estimation of Simulink.
3) Choose the parameters to estimate and their limits.
4) Set up optimization options and parallel compute options to accelerate the numerical estimation.
5) Run the estimation task and get the parameters after the needed iteration to optimize the cost function.
6) Verify the model response by comparing the experimental results to the simulated data (obtained using the estimated parameters). If the error is not small enough, in this order, or return to step 1 to change the **Model** (① in Fig. 2c), or change the **Identification method** and return to step 3 (② in Fig. 2c), or modify the **Identification current profile** and return to step 2 (③ in Fig. 2c).

B. Validation

7) Import new application or verification current profile to the model, with the estimated parameters.
8) Obtain the voltage simulated response.
9) Verify the model response by comparing the real voltage and the simulated voltage data. If the error is not small enough, in this order, or return to step 1 to change the **Model** (① in Fig. 2c), or change the **Identification method** and return to step 3 (② in Fig. 2c), or modify the **Identification current profile** and return to step 2 (③ in Fig. 2c).

III. Experimental Setup

A. Battery testing system

The experimental setup is shown in Fig. 3a. It includes a battery cell along with a data acquisition system and dynamic load. Experiments have been conducted on pouch lithium-ion polymer HRB 8048145, which specifications are listed in Table I. In order to verify the battery model's accuracy when is used in automotive applications, the experimental current profile and the data acquisition system are conducted using the following set of equipment:

1) DC electronic load: Chroma 63206A-600-420 that reproduces DC motor current consumption periods.
2) DC power source: Sorensen SGI400/38 to inject energy from the regenerative braking.

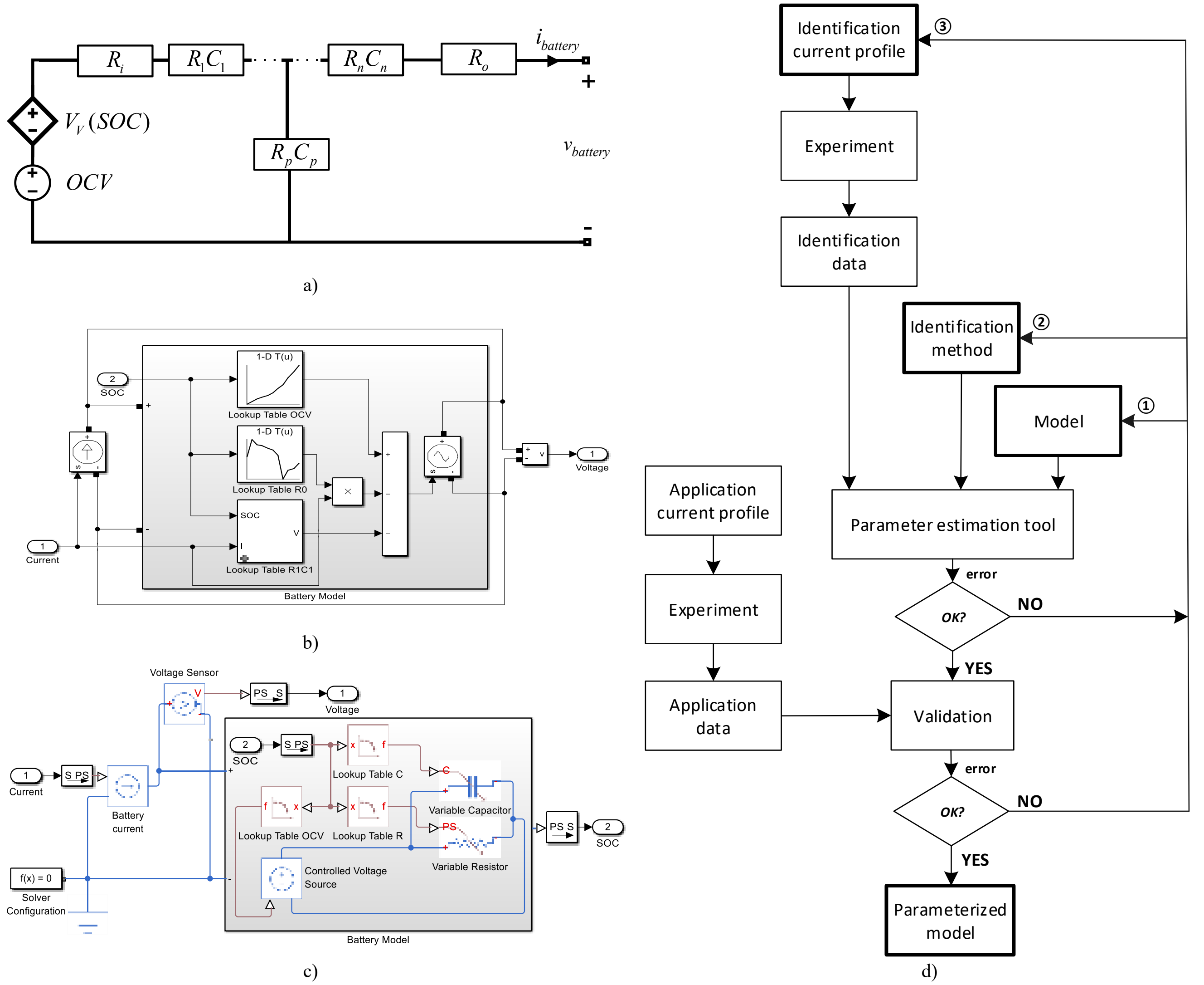


Fig. 2: Parameter estimation: (a) general equivalent circuit model, (b) equivalent circuit model in Simulink, (c) equivalent circuit model in Simscape, and (d) general identification procedure.

3) Datalogger: Agilent 34970A to measure cell voltage and current.
4) Shunt resistor: Newtons 4th HF200 (0.5mΩ) to measure the cell current.

All these elements have been synchronized by LabVIEW® software in order to produce all current pulse and specific current profile to verify the equivalent model of the battery.

TABLE I
LITHIUM ION POLYMER HRB 8048145 SPECIFICATION

Parameter	Value
Nominal voltage	3.7 V
Nominal capacity	5 Ah
Upper cut-off voltage	4.20 V
Lower cut-off voltage	3.0 V
Charging current	5 C
Continuous discharge current	50 C

B. Battery test schedule

The parameter identification procedure uses for each model, either a constant current profile test or a pulsating current discharge profile test, in order to obtain parameter estimation.

Fig. 3b shows the battery discharge curve obtained at constant current (generally equal to 20% of the rated capacity until the cut-off voltage). From this curve, the real battery capacity is obtained, Q=5.58Ah, by integrating the current as a function of time.

On the other hand, the state of charge (SOC) estimation is a challenging task due to the battery aging and temperature effect. Some techniques are presented in [24], where the tendency of estimation is a mixture of probabilistic and artificial intelligence techniques.

The Coulomb counting method is used in this paper for SOC calculation because it is simple and provides good accuracy. In order to obtain the data for battery model identification, current pulses of 10% SOC are applied, as shown in Fig. 3c.

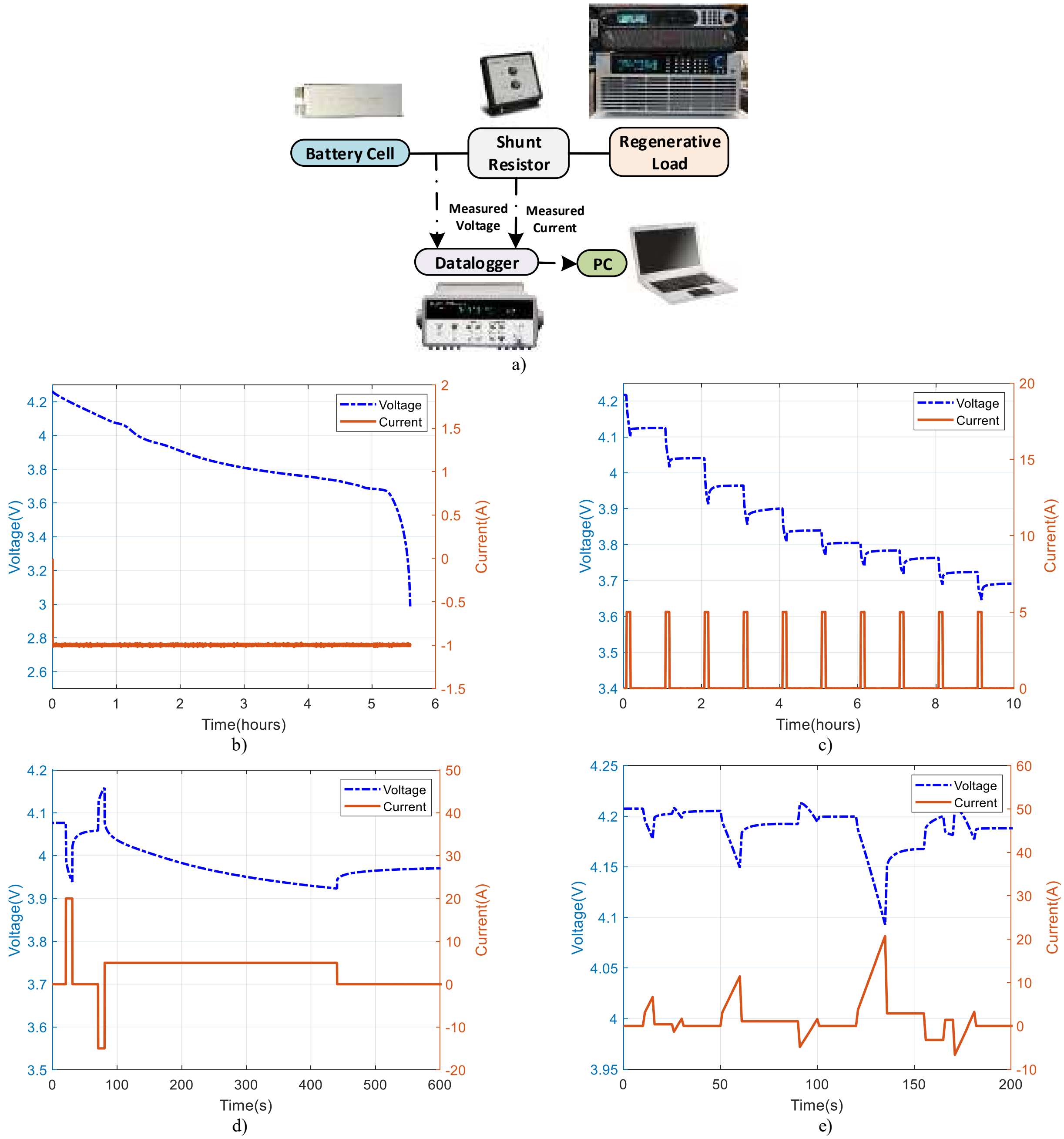


Fig. 3: a) Battery testing system. Current profiles for identification: (b) constant and (c) pulsating current discharge profile for verification: d) HPPC and e) ECE15

In addition, to verify the robustness and accuracy of the battery models, two verification test profiles are applied: HPPC profile and ECE15 profile. These profiles are widely used in the battery and supercapacitor modeling, in electric vehicles.

Fig. 3d shows the HPPC test, described in [25]. It is applied repeatedly for almost one hour to validate how robust is the battery model long-time response. Fig. 3e shows the ECE15 test, described in [26], which is applied repeatedly for almost one hour.

IV. Battery Models

This section analyses five battery models selected from the literature, on which the procedure shown in Section II has been applied.

In [27], different datasets of an HEV Li-polymer cell was used to compare mathematical models, where enhanced-self-correcting with 4 filters states gave the best performance in all cases, at the cost of greater complexity. An overview of generic battery models (mathematical and electrical) was presented in [28], where the continuous and transients current test of the RC model showed a higher performance.

Another comparative study between several models was performed in [29], where the third-order RC model with hysteresis shows a better performance. In addition, [30] shows a systematic comparative study of equivalent circuit models, in which the 2RC model has better accuracy. However, if one-state hysteresis is added to the model (2RCH), the accuracy and the reliability do not improve for LiMNC cells.

In this paper, the selected models are the Sheperd Model [31], the Nonlinear Model [32], PNGV Model [33], the 3rd Order RC Model with One-State Hysteresis [29] and the Three RC Network Model [34]. These models were selected to cover most of the applications, and they are briefly reviewed below.

A. *Shepherd Model*

The Li-ion battery model proposed in [31] is used due to the fact that this model requires only a few data from manufacturer datasheet and the battery discharge curve. This model is based on the modified Shepherd model, and it can accurately reflect the macro-level characteristics of current and voltage that are important for system-level simulations, as shown in Fig. 4.

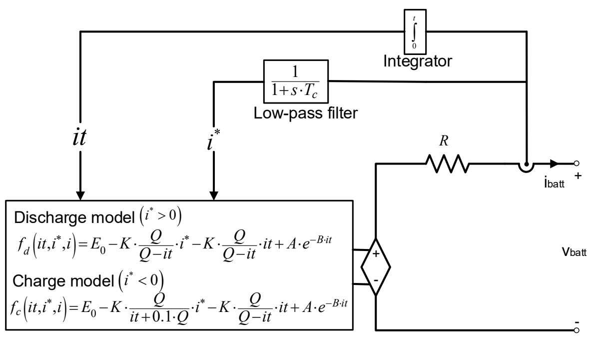


Fig. 4: Shepherd mathematical model in Simulink.

This battery model is implemented in Simulink, and it is composed of a controlled voltage source and an internal resistance. The controlled voltage source value depends on two expressions, one for battery discharge and other for battery charge. Where E_0 is the battery constant voltage (V), K is the polarization constant (V Ah^{-1}), Q is the maximum battery capacity (Ah), $i*$ is the filtered battery current (A), it is the actual battery charge (Ah), A is the exponential zone amplitude (V), B is the exponential zone time constant inverse (Ah^{-1}), Tc is the battery time constant (s), and R is the battery internal resistance (Ω) [35].

Applying a discharge curve of 0.2C and using the Parameter Estimation tool shown in Section II along with the battery model in Simulink, the different estimated parameters for this model are obtained, as shown in Table II.

TABLE II
SHEPHERD MODEL BATTERY PARAMETERS

Parameter	Value
E_0	3.7380 V
K	1.4932× 10^{-3} V Ah^{-1}
Q	5.5832 Ah
A	0.5307 V
B	0.5612 Ah^{-1}
R	5.4238× 10^{-3} Ω
Tc	10.02 s

B. *The Nonlinear Model*

The proposed model in [32] is demonstrated to be more appropriate than the well-known Randles's battery circuit model applied for lead-acid battery technologies. Despite the good results obtained with the modified Randles's model, however, for lithium-polymer battery, this model is not appropriated due to the battery nonlinearly behavior. For this reason, a nonlinear RC battery model is proposed in [36]. The proposed model consists of a nonlinear voltage source, Open Circuit Voltage, OCV(SOC) as a function of SOC in order to represent nonlinear characteristics; a capacitance C_p to model polarization effect; a propagation resistor R_b; a diffusion resistor R_p; and an ohmic resistance R_t, as shown in Fig. 5a.

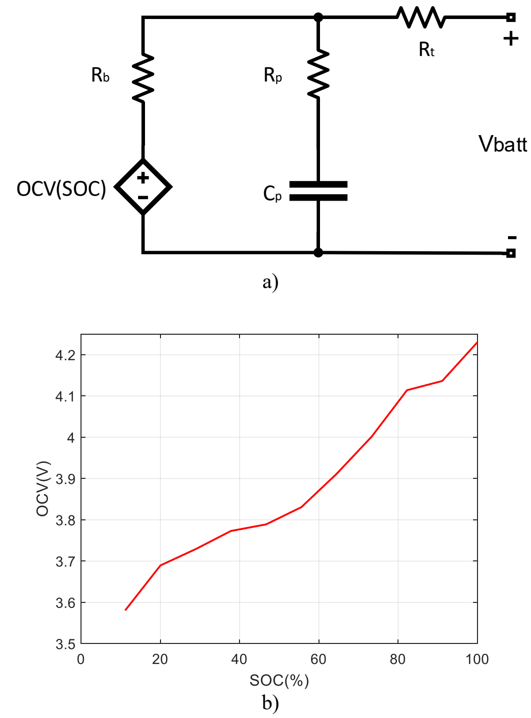


Fig. 5: Nonlinear RC Battery: a) model structure and b) OCV vs. SOC

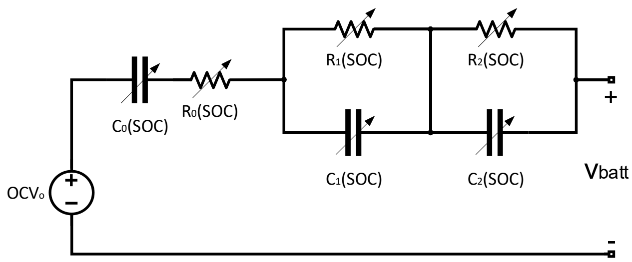
The obtained parameter values are shown in Fig. 5b and Table III, after using the identification procedure proposed in Section II. The model parameters depend on the state of charge at each current level during discharging.

TABLE III
BATTERY DYNAMIC MODEL PARAMETERS

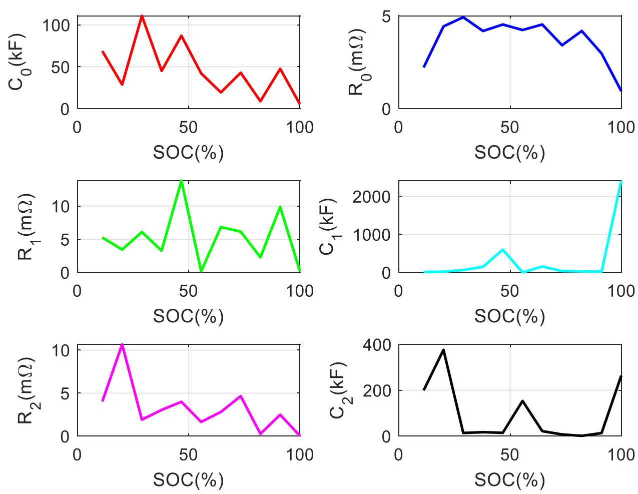
Parameter	Value
Cp	8946.5 F
Rb	5.4646× 10^{-3} Ω
Rp	0.4418 Ω
Rt	1.616× 10^{-3} Ω
Vp	3.9163 V

C. *Partnership for a New Generation of Vehicles (PNGV) Model*

The PNGV model is accurate and able to describe the battery behavior during the discharge process [33]. In [37], research about Li-ion battery enhances the PNGV model by adding variable RC components, as shown in Fig. 6a. This model is composed of the OCV_0 represents the initial constant voltage source (V), and $C_0(SOC)$ represents a variable capacitor, both connected in series represent the nonlinear voltage characteristics of the battery, which is dependent on SOC. $R_0(SOC)$ represents the battery internal resistance (Ω), and also two parallel networks based on R_1, C_1, R_2, and C_2 as a function of SOC. The values of the different parameters estimated for this model, with the procedure described in Section II, are shown in the Appendix and are depicted in Fig. 6b.



a)



b)

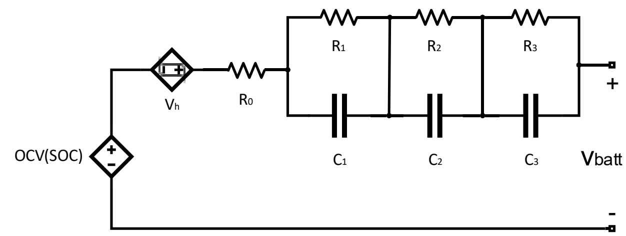
Fig. 6: PNGV model: a) electric circuit and b) parameter values.

D. *The 3rd Order RC Model with One-State Hysteresis*

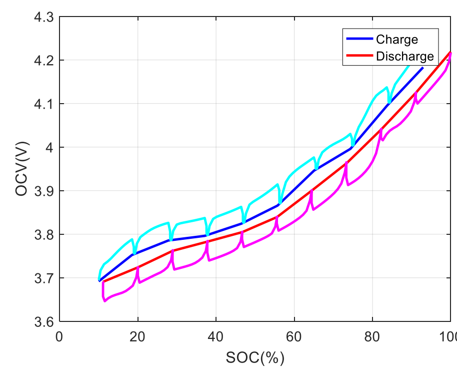
The Thevenin circuit with three RC parallel networks with hysteresis is proposed in [29]. In this model, a hysteresis voltage V_h is added in series with an ohmic resistance and three RC parallel networks, Fig. 7a. The battery hysteresis model, proposed in [27], is defined by (2):

$$h(k)=\exp\left(-\left|\frac{i(k)\cdot\gamma\cdot\Delta t}{Q}\right|\right)\cdot h(k)-\left(1-\exp\left(-\left|\frac{i(k)\cdot\gamma\cdot\Delta t}{Q}\right|\right)\right)\cdot\operatorname{sgn}\left(i(k)\right) \qquad (2)$$

The hysteresis voltage, *Vh* (in the order of few millivolts), is $M\cdot h(k)$, where M is the maximum hysteresis value, γ adjusts the changing rate of hysteresis voltage and Q is the total capacity. In [38], the authors provide a robust and consistent methodology to assess the OCV of different chemistry lithium-ion cells. This method is applied to the under-test cell to get a variation of 10% of SOC using a 1C current until the cut-off voltage, as shown in Fig. 7b. This information allows to obtain the parameter used in (2) needed to calculate *Vh*.



a)



b)

Fig. 7. The 3rd Order RC Model with One-State Hysteresis (3RCH): a) electric circuit and b) OCV versus SOC.

Table IV shows the average values of RC and the average hysteresis parameters from charge and discharge curves.

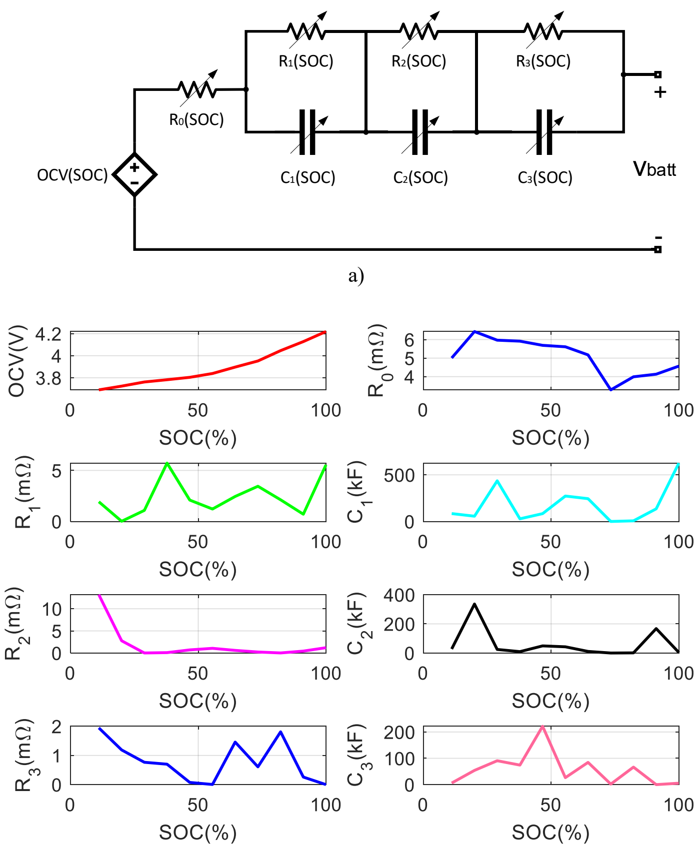
TABLE IV
DYNAMIC MODEL BATTERY PARAMETERS

Parameter	Value
R_0	4.7×10^{-3} Ω
R_1	3.6×10^{-3} Ω
R_2	1.1×10^{-3} Ω
R_3	2.8865×10^{-5} Ω
C_1	6.9437×10^{4} F
C_2	3.3455×10^{4} F
C_3	4.5765×10^{4} F
M	0.0012
γ	48.5745

E. *The Three RC Network Model*

Each element of the equivalent circuit of Fig. 8a is a function of SOC, with three RC networks that represent the slow, intermediate, and fast dynamic response of the battery. In [34], a comparison is made when one, two, and three branches are used, obtaining better accuracy as more branches in parallel are used. The disadvantage of using a higher number of RC branches is that the mathematical model becomes more complex since it includes more lookup tables [22].

In this case, three RC branches are used in order to obtain better precision, without increasing the complexity of the model response, where OCV represents the open-circuit voltage, R_0 represents the internal resistance of the battery, and three parallel networks based on R_1, C_1, R_2, C_2, R_3, and C_3. The values of the different parameters estimated for this model, with the procedure described in Section II, are shown in the Appendix and are depicted in Fig. 8b.



a)

b)

Fig. 8. Three RC Network Model: (a) electric circuit and (b) parameter values.

V. COMPARISON RESULT AND DISCUSSION

After obtaining parameters for each model, using in all cases, the same procedure shown in Section II, the output voltage accuracy and robustness analysis for the five models of the polymer Li-ion battery is performed with the HPPC test and the ECE15 test. The results are illustrated in Fig. 9a-9d for HPPC test and Fig. 9e-9h for the ECE15 test. In these figures, the current profiles are shown in Fig. 9a and Fig. 9e, the simulated and the experimental voltage are shown in Fig. 9b and Fig. 9f, the voltage relative error is shown in Fig. 9c and Fig. 9g, and the maximum and average voltage relative error are shown in Fig. 9d and Fig. 9h.

In Fig. 9c the 3rd Order RC Model with One-State Hysteresis (3RCH) and the Three RC Network Model (3RC(SOC)) have a lower mean and maximum voltage relative error, as well as with convergent tendency compared to other models, while the Nonlinear RC Model (Nonlinear RC) has the highest average voltage relative error without a convergent tendency. The Partnership for a New Generation of Vehicles (PNGV) Model has a good response for a short simulation time but without enough convergent tendency for a long simulation time. A summary of the results is shown in Table V and Fig. 9d, for the HPPC profile.

TABLE V
OUTPUT VOLTAGE ERROR WITH HPPC TEST

Model	Maximum voltage relative error (%)	Average voltage relative error (%)
Shepherd	6.3026	0.4635
Nonlinear RC	3.5664	1.2211
PNGV	3.2684	0.4853
3RCH	2.1933	0.2300
3RC(SOC)	2.2356	0.1068

The obtained results under the ECE15 test are shown in Fig. 9g, where again the 3rd Order RC Model with One-State Hysteresis (3RCH) and the Three RC Network Model (3RC(SOC)) have a lower average voltage relative error with a convergent tendency. However, the Nonlinear RC Model (Nonlinear RC) has a higher average and maximum voltage relative error without a convergent tendency. The Partnership for a New Generation of Vehicles (PNGV) Model has a good response for a short simulation time but without enough convergent tendency for a long simulation time, as in the HPPC test. The Shepherd Model (Shepherd) has the maximum voltage peak error and similar voltage relative error to the PNGV model, with a convergent tendency. A summary of the results is shown in Table VI and Fig. 9h.

TABLE VI
OUTPUT VOLTAGE ERROR WITH ECE15 TEST

Model	Maximum voltage relative error (%)	Average voltage relative error (%)
Shepherd	2.8041	0.3864
Nonlinear RC	2.7446	1.1457
PNGV	1.4791	0.4752
3RCH	1.7342	0.2141
3RC(SOC)	1.2663	0.1831

In general, models based on RC networks have a greater capacity to reproduce the different effects that appear in the battery, whether short, medium or long term, since with a sufficient number of RC networks all phases of polarization of the battery can be represented.

However, the PNGV model produces long-term accumulation of voltage on the capacitor, which increases the model voltage error.

The results obtained indicate that the Three RC Network Model, followed by the 3rd Order RC Model with One-State Hysteresis are the two models with the best results, although most of the parameters of the 3rd Order RC Model with One-State Hysteresis are constant, so this model is easier to implement.

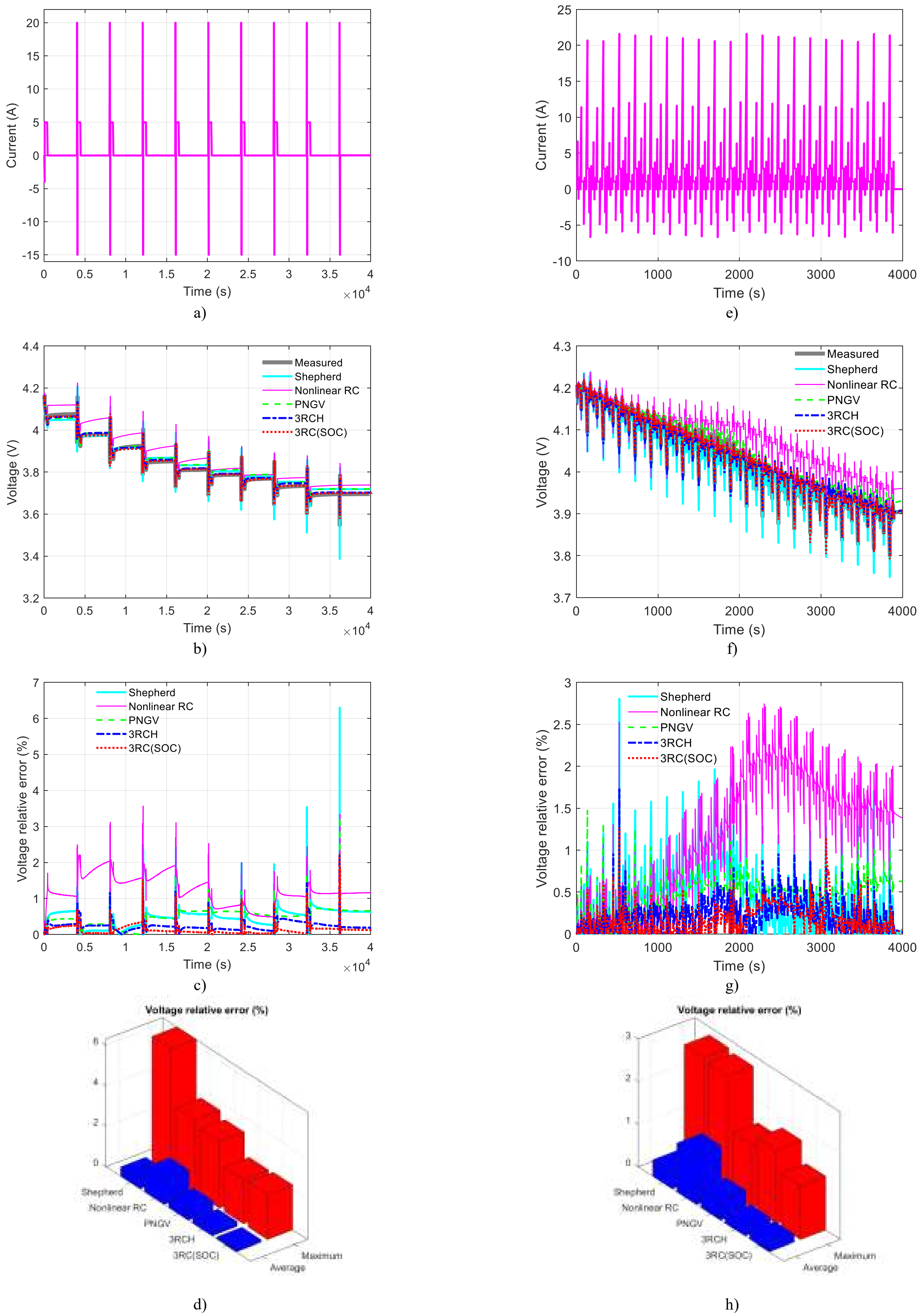


Fig. 9: Time response of lithium-ion battery: (a) – (d) current profile HPPC and (e) – (h) current profile ECE15. a) current profile HPPC, b) simulated and experimental voltage, c) voltage relative error, d) maximum and average voltage relative error; e) current profile ECE15, f) simulated and experimental voltage and g) voltage relative error and h) maximum and average voltage relative error.

VI. CONCLUSION

This paper describes a general parameter identification procedure with a reduced number of steps and an easy user interface, which requires circuits or equations to implement any type of battery model. The Parameter Estimation Tool is available in Simscape or Simulink of Matlab, and it can estimate and validate multiple parameters of the model at the same time, using multi-experiment data with specific bounds for each parameter. This parameter identification proposal can be used in offline applications.

A comparative study of five different battery models available in the literature has been made. In all cases, the model parameters have been obtained from the proposed general parameter identification procedure.

The comparison result obtained from the five models indicates that the Shepherd Model is straightforward, and it can be used as a first approximation, needing only the discharge curve of the battery to be parameterized. However, when it is used for a long simulation time, this model produces a cumulative voltage error, and it cannot represent the voltage peaks of the battery response.

The PNGV model is excellent for a short simulation time; however, once again, this model produces long-term accumulation of voltage on the capacitor, which increases the model voltage error.

The Nonlinear RC model does not accurately reflect the dynamic characteristics of the battery because this model cannot reflect the polarization phases of the Li-ion battery. Therefore, its accuracy is limited.

The 3RCH and 3RC(SOC) models do not show a cumulative error in long simulation time, and the simulated voltage is better than the previous ones. The 3RCH includes the hysteresis phenomenon that depends on the battery chemistry, and it is simpler to estimate than the 3RC(SOC) model, which is more accurate, although more complex. Therefore, it can be concluded that both models have higher accuracy and robustness than the other models in order to show the static and dynamic battery voltage. A tradeoff between complexity, robustness, and accuracy is obtained with the 3RCH model.

Considering these results, Shepherd Model is recommended for short simulation time and 3RCH model for medium and long simulation time.

APPENDIX

Models parameters of Nonlinear, PNGV and Three RC Network Models are shown in Tables VII, VIII, and IX.

TABLE VII
NONLINEAL MODEL PARAMETERS

Parameters	SOC(%)	OCV(V)
Values	11.0821	3.5805
	20.0061	3.6896
	28.9002	3.7291
	37.7848	3.7730
	46.6761	3.7890
	55.5755	3.8307
	64.4555	3.9113
	73.3533	4.0019
	82.2332	4.1140
	91.1255	4.1364
	100	4.2301

TABLE VIII
PNGV MODEL PARAMETERS

Parameters	SOC(%)	OCV(V)	C_0(kF)	R_0(mΩ)	C_1(kF)	R_1(mΩ)	C_2(kF)	R_2(mΩ)
Values	11.0821		68.7420	2.2213	12.3630	5.2583	199.580	4.0208
	20.0061		28.7140	4.4317	17.4650	3.4383	376.300	10.662
	28.9002		110.730	4.9254	63.5560	6.0789	13.9700	1.9166
	37.7848		45.1290	4.1839	147.000	3.2660	17.3140	3.0477
	46.6761		87.0250	4.5333	596.420	13.8250	14.673	3.9884
	55.5755		42.0530	4.2388	298.630	0.1776	153.620	1.6512
	64.4555		19.4130	4.5360	154.120	6.8301	21.8720	2.8152
	73.3533		42.8830	3.4158	34.4120	6.1388	7.4790	4.6487
	82.2332		8.8560	4.1868	26.0930	2.2758	1.4473	0.26945
	91.1255		47.5230	2.9751	19.2730	9.8609	13.3610	2.4883
	100		5.3872	0.9459	24118	0.18918	264.170	0.0332

TABLE IX
THEVENIN MODEL PARAMETERS

Parameters	SOC(%)	OCV(V)	R_0(mΩ)	R_1(mΩ)	C_1(kF)	R_2(mΩ)	C_2(kF)	R_2(mΩ)	C_2(kF)
Values	11.0821	3.6904	68.7420	2.2213	12.3630	5.2583	199.5800	4.0208	27.8980
	20.0061	3.7244	28.7140	4.4317	17.4650	3.4383	376.300	10.6620	336.020
	28.9002	3.7619	110.730	4.9254	63.5560	6.0789	13.9700	1.9166	24.6160
	37.7848	3.7825	45.1290	4.1839	147.000	3.2660	17.3140	3.0477	9.7176
	46.6761	3.8042	87.0250	4.5333	596.420	13.8250	14.673	3.9884	49.015
	55.5755	3.8389	42.0530	4.2388	298.6300	0.1776	153.620	1.6512	42.709
	64.4555	3.8969	19.4130	4.5360	154.1200	6.8301	21.8720	2.8152	11.177
	73.3533	3.9524	42.8830	3.4158	34.4120	6.1388	7.4790	4.6487	89.624
	82.2332	4.0462	8.8560	4.1868	26.0930	2.2758	1.4473	0.26945	1.1646
	91.1255	4.1280	47.5230	2.9751	19.2730	9.8609	13.3610	2.4883	167.580
	100	4.2192	5.3872	0.9459	24118	0.18918	264.170	0.0332	3.960

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