Particularised Kalman Filter for the state-of-charge estimation of second-life lithium-ion batteries and experimental validation

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***Abstract*— A critical issue for a proper energy management of a lithium-ion (Li-ion) battery is the estimation of its state-of-charge (SOC). There are various methods available for the SOC estimation, being some of them robust and accurate, but requiring high computational power for its applicability, which is inconvenient for their use with the usual low-cost microcontrollers that build a typical BMS. This contribution proposes an SOC estimation algorithm based on a simplified Kalman Filter, that combines a high accuracy with reduced computational requirements. The proposed simplifications result from a careful analysis of the Li-ion battery performance and linearization of processes that entail negligible loss of accuracy. The proposed algorithm is used to estimate the SOC of a second-life Li-ion battery operating in an experimental PV self-consumption facility. Its performance, in terms of accuracy, robustness and computational requirement, is compared with an Extended Kalman Filter (EKF), a Particle Filter (PF) and other low-performance estimation algorithms, proving its trade-off between accuracy and computational cost.**

Keywords— lithium-ion battery; state of charge; Kalman Filter; estimation algorithm.

I. Introduction

The relevance of energy storage systems based on Li-ion batteries (LIBs) is increasing. During the last decades, the traditional application of LIBs has been portable electronic devices, such as cell phones. Currently, the electro-mobility sector and the power sector, mainly related to the integration of higher shares of renewable energy in the power grid, are relevant consumers of Li-ion batteries [1]. In such high-power applications, which many times base their energy management strategy on the battery SOC, a suitable SOC estimation has a capital relevance [2]. Four characteristics are desirable in a SOC estimation algorithm: (i) it should have the required accuracy to allow a coherent energy management, (ii) it should be robust against measurement inaccuracy, due to the typical low-range sensors used in battery BMSs, (iii) it should be robust against a wrong estimation of battery parameters, since these parameters have a relevant dependency on variables such as temperature or battery degradation, and (iv) it should demand the minimum computational power to allow the use of low-performance microcontrollers.

This work has been supported by the Spanish State Research Agency (AEI) under grant PID2019-111262RB-I00 /AEI/ 10.13039/501100011033, the European Union under the H2020 project STARDUST (774094), the Government of Navarra through research project 0011–1411–2018–000029 GERA and the Public University of Navarra under project ReBMS PJUPNA1904.

Various research contributions have been published proposing different SOC estimation algorithms. A trade-off between algorithm simplicity and accuracy is achieved depending on the application. The proposals range from straightforward algorithms based on the measurement of the electrical charge absorbed or released by the battery in order to compute its SOC by knowing the battery capacity [3]. However, such algorithm lacks robustness against current measurement inaccuracies and capacity estimation. Other authors propose estimation methods based on neural networks [4], [5] that achieve a good SOC estimation after an intensive training period. The main weaknesses of these methods are the required training period as well as the inability of making estimations if the operating conditions do not match with the training experiments. Regarding filter algorithms, the H-infinity filter is proposed in many papers, [6], [7], given its

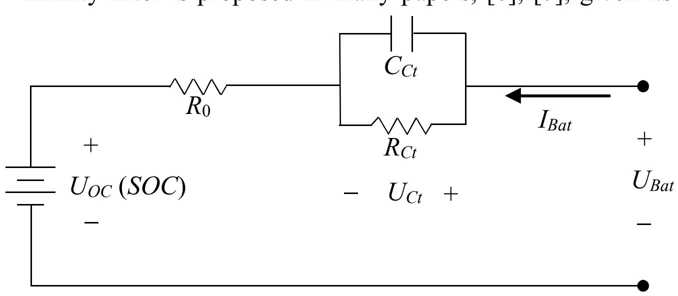

Fig. 1. Equivalent-circuit model of a LIB used for the EKF.

high estimation accuracy. However, it is not suitable for every application due to its computational complexity. Other filter proposed for the SOC estimation is the particle filter [8], which has also the drawback of its mathematical complexity. Kalman filters, with many variations, are the most used estimation algorithm, given its zero-mean estimation error. The most used Kalman filters are the Extended Kalman Filter (EKF) [9], Unscented Kalman Filter (UKF) [10] and Sigma-Point Kalman Filter (SPKF) [11].

This contribution proposes a simplification of the EKF for its application in the computation of the Li-ion battery SOC. The usefulness of this simplification remains on maintaining the accuracy offered by the EKF algorithm, substantially reducing its computational requirements. The remaining of this contribution is organised as follows. Section II is devoted to the modelling of the battery, presenting an equivalent electric circuit that achieves a current – voltage relationship as similar as possible to the real battery. The Kalman Filter is presented in Section III, where its particularisation to estimate Li-ion battery SOC is also detailed. Section IV details the performance of the proposed algorithm. Subsequently, the results obtained with this simplified Kalman Filter are compared with other algorithms proposed in the literature in Section V. Finally, Section VI presents the conclusions of this contribution.

II. BATTERY MODELLING

The estimation of the battery SOC requires the design of an equivalent-electric circuit model, which allows a direct relationship between electrical variables (voltage U_{Bat} and current I_{Bat}) and the SOC. There are various alternatives for such models published in the bibliography [12].

The estimation algorithm proposed in this contribution requires a model with a low computational cost, even at a cost of a slightly reduced accuracy. Therefore, the model shown in Fig. 1 is used, which consists in a SOC-dependent voltage source U_{OC}, an ohmic resistance R_0 and a parallel RC branch with the resistance R_{Ct} and a capacitance C_{Ct}. I_{Bat} is the battery charging current, while U_{Bat} is the voltage between its terminals. Both I_{Bat} and U_{Bat} can be measured during the battery operation. The equations that describe the operation of this equivalent circuit are shown in (1) in its continuous formulation and can be discretised as presented in (2).

$$\begin{cases} SOC(t) = SOC(0) + \int_0^t \frac{I_{Bat}(t)}{C_{Bat}}\, dt \\ \dot{U}_{Ct} = -\frac{U_{Ct}}{R_{Ct} \cdot C_{Ct}} + \frac{I_{Bat}}{C_{Ct}} \\ U_{Bat} = U_{OC} + U_{Ct} + I_{Bat} \cdot R_0 \end{cases} \qquad (1)$$

$$\begin{cases} SOC_k = SOC_{k-1} + \frac{I_{Bat,k}}{C_{Bat}} \cdot \delta t \\ U_{Ct,k} = e^{-\frac{\delta t}{\tau}} \cdot U_{Ct,k-1} + \left(1 - e^{-\frac{\delta t}{\tau}}\right) \cdot I_{Bat,k} \cdot R_{Ct} \\ U_{Bat,k} = U_{OC,k}(SOC) + U_{Ct,k} + I_{Bat,k} \cdot R_0 \end{cases} \qquad (2)$$

Note that δt is the time step between measurements $k-1$ and k, while τ is the time constant of the R-C branch, being $\tau = C_{Ct} \cdot R_{Ct}$. In this model, the $U_{OC} - SOC$ relationship is represented by a polynomial expression, which coefficients depend on the particular battery that wants to be modelled.

III. PROPOSED KALMAN FILTER ADAPTATION

Kalman filters are state estimation algorithms based on the recursive correlation of the estimation error provided by a simpler estimation method. There are various filters available for the state estimation (particle filters, Kalman filters, H-infinity filters, etc.). In particular, the main strength of Kalman filters is their robustness against measurement errors, together with the computational cost that is not extremely high.

Various approaches can be taken for the design of a Kalman Filter, depending on the algorithm used to correct the initial estimation error. The most typical approaches are the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) among others. [9], [13] and [14] provide detailed information about the mathematical background and applicability of such estimation algorithms.

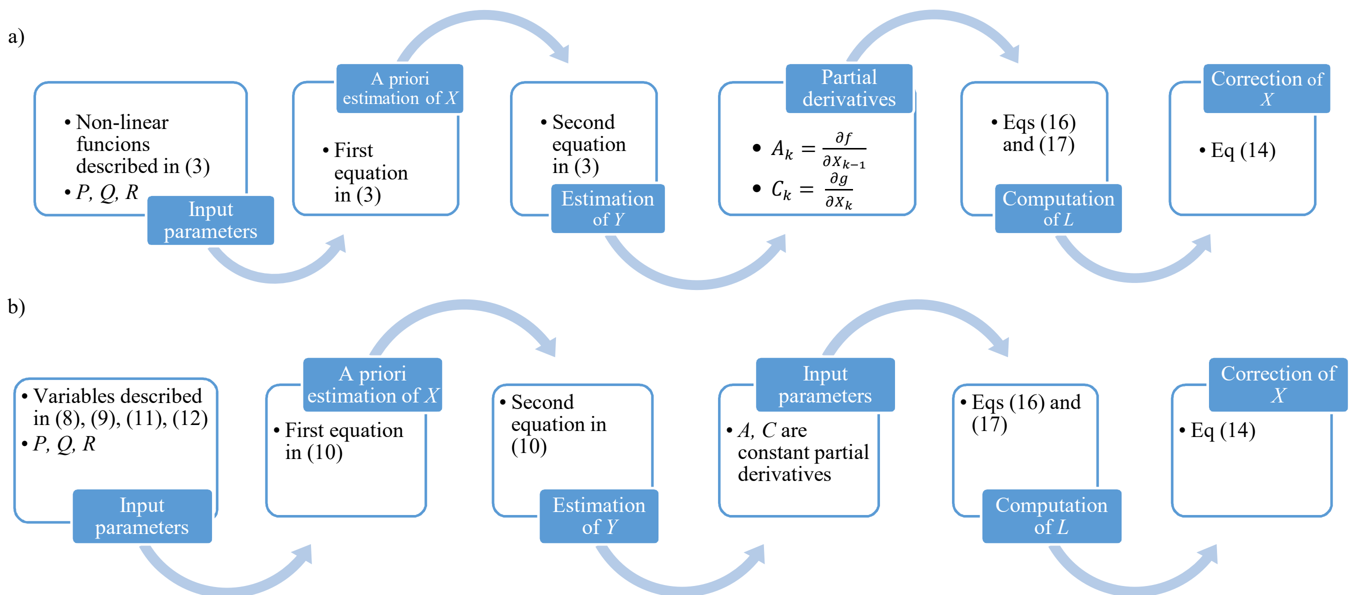

Fig. 2. Computation of the variable X in each iteration step for a) Extended Kalman Filter and b) Particularised Kalman Filter proposed in this contribution.

The algorithm proposed in this contribution is based on an EKF, with some of its calculations simplified towards a higher computation efficiency when used to estimate the SOC of a Li-ion battery with constant model parameters and constant characteristics of the measurement devices. Fig. 2 depicts the simplifications of the particularised Kalman filter compared to the typical EKF. The main computational simplification comes to the avoidance of partial derivatives calculations.

The equations required for a Kalman filter are shown in (3), where X is the state matrix, Y is the measurement matrix and u is the input:

$$\begin{cases} X_k = f(X_{k-1}, u_k) \\ Y_k = g(X_k, u_k) \end{cases} \tag{3}$$

Moreover, matrices A and C are defined, for the correction of the measurement error, as shown in (4), (5):

$$A_k = \frac{\partial X_k}{\partial X_{k-1}} \tag{4}$$

$$C_k = \frac{\partial Y_k}{\partial X_k} \tag{5}$$

Particularising the Kalman filter to the Li-ion battery proposed in the previous section of this contribution, X and Y are defined as:

$$X_k = [U_{Ct,k}, \quad SOC_k]^t \tag{6}$$

$$Y_k = [U_{Bat,k}] \tag{7}$$

Based on (2), the relationship between X_k and X_{k-1} is assumed to be linear. Therefore, A is constant (8). Moreover, the matrix C, is approximated as shown in (9).

$$A_k = diag(e^{-\frac{\delta t}{\tau}}, \quad 1) \tag{8}$$

$$C_k = [1, \quad \frac{U_{OC}(SOC_k)}{SOC_k}] \tag{9}$$

Thanks to these simplifications, the filter can be programmed avoiding the computation required for partial derivatives calculations in each estimation step, being A and C matrices input parameters for the algorithm. Therefore, (10) is obtained, with the expressions for matrices B, D, and u defined in (11)-(13):

$$\begin{cases} X_k = A_k \cdot X_{k-1} + B_k \cdot u_k \\ Y_k = C_k \cdot X_k + D_k \cdot u_k \end{cases} \tag{10}$$

$$B_k = \left[R_{ct,k} \cdot (1 - e^{\frac{-\delta t}{\tau_k}}), \quad \frac{\delta t}{C_{Bat}} \right]^t \tag{11}$$

$$D_k = [R_0] \tag{12}$$

$$u_k = [I_{Bat,k}] \tag{13}$$

The value of Y, which is the voltage estimated by the equivalent-circuit model, is compared to the real voltage measured in the battery, thereby correcting the value of X as shown in (14):

$$X_k = X_k + L_k \cdot (U_{Bat,k} - Y_k) \tag{14}$$

The matrix L, with a size of 2x2, is named Kalman gain, and weights the relevance of the direct SOC calculation based on the ampere-hour counting method with the estimation based on the equivalent-circuit model using the measured battery current and voltages at each time step. The matrices involved in the computation of L are P, Q and R, being P (2x2) the covariance of X; Q (2x2) is the covariance of the estimation error and R (1x1) is the covariance of the measurement error. Note that the value of P is updated in each iteration of the algorithm, while Q and R have constant values that need to be determined for the proper particularisation of the estimation algorithm. The equations that determine the value of L in each algorithm iteration are detailed in Section IV.

TABLE I. MATRICES INVOLVED IN THE KALMAN FILTER

Variables	*Constant arrays*	*Arrays modified in each iteration*
X: state matrix	A: relationship between X_k and X_{k-1}	C: relationship between Y_k and X_k
Y: measurement matrix	B: relationship between X_k and I_{Bat}	P: covariance of X
	D: relationship between Y_k and I_{Bat}	L: Kalman gain
	Q: covariance of the estimation error	
	R: covariance of the measurement error	

IV. ALGORITHM IMPLEMENTATION

Table I summarises the three types of matrices involved in a Kalman Filter. The application of such algorithm, which requires the computation of these matrices, is divided in three steps, each of them detailed in a subsection as stated below:

- Particularisation of the equivalent-circuit model (subsection A)
- Initialisation of parameters (subsection B)
- Computation algorithm (subsection C)

A. Battery Modelling

The first step required for the programming of an estimation algorithm is the computation of the battery equivalent-circuit parameters, specifically the parameters shown in (2). The battery used for the experimental validation of this contribution is a second-life Li-ion battery pack extracted from a Nissan Leaf. The model parameters obtained by means of an accurate characterisation of such battery presented in a previous contribution [15] are used for this estimator. These parameters are assumed to be constant during the battery operation, which requires a robust behaviour of the estimation algorithm against parameter estimation errors.

B. Initialisation of Algorithm Parameters

An initial value for matrix X, which value is actualised in each iteration, is required. The first element of this matrix is the voltage $U_{Ct,1}$, which is initialised to 0 assuming no current flow prior to the estimation. The second element of this matrix is SOC, which is the variable that wants to be estimated. Even being SOC the estimated variable, an initial value, in per unit, is required. Therefore, X is initialised as shown in (15):

$$X_1 = [0, \quad SOC_1]^t \tag{15}$$

An error in SOC_1 leads to inaccurate estimations during the first iterations. However, this error is reduced with the iterative estimations, as will be shown in the following sections. Therefore, if no estimation for SOC_1 is available, a general initial estimation of 0.5 can be used.

The measurement matrix Y, being part of the estimation algorithm, does not require an initialisation, given that its value is computed in the first iteration based on the remaining parameters. Regarding matrices *A, B* and *D*, its parameters need to be calculated based on eqs. (8), (11) and (12). Assuming a proper characterisation of the battery that leads to accurate measurement of its internal parameters, these matrices are accurate enough to lead to no mathematical error in the computation of the estimated SOC.

The matrices Q (covariance of the estimation error) and R (covariance of the measurement error) are key for the computation of L and are proposed in this contribution as tuning parameters for the filter. In our case, the following values are chosen:

$$Q = \begin{bmatrix} 10^{-5} & 10^{-5} \\ 10^{-5} & 10^{-5} \end{bmatrix} \tag{16}$$

$$R = [10^{7}] \tag{17}$$

P_k is the covariance of X_k, being its value computed in each iteration. Therefore, even though an initial value is required for the calculation of L_1, this initialisation is not relevant for practical applications. In this contribution this initialisation was set to the identity matrix.

The matrices C and L are calculated in each iteration. Therefore, they do not require an initialisation.

C. Proposed Computation Algorithm

The estimation algorithm proposed in this contribution repeats the following computations in each iteration step:

- *A priori* estimation of X_k based on $X_k = A \cdot X_{k-1} + B \cdot I_{Bat,k}$.
- Computation of C_k applying the relationship $U_{OC} - SOC$ using the SOC value estimated in the previous step.
- Computation of Y_k using $Y_k = C_k \cdot X_k + D \cdot I_{Bat,k}$.
- *A priori* estimation of P_k based on (18).

$$P_k = A \cdot P_{k-1} \cdot A^t + Q \tag{18}$$

- Computation of L_k based on (19).

$$L_k = P_k \cdot C_k^t \cdot (C_k \cdot P_k \cdot C_k^t + R)^{-1} \tag{19}$$

- Correction of X_k based on (14).
- Correction of P_k based on (20), where Id is the identity matrix with a size 2x2.

$$P_k = (Id - L_k) \cdot P_k \tag{20}$$

With this procedure, after the application of (14), the value of X at the time point k is obtained, and (20) is used to calculate the value of P at the time k, which is required for the following iteration.

V. Experimental Validation

A. Description of the Experimental PV Self-Consumption System

The SOC estimator proposed in this contribution has been experimentally validated and contrasted with other estimation algorithms by means of a research grid-tied PV self-consumption facility shown in Fig. 3. The battery used to achieve the maximum self-consumption rate is a second-life battery discarded from a Nissan Leaf. This battery is built by the series-connection of 96 cells with a capacity of 66 Ah. Given the advanced degradation stage of the battery, the current capacity has decreased to 39 Ah. The following subsection shows the performance of different SOC estimation algorithms in this type of batteries.

Besides the battery, the PV self-consumption system includes a 7 kWp PV installation, a 6 kW power electronics converter with two DC inputs for the PV field and for the battery, a connection to the power grid that guarantees the power availability during the whole year and the domestic power consumption of a 4-member family home. Given that the facility is in a research building, the power demand is measured in a near-by home and emulated on-site by means of a controllable load. This system is monitored and controlled by means of a real-time computer that includes a database used to store the relevant variables with a sampling frequency of 1 Hz. The SOC estimation algorithms compared in the following subsection are programmed in this computer, which also computes the control variables to be fed to the inverter.

B. Comparison of Various SOC-Estimation Algorithms

The proposed modification of the Kalman filter (labelled as PKF) is compared with the following estimators:

- Ampere-hour counting (Ah c), which makes the SOC estimation based on (21).

$$SOC_k = SOC_{k-1} + \frac{i_{Bat,k}}{C_{Bat}} \cdot dt \tag{21}$$

- Electric model shown on Fig. 1 (Model).
- Adaptive particle filter presented in [16] (PF).
- EKF available in Matlab (EKF).

Accurate measurements of electrical variables and battery parameters are available for this comparison. However, realistic scenarios are emulated by introducing a current measurement offset of 0.5 A, a 20% deviation in the battery capacity value and a 35% deviation in the initial SOC. The real SOC value, used to compute the error of each estimation algorithm, is assumed to be that calculated by the Ah counting method using the most accurate battery parameter values and electrical variables measurements. The validation experiment consists of 30 hours of battery operation under the PV self-consumption profile. The initial SOC is 13%, it goes down to 0% at $t \approx 2$ h, reaching its maximum value of 100 % at $t \approx 17$ h, as can be seen in Fig. 4a.

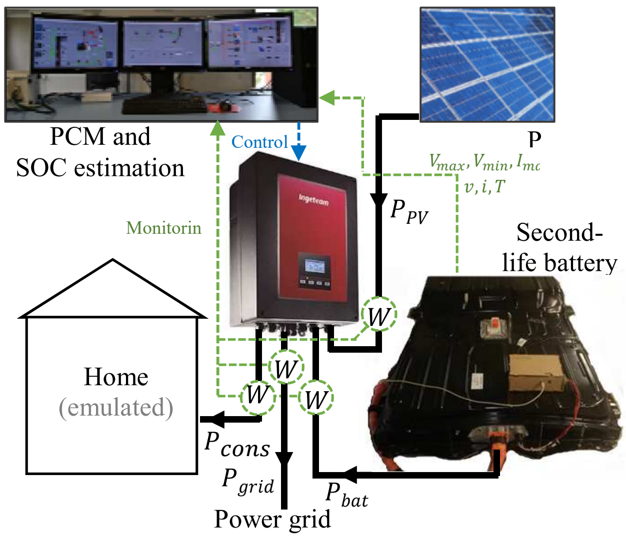

Fig. 3. Schematic representation of the experimental PV self-consumption system based on a second-life battery pack.

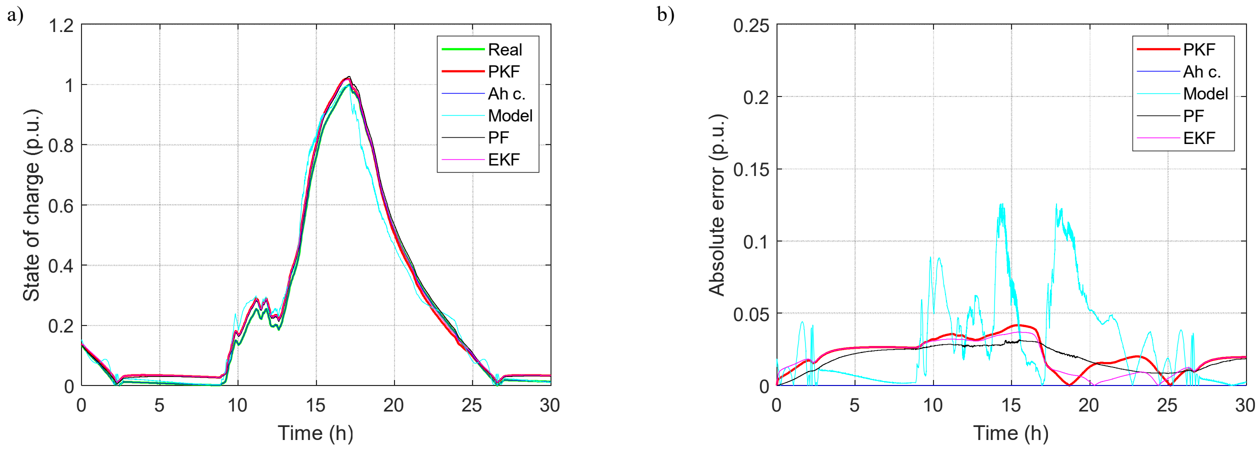

Fig. 4. SOC estimation with accurate measurements and parameter values: a) Estimated *SOC* for 30 hours and b) absolute error.

Fig. 4 shows the estimation results obtained by the five contrasted algorithms assuming that the current and voltage measurements are totally accurate and that the battery parameters (capacity, impedance, and $V_{OC}-SOC$ relationship) are known, which is not a realistic scenario for a battery application. Given the perfect knowledge of measured variables and battery parameters, the ampere-hour counting method (Ah c) achieves a perfect estimation. As shown in the figure, the proposed particularised Kalman filter (PKF), as well as the extended Kalman filter (EKF) and the particle filter (PF) have a similar accuracy. The RMSE achieved by these filters is around 2%, as shown in Table II. The method based on the electrical model achieves the worst estimation accuracy, providing a RMSE of 4.3%. This lower accuracy is because a simple electrical circuit is not able to accurately model the battery performance.

Fig. 5 shows the performance of the algorithms assuming a current measurement offset of 0.5 A, and a battery capacity error of 20%. The method based on the equivalent circuit, as well as both Kalman filters are robust against current offset and capacity estimation errors, given that they keep an accuracy similar to the previous scenario, keeping RMSE values below 5%. On the other hand, the error provided by the particle filter increases in the last part of the experiment, showing its reduced robustness compared to the Kalman filters. Finally, this scenario is especially hard for the Ampere-hour counting method, given that an offset in the current measurement leads to a cumulative integrating error, enlarging the estimation error as time increases. This proves that the ampere-hour method cannot be used by itself in real applications.

Finally, Fig. 6 shows the comparison of the estimation algorithms in the event of having a wrong value for the initial SOC. On the one hand, the estimator based on the equivalent circuit has the highest robustness against this issue, given that the initial SOC is not used as input parameters. On the other hand, the estimators based on a filter, either Kalman filter or particle filter, have an initial estimation error that is detected and corrected during the first operating hours. Note that the correction of the Kalman filters is faster, reaching the actual SOC in around 2 hours. Finally, the Ampere-hour counting method is unable to correct this initialisation error and remains with the same offset during the whole experiment.

VI. Conclusions

The proposed algorithm, based on a particularisation of an Extended Kalman Filter for a second-life Li-ion battery represents a trade-off between a high estimation accuracy and a low computational requirement. Table II shows the main figures of merit of the proposed PKF and other estimation algorithms. Especially remarkable is the column concerning computation times, which is the time required by a regular desktop computer to simulate the 30-hour test presented in this contribution with a time step of 1 second. In order to provide trustworthy values, 5 simulations were made, providing in the table the average computation time.

It is shown in Table II that the highest accuracy is achieved by the estimators based on Kalman filter and on the battery equivalent circuit. Even though the RMSE of the equivalent-circuit method is the lowest one in columns 2 and 3, it should be noted that no misestimation of the impedance parameters

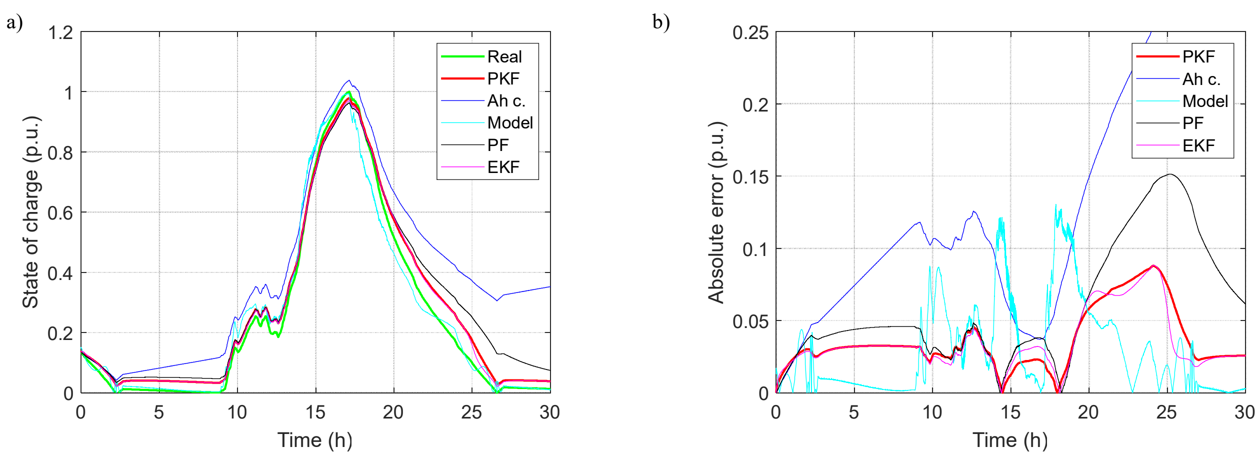

Fig. 5. *SOC* estimation with a current measurements offset of 0.5 A and capacity estimation error of 20%: a) Estimated *SOC* during 30 hours and b) abolute error.

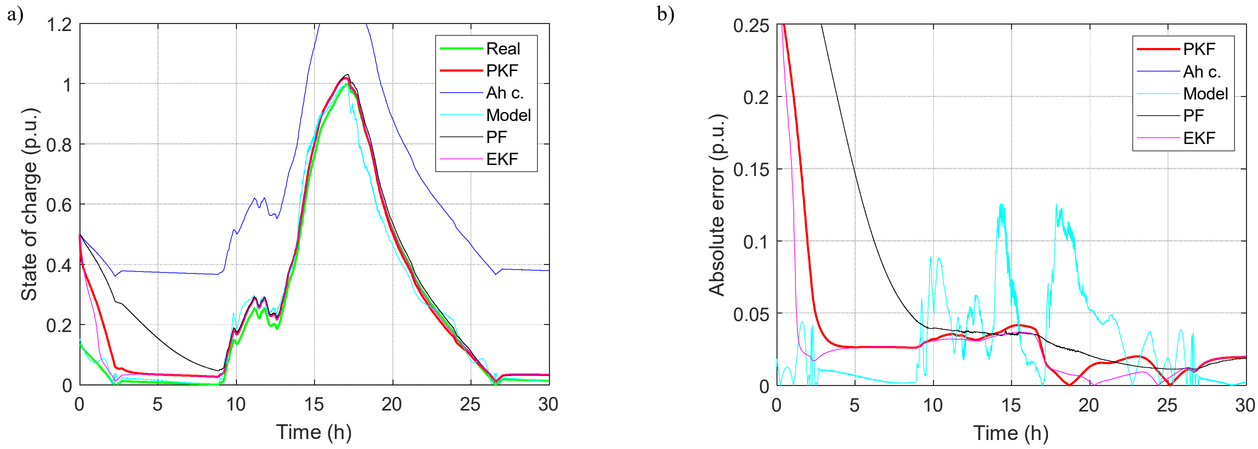

Fig. 6. *SOC* estimation with an initial SOC error: a) Estimated *SOC* during 30 hours and b) abolute error.

TABLE II. FIGURES OF MERIT OF THE COMPARED SOC ESTIMATION ALGORITHMS: RMSE IN THREE SCENARIOS AND COMPUTATION TIME

Method	***RMSE No error***	***RMSE Error: C, I***	***RMSE Error: SOC₀***	***Computation time***
PKF	2.4%	4.2%	6%	1.3 s
Ah c	--	17.0%	36.6%	0.02 s
Model	4.3%	4.3%	4.3%	0.12 s
PF	2.1%	7.4%	11.9%	0.15 s
EKF	2.2%	4.0%	5%	26.7 s

has been analysed, and that in the comparison summarised in column 3 the Kalman filters have a high initial error that is corrected in a few hours, achieving a higher accuracy from that moment on. The accuracy achieved by the PF is slightly lower than that of PKF and EKF in columns 2 and 3, while the Ampere-hour method has been proved to be useless for a real application.

Regarding the computation time, shown in column 4 of Table II, the EKF shows the highest computing demand, requiring 26.7 s for the 30-hour simulation. The second most demanding algorithm is the proposed PKF, which takes 1.3 s for the same simulation. This means a 20-times reduction in the computational requirements keeping a similar accuracy in the SOC estimation. Even more light are the methods based on Ah-counting, the equivalent-circuit model and particle filter, which require a time of 0.02 s, 0.12 s and 0.15 s, respectively.

To sum up, the proposed estimation algorithm has been validated by means of experimental results in a PV self-consumption system with a second-life Li-ion battery as energy storage system. Its low computational requirements have been proved to be combined with a good robustness against current measurement offset, wrong estimation of battery parameters and wrong initial SOC. These characteristics make this algorithm a good candidate to be used by the BMS of a second-life Li-ion battery.

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