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An on-line estimation of battery pack parameters and state-of-charge using dual filters based on pack model

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ABSTRACT

Accurate estimation of battery pack state-of-charge plays a very important role for electric vehicles, which directly reflects the behavior of battery pack usage. However, the inconsistency of battery makes the estimation of battery pack state-of-charge different from single cell. In this paper, to estimate the battery pack state-of-charge on-line, the definition of battery pack is proposed, and the relationship between the total available capacity of battery pack and single cell is put forward to analyze the energy efficiency influenced by battery inconsistency, then a lumped parameter battery model is built up to describe the dynamic behavior of battery pack. Furthermore, the extend Kalman filter-unscented Kalman filter algorithm is developed to identify the parameters of battery pack and forecast state-of-charge concurrently. The extend Kalman filter is applied to update the battery pack parameters by real-time measured data, while the unscented Kalman filter is employed to estimate the battery pack state-of-charge. Finally, the proposed approach is verified by experiments operated on the lithium-ion battery under constant current condition and the dynamic stress test profiles. Experimental results indicate that the proposed method can estimate the battery pack state-of-charge with high accuracy.

1. Introduction

With the increase of environment pollution and energy crises, many people are paying great attention to the high efficiency energy usage. The lithium-ion battery has been widely used in distribution energy storage system and electric vehicles [1] because of its high energy density, long cycle life, low self-discharge rate and environmental friendliness. However, single cell has low voltage platform, low capacity and energy storage which may not meet the requirements, so hundreds and thousands of cells are always composed through series or parallel to make up a battery system. The SOC as an important parameter for battery operation, which is related to the battery behavior in practice especially for electric vehicles, needs to be precisely predicted. Unfortunately, the inconsistent cells in the process of production and usage make it difficult to directly estimate battery pack SOC with conventional approaches.

Accurate estimations of cell SOC for series-connected battery pack are remaining challenge due to the inhabited inconsistency characteristic. Dr. Xiong in Ref. [2] proposed a screening process and bias correction based method to solve this problem. This approach showed excellent performance and high accuracy respectively against uncertain diving cycles and battery packs. Wang et al. [3] developed a method for SOC estimation which used four typical battery models at different charging/discharging stages and employed the extended Kalman filter (EKF) to improve the SOC estimation accuracy. The results showed that accurate estimation and reasonable program execution time can be obtained by this method. In order to maximize the capacity/energy utilization of battery packs used in electric vehicles, Dr. Xiong in Ref. [4] proposed a novel systematic SOC estimation framework for battery pack. This study employed the uncertainty quantification method to solve the uncertainty modeling problems innovatively. This approach showed excellent performance and high accuracy respectively against uncertain diving cycles and battery packs. Moreover, Dong et al. [5] introduced an invariant-imbedding-method that analyzed the influence of open-circuit voltage (OCV) hysteresis phenomena on estimating SOC and also presented a method based on wavelet-neural-network-based battery model [6] to solve the nonlinear problems. Feng et al. [7] used an adaptive joint extend Kalman filter algorithm to identify the parameters of the function of the relationship between OCV and SOC under

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Nomenclature

SOC	State-of-charge
OCV	Open-circuit voltage
DST	Dynamic stress test
EKF-UKF	Extend Kalman filter-unscented Kalman filter
MaxAE	Maximum absolute error
RMSE	Root-mean square error
DC	Direct current
MAPE	Mean absolute percentage error
PC	Personal computer
η	Coulomb efficiency
EKF	Extend Kalman filter
UKF	Unscented Kalman filter
STSPKF	Strong tracking sigma point Kalman filter
PF	Particle filter
AEKF	Adaptive extended Kalman filter
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial neural network
RLS	Recursive least square

various temperatures in estimating SOC. In Ref. [8], Tang et al. proposed a dual-circuit based a proportional-integral to restrain the influence of drifting current, and the estimation SOC is less than 2.5%. The method of particle filter (PF) in Ref. [9] was also employed for SOC estimation, which was a novel algorithm in solving optimal estimation problems with high accuracy. The PF was also proposed for battery states joint estimation in Ref. [10]. In addition, Li et al. [11] built an equipment circuit and estimated the battery SOC based on strong tracking sigma point Kalman filter (STSPKF). Xiong et al. [12] used four different charge-discharge current to analyze the battery characteristics and proposed the adaptive extended Kalman filter (AEKF) in SOC estimation, besides the neural network including Neuro-Fuzzy Inference Systems (ANFIS) [13] which was also used in optimal estimation problems by analyzing the battery charge and discharge process, and artificial neural network (ANN) [14] which was simple and easy to implement in nonlinear analyzation.

Due to the battery inconsistency, the approaches of SOC estimation for battery pack are different from single cell. Through the literature analysis and practical research, the solved methods can be concluded as follows: the first method is based on the consistency of cells as shown in Ref. [15], the similar electrochemical characteristics were selected through the screening process. And in Ref. [16], the approach of screening process was proposed to minimize few problems of voltage balancing. Moreover, Plett et al. in Ref. [17] regarded the battery pack as a cell, and used the EKF to estimate the battery pack SOC. Xiong et al. [18] also proposed a filtering approach for ensuring the performance of capacity/resistance conformity in battery pack. This method regards the battery pack as a big cell by selecting the cells having similar states in capacity and other aspects. And then the battery pack SOC can be estimated like the cell. This kind of method is simple and easy to complete. Unfortunately, the inconsistency of cells will change during the battery operation, thus the battery pack cannot be taken as a cell. The second approach is the OCV reference method [19] in which the relationship between the OCV and SOC is built based on a given convention. However, to obtain the OCV, the battery must be rested for several hours, which makes this method only used in some special situations. The third method is based on active equalization and passive equalization. In the case of equalization, the behavior of battery pack is equal to the worst cell in passive equalization [20] or equal to the mean of cells in the active equalization [21]. The complex topologies and control algorithms limit the use of this method. The final method regards battery pack as an "average cell" which can reflect the characteristics of battery pack, and the parameters of the "average cell" can be acquired by the average of cells [22]. In this case, the performance of battery pack can be replaced by a special cell. This method is simple, but the process of implement equivalent is very difficult.

In this paper, to estimate the battery pack SOC with a simple way, the definition of battery pack SOC is first introduced, and then a lumped parameter battery pack model is proposed based on the data-driven model using the measured data to update the model parameters. Secondly, the algorithm of EKF-UKF is employed to estimate the parameters and SOC concurrently. In the algorithm of EKF-UKF, the EKF is used to update parameters of battery pack online, while the UKF is used to estimate battery pack SOC using the parameters updated by EKF. Meanwhile, EKF re-identifies the parameters using the UKF estimation of SOC. Finally, the proposed approach is verified by experiment under constant current condition and dynamic stress test (DST) conditions. In addition, the efficiency of battery pack influenced by battery inconsistency is analyzed at the end of this paper.

This paper is organized as follows. In section 2, the definition of battery pack SOC and the model of battery are proposed. In section 3, the state space equations of battery pack estimator are elicited, furthermore the algorithm of EKF-UKF and its implement flowchart are introduced. Section 4 describes the test bench and analyzes the experimental results. Moreover, the relationship between consistency of cells and battery pack capacity is explained. Section 5 gives the conclusions.

2. Battery pack model

Nowadays, the researchers have built up a complete estimation system in predicting single cell SOC including the definition of cell SOC, the way of modeling, and the approaches of battery states estimation. In Ref. [23], Deng et al. gave a typical definition of cell SOC. In Ref. [24], Li et al. proposed a dynamic parameter battery model to analyze the dynamic battery performance. Firouz et al. [25] used the best linear approximation in SOC estimation. Before the battery pack states estimation, the definition of battery pack SOC and the battery pack model should be first introduced.

2.1. The definition of battery pack SOC

A battery pack is usually comprised by hundreds or thousands of cell connected by series or parallel. However, even the battery group is rigorously selected in practice, different cells performance will lead to the battery inconsistency in the process of production and usage. When any cell reaches the cut-off voltage, the charging/discharging process should be stopped to avoid cells over-charging/over-discharging, thus the pack cannot be fully charged/discharged. To solve the problem, the capacity of pack can be elicited as the sum of the minimum of the remaining cell capacity and the minimum charging capacity [26] formulated as:

$$C_{PACK} = \min_{1\le i\le n}(SOC_iC_i) + \min_{1\le j\le n}((1-SOC_j)C_j) \tag{1}$$

where C_{PACK} denotes the capacity of battery pack, $\min_{1\le i\le n}(SOC_iC_i)$ is the minimum of remaining cell capacity, $\min_{1\le j\le n}((1-SOC_j)C_j)$ is the minimum charging capacity, n is the number of cells in the battery pack, i, j are the battery number.