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Enhanced closed loop State of Charge estimator for lithium-ion batteries based on Extended Kalman Filter

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HIGHLIGHTS

- Based on a general model valid in full range of SOC considering varied dynamics.
- Integration of an accurate OCV model in EKF taking into account hysteresis effect.
- Experimental validation with different current profiles: pulses, EV and lift.
- Validated with specifically designed profile demanding accurate OCV modeling.

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ABSTRACT

The accurate State of Charge (SOC) estimation in a Li-ion battery requires a suitable model of the cell behavior. In this work an enhanced closed loop estimator based on Extended Kalman Filter (EKF) is proposed, considering a precise model of the cell dynamics valid for different current profiles and SOCs, and a complete model of the Open Circuit Voltage (OCV) which takes into account the hysteresis influence. The employed model and proposed estimator are validated with experimental results obtained from the response of a 40 Ah NMC Li-ion cell to several current profiles. These tests include current pulses, FUDS driving cycles, residential lift profiles, and specially designed profiles which demand an accurate modeling of the transitions between OCV boundaries. In each case, it is demonstrated that the enhanced model can reduce the estimation error nearly by half compared to an estimator ignoring the hysteresis effect. Furthermore, the good performance of the cell dynamics model allows an accurate and stable estimation over different conditions.

1. Introduction

The State of Charge (SOC) estimation is one of the most important aspects in the applications whose performance depends on an energy storage system. Nowadays, energy storage is present in a great number of scenarios, from consumer to industrial applications. This includes among other cases smart grids, renewable energies, transport or elevation [1–5]. The Li-ion technology has been widely extended during the last years in all kind of energy storage systems, which means that a Battery Management System (BMS) must continuously control the operation of the battery, due to the particular characteristics of these cells.

Besides being one the essential parameters to be determined by a BMS, the accurate SOC determination can be critical in certain applications. This happens for instance in electric vehicles where the SOC is related with the autonomy, which is one of the main concerns about this application [6]. In general, a precise estimation of the SOC indicates the available energy stored in the battery, easing the management of the application, optimizing the charge and discharge processes and avoiding a premature deterioration of the battery [6–8]. All these issues have made the SOC determination an extended research topic which is still under study [9].

A great number of SOC estimation techniques have been proposed in the literature. The most extended algorithms are based in the Coulomb Counting method [10], but they present cumulative errors over time and they are not capable of determining the initial value of SOC. Other basic techniques are grounded in the relationship maintained between the Open Circuit Voltage (OCV) and the SOC [11]. The main disadvantage is the long time required to the stabilization of the battery dynamics after which the cell voltage matches the OCV, and the dependence of the OCV with other factors like temperature or hysteresis [12,13]. More complex approaches have appeared to solve some of the problems of the

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basic methods, by means of a dynamic recalibration [13,14], neural networks [15,16], fuzzy logic [17] or closed loop estimators like an observer or an adaptive filter [6,7,9,18–23]. This last type of algorithms has been commonly employed because they present certain advantages as their capacity for correcting estimation errors.

Among these techniques, Kalman Filter based algorithms are widely used due to their accurate SOC estimation, capability of being computed on-line and their flexibility to operate in various working conditions. Plett proposed in [24] an Extended Kalman Filter to perform this task. The model used, which was described in [25], considered a hysteresis model based on a differential equation in SOC, which allowed him to approximate the shape of the scanning curves between the OCV boundaries. Nevertheless, the model identification of the cell dynamics was performed also using a Kalman Filter, which was computationally costly and did not guarantee a solution with physical sense [26]. Later works have explained other similar techniques which also presented these problems, with convergence difficulties in the parameter determination or no physical meaning [27–29]. In some of the cases, the adjustment methodology provides parameters dependent on the specific test used in the process. Other approaches use a simplified model which is not capable of representing all the cell dynamics in a wide range of frequencies [9,12,21,22,27,30–32] or they validate the model in a limited SOC range [30].

In addition to the cell dynamic modeling, the accurate OCV computation has been identified as another important element. Although Plett proposed a hysteresis model in his works, this effect has been ignored later in many studies [9,27,33,34] or modeled in a very simple way with a zero-state model [22,32]. More advanced techniques use the differential equation in SOC [28,29,31] and a new model was presented by Roscher et al. in [12] to achieve an accurate representation of the OCV behavior. Nevertheless, in this case the adaptive filter does not include the coulomb counting estimation and it must be included later with a weighting factor. Finally, some studies used a simplification of the Roscher's model to integrate it in the EKF [21,23]. However, this simplification reduces the accuracy of the original model.

In view of the aforementioned approaches, some lacks have been identified. Sometimes, the applicability of the algorithms is reduced to specific conditions defined by certain current profiles with a reduced bandwidth or a limited SOC range. In other cases the hysteresis effect in the OCV–SOC relationship is not considered, neglecting the difference between charge and discharge processes and using the average curve in every situation even with cells of $LiFePO_4$ chemistry or it is described using a simple approximation. In general, the previously proposed algorithms use simplified models to ease their implementation in the Kalman Filter. Moreover, in many occasions, the problems caused by an inaccurate model are mitigated by modifying the filter behavior, adapting the values of the noises' covariance to reduce the influence of the model or weighting the estimation of the Kalman Filter. Hence, the correction capability of the algorithm is compromised because its operation is approaching the results of a basic coulomb counting. In addition, none of the commented studies validates the SOC estimator with a demanding test regarding the hysteresis model.

In our work, a new SOC estimator is proposed. It uses an enhanced closed loop algorithm, employing a precise model of the cell dynamics and taking into account the hysteresis dependence in the OCV–SOC relationship of the cell, integrating an accurate OCV model whose performance has been demonstrated. The information from the voltage prediction and the coulomb counting reference are concurrently used inside the filter, maintaining its natural behavior to achieve an accurate and stable estimation. As a result, the algorithm is valid with different current profiles and in the whole SOC range. Additionally, the need of considering the hysteresis effect and the improvement in the SOC determination achieved with the enhanced estimator are also analyzed, using a specially designed test to check the model and estimator performance when the path followed by the OCV covers a significant region of the scanning curves. All the different profiles used show that the proposed estimator has been strongly validated to demonstrate its proper operation in different conditions.

This paper is structured in the following sections. Section 2 presents the basic principles about Kalman filters, Sections 3 and 4 describe the model required to implement the closed loop estimator and the considerations needed to carry out its integration respectively. Section 5 shows the experimental results used to validate the proposed algorithm, and finally, Section 6 presents the conclusions of this work.

2. Fundamentals of EKF

In this section the principles of a Kalman filter are briefly commented to present the notation employed in this paper and to set a basis to explain the modifications proposed in Sections 3 and 4. A Kalman filter (KF) can be used as an optimal estimator of the internal states of a dynamic system [35]. Therefore, it can be used to estimate certain parameters if they are expressed as internal states in a model of the system under study. The algorithm is computed recursively using the information of inputs and outputs with each new sample, allowing the simulation in real time.

The filter can be described with a set of equations related to a discrete system defined in state space. In many systems, their outputs can be calculated according to the values of past and present inputs, although they can also be expressed establishing an internal state which is reached according to all the past inputs. Even though the system consisting in the cell or the battery is actually a continuous system, the BMS samples the continuous magnitudes to obtain the discrete data used in the calculations. A non-linear discrete system can be represented as the pair of equations in (1).

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) + w_k \\ y_k &= g(x_k, u_k) + \upsilon_k \end{aligned} \tag{1}$$

The parameter x_k represents the states of the system in the instant k, u_k identifies the known system inputs, while w_k models the noise affecting the state of the system which is related to unmeasured inputs affecting the internal states or inaccuracies of the model. The system output is represented with the vector y_k, and it is determined using the current internal states and the system inputs. Similarly to the previous equation, υ_k models the measure noise, which is the noise that affects to the measured output but not to the internal states. The functions $f(x_k, u_k)$ and $g(x_k, u_k)$ define the system dynamics.

The Kalman Filter minimizes the square error between the real states and the estimation $\hat{x}_k$. However, this algorithm is only valid if the modeled system is linear. When, as in the case of a battery, the system is non-linear, a linearization method must be used to approximate the real system using a linear time variant system (LTV). The modification of the Kalman Filter taking into account this approximation is called the Extended Kalman Filter. Although this approximation produces a non-optimal estimation, this technique is widely used in the literature and provides quite good results [8].

The EKF is defined by Eqs. (2)–(5) which are shown in Table 1 as reference [8].

$\tilde{x}_k = x_k - \hat{x}_k$ represents the state estimation error, and $\Sigma_{\tilde{x},k}$ is its covariance matrix, which is directly related with the uncertainty of the estimation. Two different steps can be distinguished in the EKF computation. In the first step a time update or prediction of the internal state $\hat{x}_k^-$ according Eq. (3) is performed. The second step involves the measurement update, which provides a correction