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Online parameter and state estimation of lithium-ion batteries under temperature effects

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ABSTRACT

In this paper, a hybrid estimation technique is proposed for lithium-ion batteries. This strategy makes use of state-space observer theory to reduce the complexity of the design and the stability analysis. However, the battery's parameters knowledge is required for the state-space model, which limits the performance as the battery's parameters vary. Therefore, an online parameter identification strategy is proposed to track the parameters deviation. The stability of the closed-loop estimation scheme is guaranteed by Lyapunov's direct method. Unlike other estimation techniques where temperature effects are ignored, this paper proposes a universal compensation strategy which can be used with many estimation algorithms available in the literature. The performance of the proposed scheme is validated through a set of experiments under different currents and temperatures along with comparison against an adaptive observer.

List of abbreviations

AC	alternating current
CCCV	Constant Current Constant Voltage
EKF	extended Kalman filter
EOL	end of life
HIL	hardware in the loop
$LiFePO_4$	lithium-iron phosphate battery
NiCd	nickel cadmium
NiMH	nickel metal hydride
OCV	open circuit voltage
PF	particle filter
SOC	state of charge
SOH	state of health

1. Introduction

Lithium-ion batteries offer a higher power density and energy efficiency as opposed to other types of batteries such as lead acid, NiMH, and NiCd [1,2]. They have received an increasing interest because of their other numerous advantages such as rapid charge capability, low steady-state float current, wide temperature operation range, small size, light weight, low self-discharge rate, long life cycle, and absence of hydrogen outgassing, which make them good candidates for many applications such as electric vehicles and laptops [3]. SOC and SOH are crucial aspects in these applications since they are considered as the battery's energy and lifetime gauge, respectively. Henceforth, a bad SOC and SOH estimation would ultimately result in damaging the battery and reducing its lifespan.

A straightforward way to estimate a battery's SOC is the Amp-hour (Ah) balancing technique, also called Coulomb counting method [4,5]. In this approach, SOC is determined by integrating through time the battery's entering and leaving currents. But, the accumulation of the start-up and current sensor errors results into a drift and poor accuracy [6]. Although this technique has some serious drawbacks, it remains the simplest approach for real-time industrial applications [4]. Another rational way to determine SOC is to use the OCV since the battery's voltage is directly correlated to its charge status [7,8]. But, this correlation holds only when the battery gets to an equilibrium state (i.e., no operation for several minutes or hours). A hybrid estimation technique consists of combining the aforementioned two methods. Thus, Coulomb counting technique is then used and whenever equilibrium is reached, a reset of the accumulated errors is performed by updating the SOC

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with the OCV technique. Yet, batteries cannot reach an equilibrium state in many applications where continuous operation is needed, which calls on the necessity of examining other SOC estimation alternatives.

Several advanced estimation strategies are proposed at the cost of a higher computational complexity [9,10]. A sliding mode observer is proposed in [11] to compensate for modeling uncertainties. In [12], the SOC is derived from the charge/discharge experimental data under different constant currents and temperatures for a NiMH battery. In [13], measured current/voltage profiles are used with an optimization procedure to estimate online the battery's parameters. As such, the model captures the battery's parameters variation. Another SOC estimation method is presented in [14] using a reduced-order state observer. But, the knowledge of battery's parameters are needed for the estimation, which reduces its precision with aging. To overcome this shortcoming, an adaptive SOC estimation strategy is proposed for lead-acid and lithium-ion batteries in [15,16], respectively. Then, a proportional–integral observer is proposed in [17] to estimate the SOC of lithium-ion batteries in electric drive vehicles. EKF has been used extensively to estimate SOC and SOH [9,18,19]. Recently, in an effort to overcome the shortcomings of Kalman filters, an adaptive EKF is suggested in [20] for SOC estimation. In [21], support vector regression is used for its approximation and generalization capability to determine the battery's SOH. Finally, online estimation of battery impedance is achieved in [22] using excitation current generated by a motor controller. But, many of the aforementioned techniques do not take into consideration the impact of temperature on the estimation which limits their use in industry. Moreover, the absence of stability proof is another factor limiting their abundance use in the vehicular industry.

Other state-space estimation techniques are based on particle filter which is a sequential Monte Carlo method that use weighted random samples (particles) to estimate the probability distribution function of any nonlinear system. Several PF-based battery SOC estimation methods are suggested in the literature for lithium-ion batteries [23–25]. In [23], the battery is considered as a nonlinear dynamic system with the SOC of the battery as the only state variable. Classical Kalman filtering approaches show limitations in handling nonlinear and non-Gaussian error distribution problems. In addition, uncertainties in the battery model parameters must be taken into account to describe the battery degradation. In [24], a model-based method is presented combining a sequential Monte Carlo filter with adaptive control to determine the cell SOC and its electric impedance. The applicability of this dual estimator is verified using measurement data acquired from a commercial $LiFePO_4$ cell. Due to a better handling of the hysteresis, results show the benefits of the proposed method against the estimation with an extended Kalman filter. In [25], another state estimation technique is presented for lithium-iron phosphate batteries where a PF overcomes the problem of the variance and the mean of a Gaussian probability density function by using Monte Carlo sampling.

On another aspect, soft-computing tools such as neural network and fuzzy logic systems have been acknowledged in numerous applications as robust tools for systems under uncertainties [26–29]. Several intelligent algorithms have been proposed for the SOC and SOH estimation, which have performed satisfactorily [30,31]. But, neural networks remain incapable of incorporating any human-like expertise already acquired about the dynamics of the system in hand, which is considered one of the main weaknesses of such methodologies. This weakness has been overcome in [32] with a fuzzy neural network. However, these tools achieve outstanding performance at the expense of a heavy computation. Furthermore, they are based on heuristic and tuning may not be trivial. Additionally, many soft-computing based observers lack stability proofs in several estimation applications.

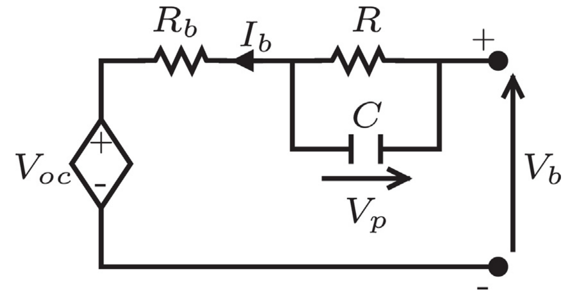

Fig. 1. Equivalent electric circuit of a lithium battery.

The battery's open circuit voltage estimation scheme is based on a state-space observer, which reduces design complexity. However, it requires the battery's parameters, which are known to be time-varying. Therefore, an adaptive parameters identification strategy is proposed using a Lyapunov-based adaptation law for online parameters estimation. Thus, robustness to parametric uncertainties is achieved, which yields better accuracy as the battery ages compared to classical methods. Henceforth, accurate estimation of the battery's open circuit voltage and equivalent series resistance leads to precise state of charge and state of health determination. The stability of the closed-loop estimation scheme is guaranteed by Lyapunov's direct method unlike many online estimation methods. But, temperature is known to introduce a drift in the estimates. In this paper, a universal temperature compensation method is also proposed, a weakness of many estimation strategies in the literature. This work is one of the first attempts, if any, in achieving both SOC and SOH estimation with guaranteed stability taking into account temperature effects. The effectiveness of the proposed method is verified experimentally under different currents and temperatures.

The rest of the paper is organized as follows: Section 2 outlines the circuit model for lithium-ion batteries along with their dynamics. The proposed estimation approach along with the temperature compensation technique is detailed in Sections 3 and 4. In Section 5, experimental results are reported and discussed. We conclude with some remarks and suggestions for further studies pertaining to this problem.

2. Lithium-ion batteries

2.1. Modeling

The electric circuit model of a lithium battery is shown in Fig. 1. This model is used to describe the electrochemical phenomena such as double layer and mass transport effects. Although there is physical explanation between the electric circuit model components and the battery's chemical reactions, an equivalent circuit model is mainly established to match experimental data for a practical operating frequency range. The voltage-current characteristic dynamic mathematical model can be described by the following equations [33–35]:

$$\dot{V}_p = \frac{1}{RC} V_p - \frac{1}{C} I_b \tag{1}$$

$$V_b = V_{oc} + V_p + R_b I_b \tag{2}$$

where $V_{oc}$is the open circuit voltage, V_b and I_b are respectively the voltage and the current at battery terminals, R_b is the internal resistance, R and C are the equivalent resistance and capacitance, respectively, and V_p is the voltage across the RC network.