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Research paper

Modelling Li-ion batteries using equivalent circuits for renewable energy applications

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ABSTRACT

During the last decades, environmental policies have advanced the promotion of renewable energy sources, opening a market for smart-grids both connected and disconnected from the main electrical grid. In the field of renewable energies, such as solar or wind ones, batteries are an essential component since they allow to easily store the energy excess that can be dispensed during periods of scarcity of these sources. This paper presents a dynamic Li-ion battery model for renewable purposes based on an electrical equivalent circuit model. This model takes into account both charge and discharge processes using the same equation, while most models found in the literature only contemplate the discharge process. Several tests were carried out in an experimental micro-grid bench at different state of charge to adjust the model parameters including the non-linear relation between the state of charge and the open circuit voltage. Finally, different experiments were performed to experimentally validate the model. The model predicts, with a low error, the battery voltage as well as the state of charge.

1. Introduction

Smart grids play a critical part in the transformation of the existing electric grids and distribution networks in order to achieve the new environmental targets ensuring security, quality, and economic efficiency of electricity supply. They are electricity networks that integrate the actions of all users connected to it in order to ensure a sustainable and economically efficient energy system with high levels of quality and security of supply. This conception is a game changer as it includes the concept of 'prosumer', individuals who can both consume and produce electricity from the grid, opening the door to small-medium renewable energy producers. In this sense, the Thermal Engineering Research Group of the University of Seville has experience in smart grids research for energy management (Valverde et al., 2016b; Petrollese et al., 2016), operation modes (Valverde et al., 2016a) and economic studies (Navas et al., 2022), owning an installation that will be described in the following section, that way, the modelling of some part of this set up is a natural path in their research interest.

The discontinuity of supply associated with renewable sources leads to the installation of energy storage systems. Batteries are one of the most widely used storage methods for this purpose because of their high energy density, efficiency, and low operating cost and maintenance. Traditionally, lead–acid batteries have been the most extended for renewable energy uses, but, in the last years, lithium batteries are likely to replace them due to their high efficiency, large capacity, long cycle life, and lack of memory (Rivera-Barrera et al., 2017). However, this kind of batteries are more expensive and require careful monitoring in order to extend its lifespan, to avoid deterioration of battery performance, and prevent battery damage or explosions. Nonetheless, its wide application as an energy storage device for electric vehicles makes them a reliable choice (Farhad and Nazari, 2019; Weiss et al., 2018) if some practical concerns for its design are carefully taken into account (Bayati et al., 2021).

For all the reasons above mentioned, a real-time battery management system is necessary to on-line monitor the state of charge (SOC) and other battery parameters such as battery voltage. Different approaches have been considered to address this issue before, such as analytic expressions based on an equivalent circuit model, Kalman filter or particle filter-based estimation, and neural networks. The Kalman filter algorithm can assess the optimal state of complex dynamic systems according to the principle of minimum mean–variance. That way, it can correct the system in operation while suppressing the noise. However, this

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method had the disadvantage of relying on the accuracy of the battery model, and it is susceptible to the dynamic parameters of the battery. Besides, they can be sometimes computational load demanding (He et al., 2011, 2020; Huang et al., 2021; Kai et al., 2020; Sun et al., 2014; Xiong et al., 2013; Zhang et al., 2015). Kai et al. (2020) proposed the use of an adaptive square root Unscented Kalman Filter under a second-order Thevenin equivalent circuit to improve the SOC estimation. He et al. (2020) suggested a new method that consist of an adaptive extended Kalman filter combined with a parameter identification algorithm based on adaptive recursive least squares. He et al. (2011) present an improved Thevenin equivalent circuit with an adaptive extended Kalman filter. In Sun et al. (2014), a data-driven estimator based on the adaptive extended Kalman filter is used to estimate the SOC against varying degradations. Zhang et al. (2015) proposed the use of the adaptive unscented Kalman filter to develop a state estimator for battery state of energy and power capability. Xiong et al. (2013) developed a multi-state joint estimator based on an adaptive extended Kalman filter. Huang et al. (2021) present a noise-adaptive interacting multiple model algorithm combined with an unscented Kalman filter to improve the accuracy of the SOC estimation.

An alternative to the Kalman filter is a particle filter since it eliminates the limiting assumptions forced on dynamic and form of conditional density, Actually, it can estimate the later distribution of the states making use of a set of weighted samples. Besides, it is independent of the battery model and is not subject to linearization error or Gaussian noise assumption (Burgos-Mellado et al., 2016; Samadi et al., 2012; Xia et al., 2017; Ye et al., 2018). Burgos-Mellado et al. (2016) present a first order particle filtering based model for the estimation of maximum available power state and SOC in Lithium-Ion batteries. Ye et al. (2018) developed a double-scale dual particle filter to determine the battery parameters and SoC estimation with higher accuracy. In Xia et al. (2017), three model-based methods, including extended particle filter (EPF), cubature particle filter (CPF), and unscented particle filter (UPF), are compared in terms of complexity, accuracy, and robustness for determining the SOC of Li-Ion batteries. All investigations indicate that particle-filtering models have better accuracy compared to experimental data, but they are complex to be implemented in supervisor and control systems. On the other hand, strategies involving classic machine learning algorithms present the benefit of being trained with real world data and self-learning without the need for preconceived models. Fleischer et al. (2013) proposed an online battery voltage prediction using an adaptive neuro-fuzzy inference system with a prediction error of less than 1%. Hussein (2019) makes a comparison between some equivalent circuit models and new ones based on artificial Neural Network. Charkhgard and Farrokhi (2010) presents a neural network model with an extended Kalman filter to estimate the state of charge. In Chemali et al. (2018) a new method for the SOC estimation based on Deep Feedforward Neural Network is described. These models present the main disadvantage of requiring a high computational effort. However, advances in the field of machine learning techniques are rushing along with the development of computer power and it is expected that in the next few years this kind of approximation beats their disadvantages. Equivalent circuit models do not consider the chemical nature of the battery. Instead, they represent battery behaviour from its electrical point of view and it is widely used because of the model simplicity and accuracy (Feng et al., 2015; Jin et al., 2021; Lai et al., 2018; Shaheen et al., 2021; Song et al., 2019; Wik et al., 2015). Wik et al. (2015) developed a state of power algorithm based on an equivalent circuit model that showed high robustness when tested on a complex nonlinear virtual battery system. In the same line, Feng et al. (2015) proposed an equivalent circuit model included in a state of power prediction algorithm that includes a moving average noise. The model can replicate the battery dynamic and satisfactorily predict the state of power with low error and computing resources. A fast method to estimate the state of charge vs. open circuit voltage curve was proposed by Song et al. (2019) making use of an equivalent circuit model with parameter identification of recursive least square algorithm. They checked the accuracy of the estimation experimentally, finding that this new methodology, which does not need to carry out preliminary experiments of measuring open circuit voltage, reproduced the curve in a precise way. Shaheen et al. (2021) proposed a reduced model for estimating the state of charge for vehicle batteries. The model was based on the state–space representation to identify an equivalent electric circuit. The result was higher accuracy and 16% less computational times of the proposed model when compared with linear and non-linear models. An interesting study was carried out by Lai et al. (2018). They tested eleven equivalent circuit models for estimating the state of charge of lithium-ion batteries finding that first and second order models have the best balance of accuracy and reliability while a higher order did increase robustness. Also, other authors found that this kind of models does not always improve its accuracy by increasing its order. In fact, first order models present excellent reliability, while second order ones show better accuracy (Lai et al., 2018). An extra step in the modelling of batteries for renewable energy sources is include this models in a real time simulation that allow to analyse the performance of the whole system, assessing the influence of the battery storage system in the electrical grid (Caldeira et al., 2019).

Due to the fact that, nowadays, the capacity and the voltage of Li-ion cells are low for its application in renewable energy storage systems, they are usually found in packs connected one to the other. Most of the studies found in literature for Li-ion battery modelling focus on the study of a single cell, but it has been demonstrated that the pack behaviour is quite different than single cells (Wang et al., 2019). That way, this study contributes to the current state of the art by the development of a simple dynamic model for battery packs in the field of renewable applications making use of a modelling methodology based on electrical circuit model. In this sense, the main novelties of this paper are highlighted in the following bullet points:

- The intermittent nature of the renewable sources connected to the batteries requires a model with a low computational time that allows to make control decisions quickly rather than high precision on the estimation. This is contrary to most of the studies that describe complex models in order to improve the accuracy of the predictions.
- The model takes into account the parameters of both charge and discharge processes in the same equation, that is important when the batteries are coupled with a renewable energy source. Most of the models found in the literature only contemplate the discharge process and our study reveals that the dynamic of both processes is quite different.
- The model was developed and validated using a stack of batteries that are part of a real smart-grid facility, since most of the publications focus on a single cell of low capacity. For this reason, the variation of the battery parameters with the SOC is included since it becomes relevant as battery capacity increases.

This article is structured as follows. In Section 2, the equivalent circuit model and the methodology followed by the parameter estimation are described. The resulting model is explained in Section 3 along with its validation. Finally, Section 4 gathers the conclusions of this study.

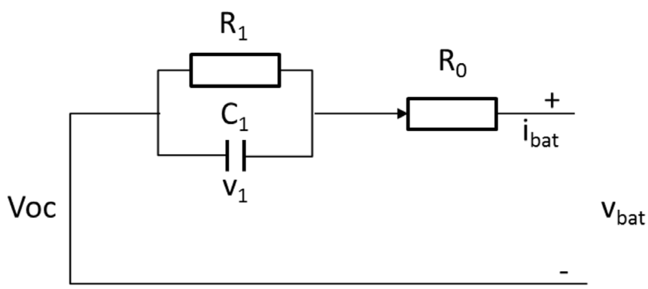

Fig. 1. First order equivalent circuit used to model the Li-ion batteries.

2. Methodology

2.1. Model description

A worthy battery model should predict both the battery storage capability or state of charge (SOC) and the voltage response to the load. Equivalent electrical circuit models (EECM) can describe both characteristics. In this paper, two different EECM have been assessed; one of a first order (Fig. 1), consisting of one resistance (internal ohmic resistance R_0) in series with an element that includes a polarization resistance (R_1) set in parallel with a capacitor (C_1), what characterizes the transient response during the charge–discharge process. And the other one, a second order model (Fig. 2), consisting of one resistance (internal ohmic resistance R_0) in series with two elements consisting of a polarization resistance (R_1 and R_2) set in parallel with a capacitor (C_1 and C_2), what characterizes the long and short time transient response during the charge–discharge process.

This kind of circuit is modelled as follows

$$\dot{v}_{\mathrm{i}} = -\frac{1}{R_i C_{\mathrm{i}}} v_{\mathrm{i}} + \frac{1}{C_i} i_{bat} \tag{1}$$

$$v_{bat} = Voc - R_0 i_{bat} - \sum_{i=1}^{i=2} v_{\mathrm{i}} \tag{2}$$

being R_i and C_i the values of the resistance and the capacitor respectively that describe the transient behaviour, v_i the voltage value of the corresponding RC element, $\dot{v}_i$ the derivative of the voltage, Voc the open circuit voltage, subscript i the order of the model, and i_{bat} the value of the battery output current, defined as positive while discharging.

Eq. (1) can be discretized using a sample time (Ts) of 1 s, resulting in Eq. (3), where subscript k denotes the time instant.

$$v_{\mathrm{i,k}} = v_{i,\mathrm{k}-1} e^{\frac{-Ts}{R_i C_i}} + R_i \left(1 - e^{\frac{-Ts}{R_{\mathrm{i}} C_i}}\right) i_{bat} \tag{3}$$

Because the dynamics of the charging and discharging processes are different from each other, and that, likewise, they depend on the current value of the SOC, a small variation of the above-mentioned equations was made so that, with a single model, these differences can be taken into account. Not having two different models that consider each dynamic separately is an advantage, since the value of the batteries Voc and SOC during a typical operation with renewable energy sources involves constant changes between charge and discharge processes due to the intrinsic intermittence of the source. That way, Eq. (4) replaces Eq. (2), where the subscripts c and d represent the charging and discharging processes, respectively.

$$v_{bat} = Voc - R_{0\mathrm{c}} i_c - v_{\mathrm{ic}} - R_{0\mathrm{d}} i_d - v_{\mathrm{id}} \tag{4}$$

On the other hand, the different parameters of the model have been obtained as a function of the battery SOC, each one for the charging and discharging processes, respectively. This model does not take into account the dependence of the different parameters on temperature, as it is expected if the place is indoors and well ventilated. It does not also consider the ageing of the batteries, so it will be valid for a certain period of time, from which the relationship between Voc and SOC, and the parameters of the equivalent circuit model, will have to be reevaluated.

As aforementioned, the model will be used to estimate both the SOC of the batteries and their voltage. The real time SOC assessment is key in a smart-grid operation to evaluate the use and distribution of the energy generated by different sources. Also, the estimation of the battery voltage would be of interest for regulatory control purposes. To obtain the SOC, it will be necessary to calculate the value of the Voc firstly. That will be done through Eq. (4), since the values of v_{bat}, i_d, and i_c are known as they are measured in the field. In this step, it is important to add to Eq. (4) the measured error between the real and predicted value of v_{bat} to avoid the error of the voltage model to be transferred to the SOC prediction. Then, the value of the SOC is calculated making use of a linear interpolation between the values that relate SOC and Voc (see Fig. 5). On the other hand, the voltage of the batteries will be obtained calculating the SOC by integration of the i_{bat} value. Then, the Voc will be calculated using an equation that relates Voc and SOC (see Fig. 5). Finally, the value of the Voc will be introduced in Eq. (4) in order to obtain the battery voltage.

2.2. Experimental set up

In order to carry out the experiments for the battery modelling, the Hylab smart-grid facility located at the University of Seville was used. This grid is an extremely adaptable facility designed for the research on the integration of renewable sources using hydrogen as a storage mechanism for the renewable energy surplus (Fig. 3). An extended description of the complete system can be found in the literature (Petrollese et al., 2016; Valverde, 2013; Valverde et al., 2016a,b, 2013; Velarde et al., 2017), but the subsystem used to develop the model only includes the Li-ion batteries, the electronic load, and the electronic power source.

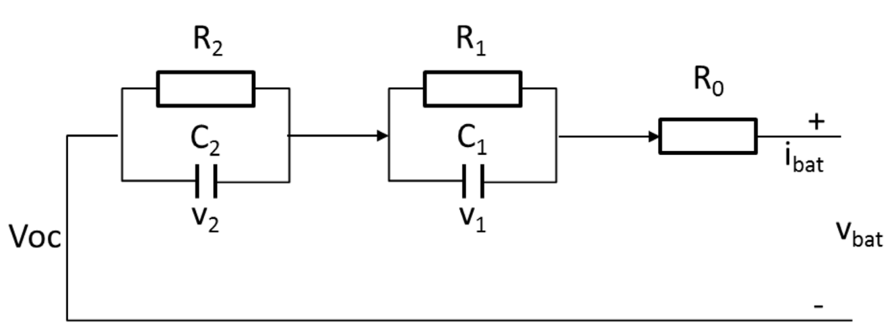

Fig. 2. Second order equivalent circuit used to model the Li-ion batteries.

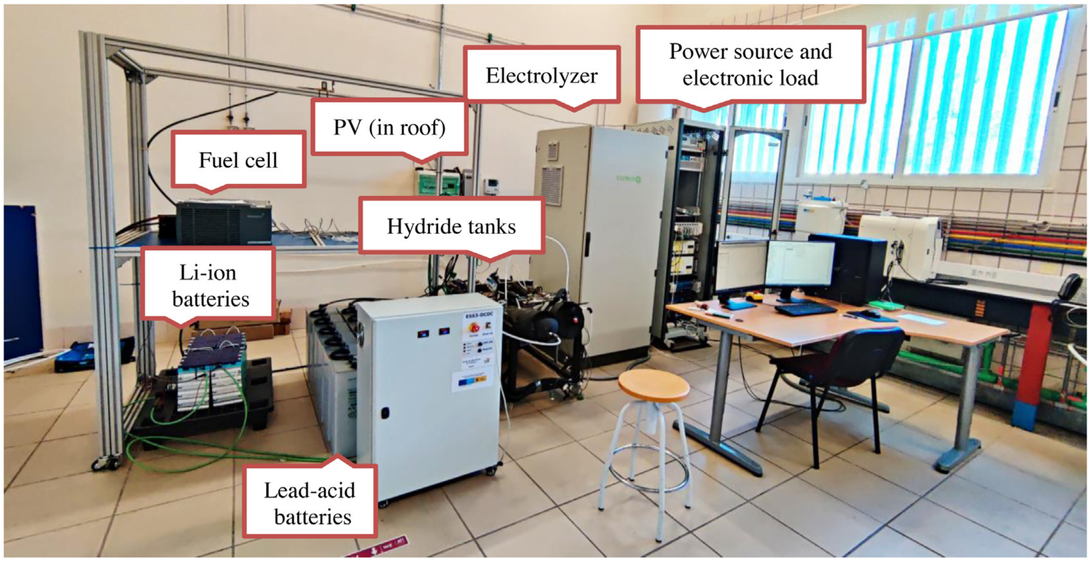

Fig. 3. General view of the HyLab laboratory smart-grid.

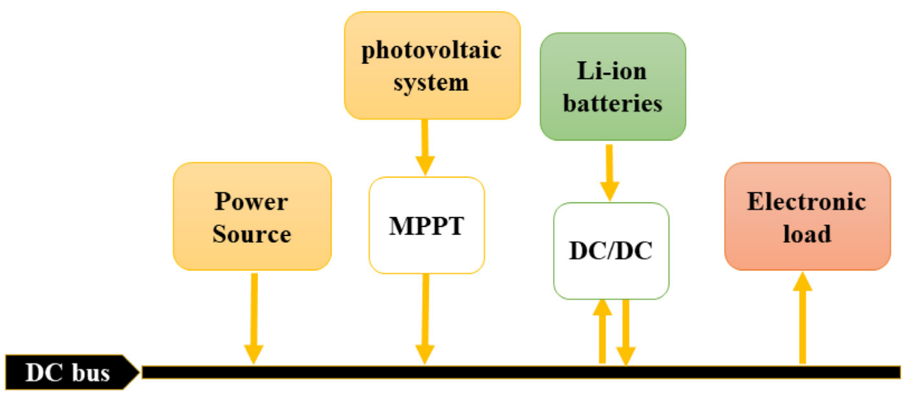

Fig. 4. Energy conversion chain.

The smart-grid also includes a PV as shown in Figs. 3 and 4. However, the experiments were carried out using the power source instead of the PV due to the possibility of keeping the current delivered to the batteries at a constant value. The Li-ion battery bank comprises 16 cells (4pcs) of the GBS 100 Ah with a nominal voltage of 51.2 V (4 × 12.8 V). On the other hand, the electronic power source used to charge the batteries is a POWERBOX LBX 6 kW (0–60 V/0–100 A), while the electronic load, employed in the discharge process, is an AMREL PLA 2.5 kW (0–60 V/0–1000 A).

2.3. Experimental procedure

The different tests used to determine the value of the parameters of the model were carried out in the pilot smart-grid. Only three elements were used: the Li-ion batteries, the electronic power source, and the electronic load.

2.3.1. Determination of the relationship between Voc and SOC

For all types of batteries, the voltage at their terminals decreases or increases depending on their level of charge, being highest when the battery is fully charged and lowest when it is empty. The relationship between the open circuit voltage and the state of charge is directly dependent on the battery technology and it will be used in for the approximation of the battery voltage as well as for the SOC estimation.

The tests carried out to determine the Voc–SOC relationship include two different types of experiments. On the first hand, three discharge tests, reducing the SOC value in a 20% each, were carried out starting at SOC 100%. For that, a constant value of 7.3 A was subtracted, and the voltage value was measured after twenty hours resting to assure the measure of the battery voltage steady value, that will be considered the best approximation to the Voc. That way, Voc values were obtained for 100, 80, 60 and 40% SOC. Values below 40% were not considered because the batteries presented an errand behaviour and are not expected to work on these SOC values. Then, on the other hand, three charge tests were performed from a starting SOC of 40%, adding the same intensity during the same period that was subtracted before for each test. In addition, the same resting time was considered before acquiring the voltage value. This set of tests will result in the battery pack Voc–SOC curve presented in Section 3.

2.3.2. Determination of the model parameters

For the R and C model parameters, a set of seven experiments was carried out at different values of SOC. This test consists of three cycles of charge–discharge of the batteries starting each cycle with a discharge process of 7.3 A for ten minutes. Then, the batteries rest (0 A) for twenty minutes before charging at 7.3 A for another ten minutes. The cycle ends with another twenty minutes resting period before starting again.

The model parameters adjustment has been determined by minimization of the sum of square errors between the measured

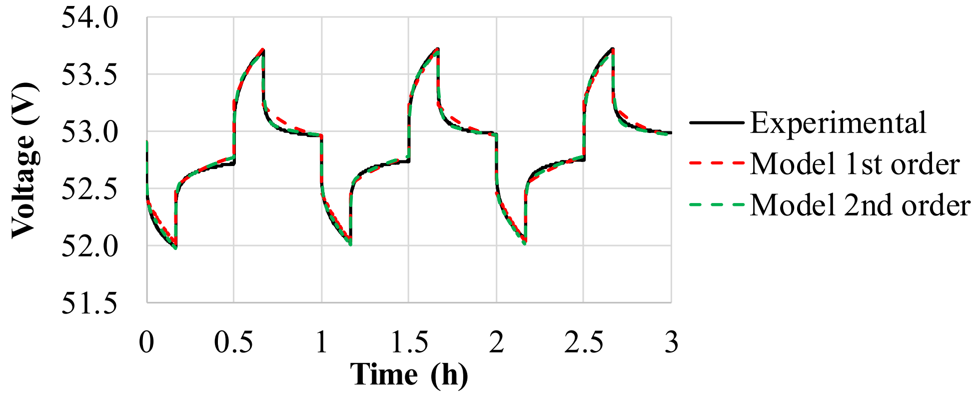

Fig. 5. Battery voltage measurement vs. model estimation after fitting model parameters for a starting SOC of 55.6%.

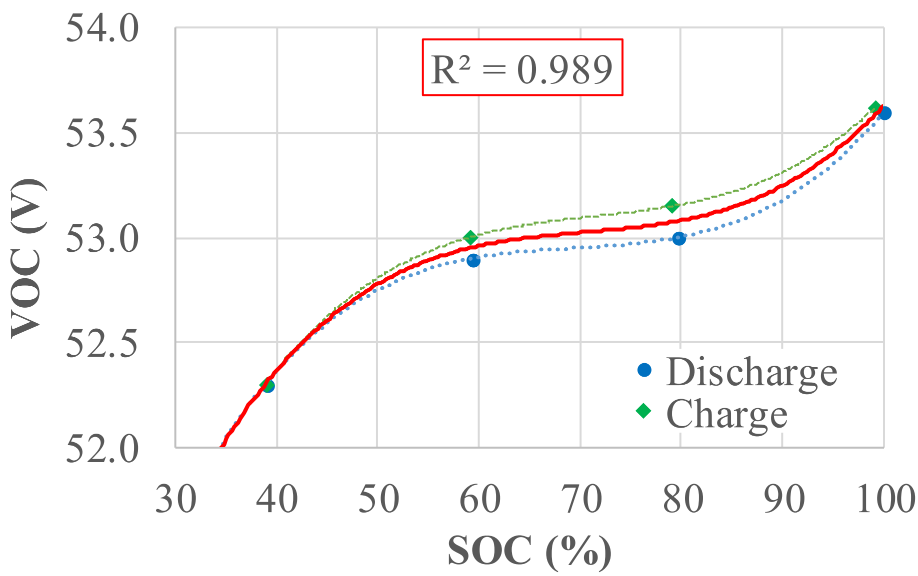

Fig. 6. Open circuit voltage as a function of the state of charge. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

battery voltage and the one calculated by the model for each different SOC. As model parameters change with the state of charge of the battery pack, each one was correlated with the SOC. In this way, it is possible to instantly calculate the parameter value corresponding to the actual SOC value. In Fig. 5 it can be seen that the second order model presents a better adjustment (a mean relative error of 0.03% and a maximum relative error of 0.71%) than the first order model (a mean relative error of 0.06% and a maximum relative error of 1.04%). However, as will be seen in Section 3, it is nearly impossible to find a simple correlation between the second-order model parameters and the SOC value. In general, both models' adjustment for a certain SOC is reasonable, being the voltage resting time curvature the part that presents more discrepancy.

Since the charge and discharge process present differences, different parameters have been determined for each process. This phenomenon has also been considered by other authors in the literature (Vyroubal and Kazda, 2018; Yu et al., 2018).

2.3.3. Validation of the model

For the validation of the model, some experiments were proposed where the battery pack was subjected to a three discharge–charge cycles varying the current value for each one. Each cycle starts with a 10 min discharge, then a 20 min resting period followed by a 10 min charge, to end with another 20 min resting time. The current values of each cycle were 3.4, 7.3, and 14.4 A. That way, the robustness of the model was tested at different operating points.

3. Results and discussion

The set of experiments carried out to determine the Voc–SOC curve resulted in a curve that presents the typical tendency for this kind of batteries with a sudden increase in V_{OC} when the SOC is close to 100%. Also, the V_{OC} drops for low values of the SOC. Authors in literature fit this kind of tendency into a double exponential curve (Yu et al., 2018) ignoring the charging–discharging hysteresis phenomenon. In Fig. 6, it can be seen that the curve presents two separate dotted lines with different slopes, one for the charge tests and another one for the discharge ones. Hence, a certain degree of hysteresis is present as is usual for batteries (He et al., 2011; Rahimi Eichi and Chow, 2012). However, this grade is not high enough to use a complex solution that includes this variation, and so, neglecting hysteresis, a regression line was drawn of both charge/discharge points, represented by a continuous red line that stays in a central value, since the incurred error seems acceptable.

Eq. (5) relates VOC and SOC and it will be employed to calculate the value of *Voc* when the model is used to estimate the battery voltage. However, the value of SOC when the model is

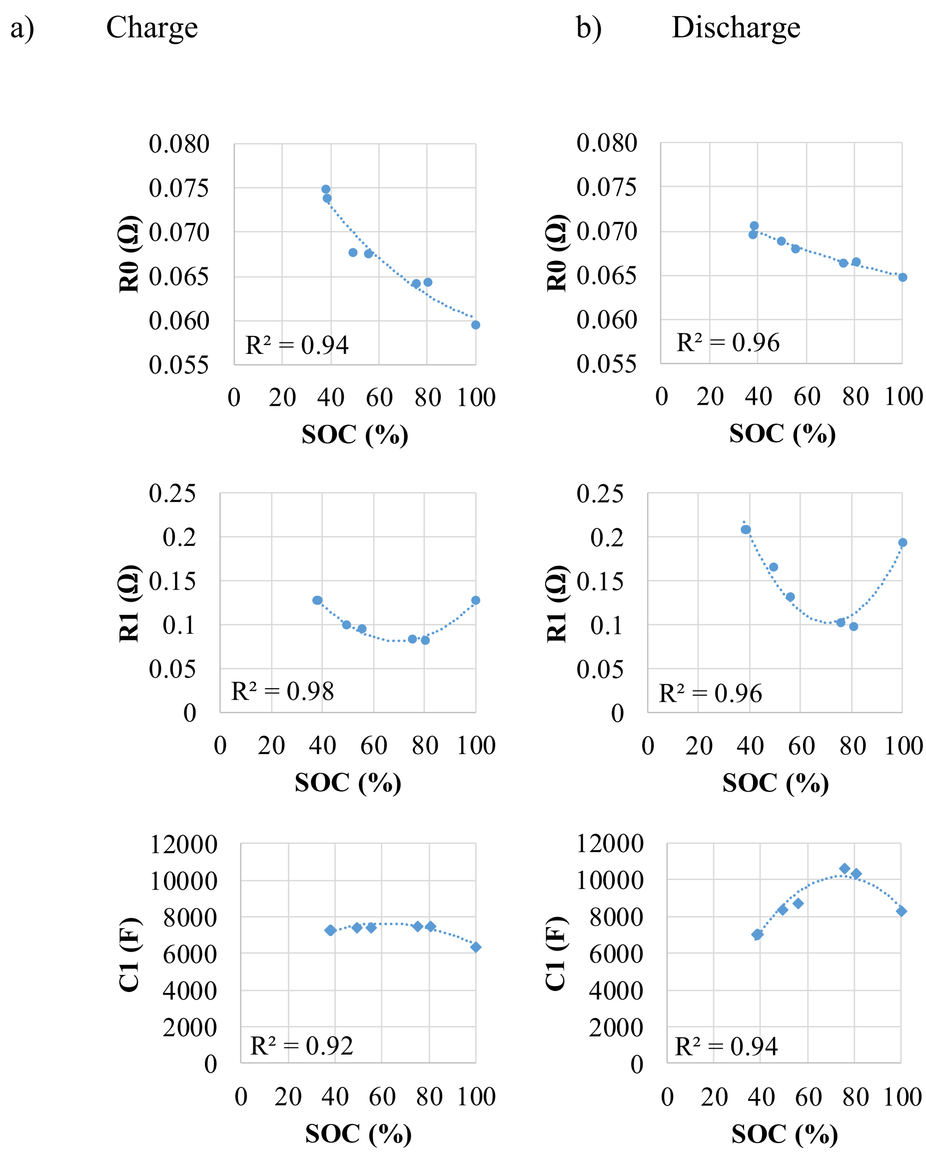

Fig. 7. First order model parameters as a function of SOC for (a) charge and (b) discharge process.

used to estimate the batteries SOC will be calculated using a linear interpolation between the values that relate SOC and *Voc*.

$$Voc = 0.000019 \cdot SOC^3 - 0.00396 \cdot SOC^2 + 0.284 \cdot SOC + 46.158 \quad (5)$$

The relationship between each parameter and the value of the SOC for the first order and the second order models is shown in Figs. 7 and 8 respectively. It seems clear that for the second order model the correlation between the parameters and SOC cannot be easily achieved and therefore, it goes out of the scope of this paper that aims to make a simple model. For that reason, the second order model was discarded, and the study continued with the first order model.

The mathematical equations that relate the first-order model parameters, for both charge and discharge processes, are listed below.

- Charge process

$$R_{0c} = 0.00000204 \cdot SOC^2 - 0.000495 \cdot SOC + 0.0895 \quad (6)$$

$$R_{1c} = 0.0000476 \cdot SOC^2 - 0.00662 \cdot SOC + 0.311 \quad (7)$$

$$C_{1c} = -0.784 \cdot SOC^2 + 96.632 \cdot SOC + 4664.594 \quad (8)$$

- Discharge process

$$R_{0d} = 0.000000510 \cdot SOC^2 - 0.000153 \cdot SOC + 0.0752 \quad (9)$$

$$R_{1d} = 0.000104 \cdot SOC^2 - 0.0147 \cdot SOC + 0.627 \quad (10)$$

$$C_{1d} = -2.580 \cdot SOC^2 + 383.068 \cdot SOC - 4057.595 \quad (11)$$

As it can be seen, all parameters show a strong dependency on SOC (see Table 1). All resistances exhibit an inverse behaviour versus SOC for both charge and discharge, except for R1, whose tendency abruptly changes from SOC 80%. The same lean change from SOC 80% can be observed in C1 for charge and discharge.

To the best of our knowledge, the only comparable model, in terms of size and aggregation of the battery cells, is the one proposed by Wang et al. (2019) with an AVIC lithium battery CFP50AH. They proposed a complex model composed by a Thevenin circuit in series with other systems that include the polarization effect among others, and whose parameters that does not separate charge from discharge were identified by hybrid pulse power characterization. Anyway, the ohmic resistance curve also presents a decreasing tendency as the SOC rises. This effect can also be spotted for smaller lithium batteries (He et al.,

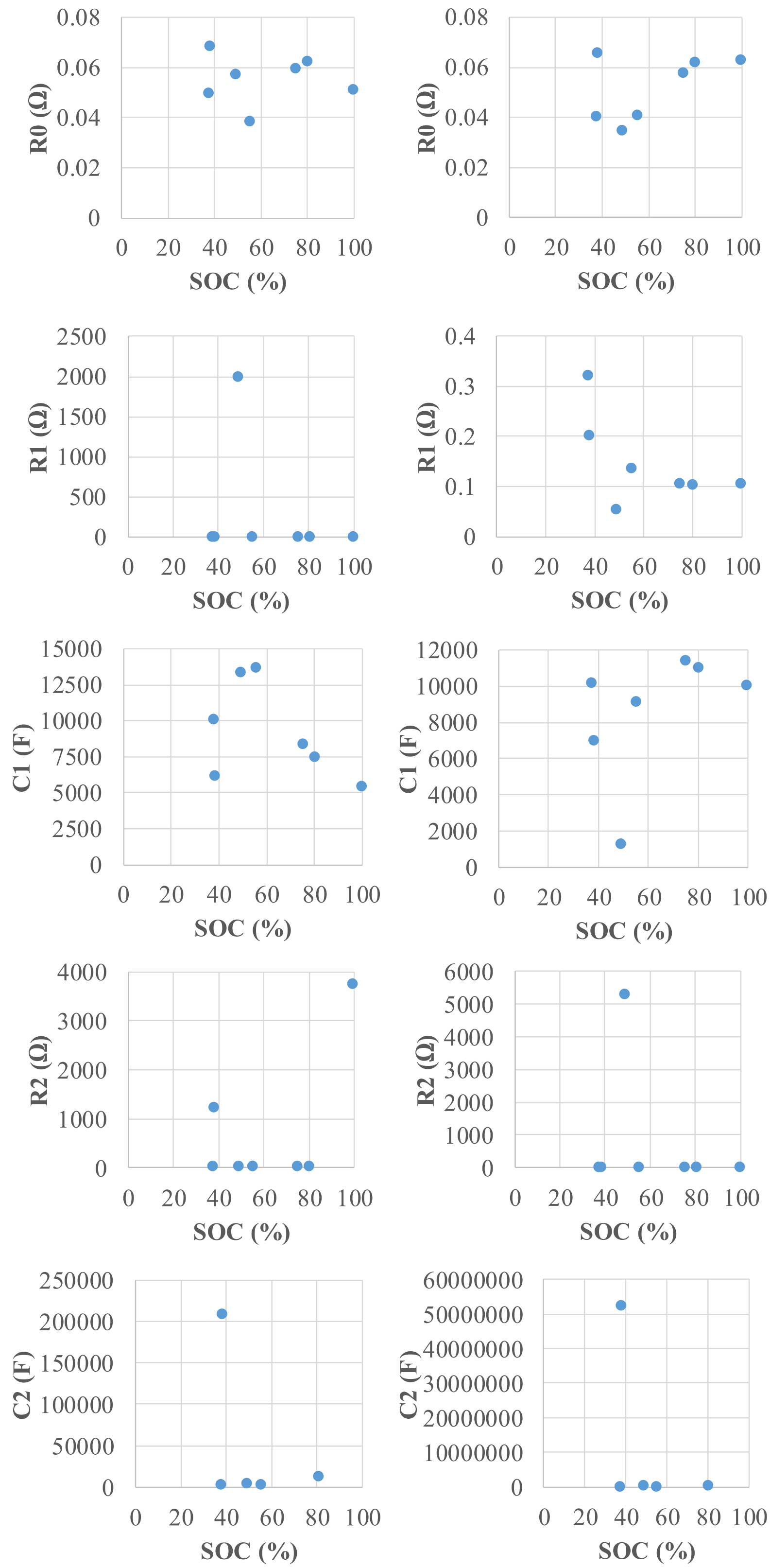

Fig. 8. Second order model parameters as a function of SOC for (a) charge and (b) discharge process.

2011; Vyroubal and Kazda, 2018). The rest of the parameters vary in different ways probably due to the fact that the proposed electrical models are different as well as the type and capacity of the batteries.

The experiments were made with a real Li-ion battery pack and the measured variables were registered with a sample time of one second. The predicted voltage value obtained with the model was calculated using the same current input to the batteries and

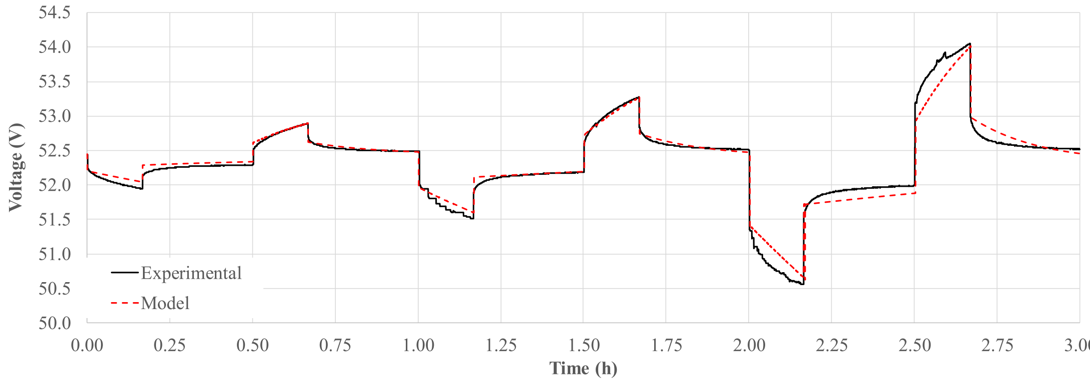

Fig. 9. Battery voltage measurement vs. model estimation.

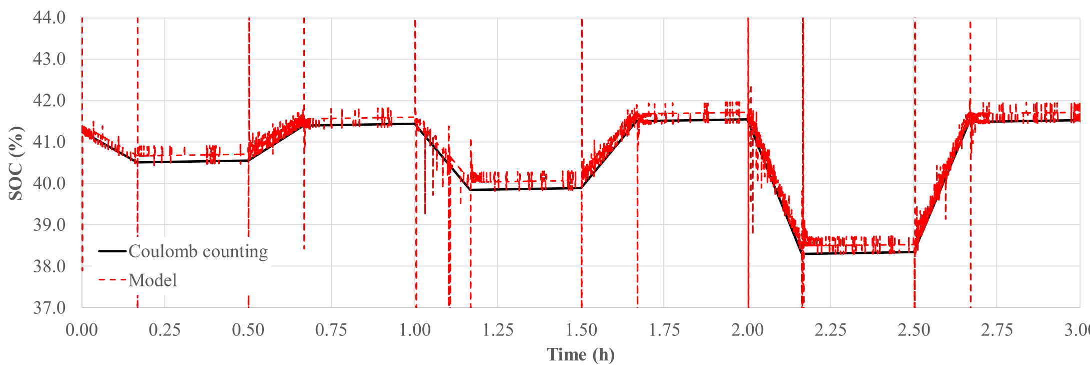

Fig. 10. Battery SOC estimated by Coulomb counting method vs. model prediction.

Table 1
Variation of the model parameters with the battery SOC.

SOC	R0c	R1c	C1c	R0d	R1d	C1d
100	0.060	0.125	6487.794	0.065	0.197	8451.400
95	0.061	0.112	6769.034	0.065	0.169	9051.355
85	0.062	0.092	7213.914	0.066	0.129	9864.295
80	0.063	0.086	7377.554	0.066	0.117	10 077.280
75	0.064	0.082	7501.994	0.067	0.110	10 161.275
70	0.065	0.081	7587.234	0.067	0.108	10 116.280
65	0.066	0.082	7633.274	0.067	0.111	9942.295
60	0.067	0.085	7640.114	0.068	0.119	9639.320
55	0.068	0.091	7607.754	0.068	0.133	9207.355
50	0.070	0.099	7536.194	0.069	0.152	8646.400
45	0.071	0.109	7425.434	0.069	0.176	7956.455
40	0.073	0.122	7275.474	0.070	0.205	7137.520

was registered at the same time as the real one. Therefore, the computational time was verified to be less than a second.

The tests carried out at different intensity values for the charge–discharge process to validate the reliability of the model (Section 2.3.3) show a reasonable capability of estimation of the battery voltage, being the low and medium (the operation point used for the model parameters adjustment) intensity values the ones that presented the best estimation. As it can be seen in Fig. 9, the value of the current influences the model parameters, as expected (Yu et al., 2018), in both charge and discharge processes since they would need to be slightly attuned to better fit for higher and lower currents than the one used for parameter adjustment. Anyway, the error incurred is considered to be acceptable and, as it is expected that the smart grid does not operate with current values beyond the studied range, it will not be necessary to further complicate the model. The maximum relative error, and mean relative error is 2.46%, and 0.15% respectively.

Fig. 10 presents the difference between the batteries SOC estimated with the Coulomb counting method and the model proposed in this paper. Coulomb counting relies on the integration of the current drawn from and supplied to a battery over time, and it is not an accurate measure of the variations on the battery SOC in long-term measurements since it accumulates sensor error and also depends on defining a starting point. However, the model proposed in this paper will use the starting point provided by the correlation between V_{OC} and SOC (Fig. 6), and the SOC value is calculated based on the measured value of the battery voltage. If the Coulomb counting is taken as reference, the model presented in this paper presents a mean relative error of 0.54%. The maximum relative error is not representative in this case due to the instant high peaks produced when there is a big change in the current value.

As a result, the dynamic model of the Li-ion battery pack proposed in this paper can be considered accurate for the proposed application.

4. Conclusions

In this paper, a simple method for modelling the dynamic behaviour of a Li-ion battery pack for renewable energy storage purpose has been proposed based on an equivalent electric circuit model. This model takes into account the non-linear relationship between SOC and V_{OC} and between the model parameters and SOC, as well as the difference between the charge and discharge process. The method consisted of three steps that can be applied to Li-ion batteries with different capacities or manufacturers. The first step is to determine the relationship between SOC and V_{OC}; the second one is to select the equivalent circuit model and then to obtain the value of the model's parameters as a SOC function; and the last one is the validation of the model. In this paper, two different equivalent electric circuit models were assessed, one of first order and one of second order, but only the first order model was finally proposed due to the difficulty of correlating the second order model parameters with the SOC value, and the good results achieved with it. The model presented can predict with accuracy the battery voltage, with a mean relative error of 0.15% and a maximum relative error of 2.46%; as well as a reasonable approach to the SOC of the battery pack, that compared to the Coulomb counting method presents a mean relative error of 0.54%. The highest error value appears, as expected, at current values that are far from the current operating point selected to obtain the model parameters. The presented methodology is expected to be valid for any kind of Li-ion battery, although the model parameters will vary depending on the kind and capacity of the stack.

CRediT authorship contribution statement

Sergio J. Navas: Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Supervision, Project administration. **G.M. Cabello González:** Methodology, Validation, Formal analysis, Data curation, Visualization, Writing – original draft. **F.J. Pino:** Writing – review & editing, Supervision, Funding acquisition. **J.J. Guerra:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request

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