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# A generic model-free approach for lithium-ion battery health management

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## HIGHLIGHTS

- A new ANN based battery model is developed and integrated with the Kalman filtering technique for battery health management.
- The developed ANN based model can be updated along with the Kalman filtering process at the battery operating stage.
- The developed model is adaptive and eliminates the dependency of expensive empirical battery models.
- The developed approach enables accurate estimations of both short term SoC and long term capacity.
- Experimental results demonstrated the efficacy of the developed battery health state estimation approach.

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ABSTRACT

Accurate estimation of the state-of-charge (SoC) and state-of-health (SoH) for an operating battery system, as a critical task for battery health management, greatly depends on the validity and generalizability of battery models. Due to the variability and uncertainties involved in battery design, manufacturing and operation, developing a generally applicable battery model remains as a grand challenge for battery health management. To eliminate the dependency of SoC and SoH estimation on battery physical models, this paper presents a generic data-driven approach that integrates an artificial neural network with a dual extended Kalman filter (DEKF) algorithm for lithium-ion battery health management. The artificial neural network is first trained offline to model the battery terminal voltages and the DEKF algorithm can then be employed online for SoC and SoH estimation, where voltage outputs from the trained artificial neural network model are used in DEKF state–space equations to replace the required battery models. The trained neural network model can be adaptively updated to account for the battery to battery variability, thus ensuring good SoC and SoH estimation accuracy. Experimental results are used to demonstrate the effectiveness of the developed model-free approach for battery health management.



## 1. Introduction

With the prevalence of portable electronic equipment, application of lithium-ion batteries as major energy storage devices has spread into an increasing number of fields related to human life such as smart phones and electric vehicles. Safe and reliable operation of lithium-ion batteries is of vital importance, as unexpected battery failures could result in enormous economic and societal losses. Capacity fade and resistance increase due to aging of battery cells directly affect the performance of a battery pack by decreasing both energy and power outputs [1]. Thus, developing an effective battery management system (BMS), which can monitor degradation of battery performance and predict remaining useful life (RUL) in real time, becomes an indispensable task. For a BMS, state-of-charge (SoC) and state-of-health (SoH) are two important parameters indicative of battery health conditions; thus, accurately estimating them becomes a paramount task in BMS development [2,3].

Extensive Research has been conducted on lithium-ion batteries in the last decade with an aim to enhance reliability and safety, resulting in a number of SoC and SoH estimation techniques. One of the most commonly used SoC estimation approach is the ampere hour counting technique [4], which calculates SoC values by integrating current with respect to time. Although this technique can generally provide accurate SoC estimations, it requires not only accurate initial SoC information but also high precision current

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sensors to acquire real time current information. Because of these limitations, the ampere hour counting technique has been mainly used as a benchmark method in research due to its high accuracy. In common practice, battery manufacturers generally utilize open circuit voltage (OCV) measurements to find out corresponding SoC values from SoC–OCV tables, which are made based on experiments by comparing SoC and OCV under different temperature conditions [5]. In order to avoid expensive experimental effort in making SoC–OCV tables under practical dynamic loading conditions, several advanced SoC and SoH estimation techniques have been recently developed in the literature [6–12]. Artificial neural network (ANN) models have been employed for direct estimation of SoC or SoH with batches of training samples [6,7]. Electrochemical impedance spectroscopy (EIS) has also been used for the same purpose [8,9]. Further study on EIS has employed a fuzzy logic approach to estimate SoC with EIS data [10]. In addition, the autoregressive moving average (ARMA) model has been developed to compute SoC while using measured impedance data for model validation purposes [11]. Moreover, a Bayesian framework particle filter technique has been used within a Bayesian framework for battery RUL prediction, whereby an empirical circuit model is developed for characterization of battery system dynamics [12]. More recently, He et al. [13] developed an approach using Dempster-Shafer theory (DST) and the Bayesian Monte Carlo (BMC) method for the estimation of both SoH and RUL. Hu et al. developed different approaches to estimate capacity and predict RUL [14,15]. A model based dynamic multi-parameter method was proposed to estimate the peak power of Li-ion batteries by Sun et al. [16]. Waag et al. [17] investigated the battery impedance characteristics at different conditions and demonstrated the significant decreasing of SoC range due to aging. Miranda and Hong [18] developed an integrated model for high power cylindrical batteries to improve the SoC accuracy under extended operating conditions. He et al. [19] employed the unscented particle filter to estimate SoC using their developed new working model. Zheng et al. [20] developed a mean-plus-difference model to estimate SoC. Sun et al. [21] developed a health diagnosis method based on the approximate entropy. Raza et al. [22] developed a sustainability index approach to quantify the qualitative aspects of battery systems, which could choose the ideal energy storage system for specific scenarios. Besides the SoC and SoH estimation, a few experimental explorations have been done for battery aging under various conditions. McManus [23] investigated the environmental impact in low carbon systems for the charge and discharge cycles. Dai et al. [24] overviewed the potential reliability risks from free air cooling (FAC), and presented a prognostics and health management (PHM) for failure prediction. Bishop et al. [25] evaluated the impact of V2G services on the degradation of batteries.

Because of the capability to deal with battery system dynamics for long-term battery health management, Kalman filtering based techniques have been employed by researchers to estimate battery SoC and SoH. Plett [26,27] implemented the extended Kalman filter (EKF) technique to estimate the SoC for hybrid-electric-vehicle (HEV) applications, in which a physical-based circuit model, namely the enhanced self-correcting (ESC) model, was developed to facilitate the EKF implementation. Hu et al. [28] improved the algorithm by estimating the SoC and SoH using a multi-scale dual extended Kalman filter (DEKF). He et al. [29] used unscented Kalman filtering (UKF) to estimate the SoC. The UKF is considered as an improved algorithm to addresses highly nonlinear problems, which the EKF technique could have difficulty to handling. The adaptive EKF is also a very popular technique for SoC estimation [30,31]. Among existing techniques for SoC and SoH estimation, Kalman filtering has been considered to be more capable of handling battery system dynamics for long-term health management. However, explicit battery models are generally required to provide inputs, such as the battery terminal voltage estimations, while using the Kalman filtering technique. Although two types of analytical models have been developed in the literature, namely electrochemical models [32,33] and equivalent circuit based models [1,26,27,34,35], there are three key limitations prohibiting the Kalman filtering based techniques from broad applications: (i) developing a valid analytical model to characterize inherent battery system dynamics and accurately estimating model parameters generally require expensive and labor-intensive experiments; (ii) maximum available capacity of an aged battery system is generally much lower than the rated capacity due to the battery aging effect; however, analytical models used by Kalman filtering could not effectively capture the capacity fade over time, thus, existing Kalman filtering based techniques are generally not capable of providing accurate long-term SoH prediction; and (iii) estimated model parameters for battery analytical models used by Kalman filter could vary significantly due to variability in battery materials and operating conditions, which accordingly leads to large variations in SoC and SoH estimation. Besides working on analytical models, a data-driven model based Kalman filter method has rarely been investigated in the literature. Charkhgard and Farrokhi [36] developed a novel SoC estimation approach using neural networks and an extended Kalman filter. Comparing with analytical models, the developed approach is a data-driven technique that avoids the effort required to analyze battery system dynamics and estimate model parameters, thus can be generally applied to a wide variety of rechargeable batteries. However, the developed method employs a rated capacity for SoC estimation without considering the effect of capacity fade, which could cause substantial SoC estimation errors for the long-term operation of a battery system.

There remain two challenges for battery SoC and SoH estimation: the dependency of SoC and SoH estimation on analytical models, and the lack of effective SoH estimation techniques considering the effect of capacity fade. To address these challenges, this paper presents a new data-driven approach to estimate SoC and SoH for health management of lithium-ion battery systems. The developed approach overcomes the aforementioned limitations of existing Kalman filtering based techniques by eliminating the dependency on a battery physical model. Instead, the relationship between the terminal voltage, SoC, current, and capacity of an aged battery will be approximated by an artificial neural network (ANN). The ANN will be trained with offline data and adaptively updated with online measurements. The trained ANN will be employed in state space equations by the DEKF method to perform the online estimation of SoC and SoH for an aged battery. Because the developed approach employs an ANN model, it can avoid expensive model development process compared to existing approaches based on physical or electrical models. Moreover, because the ANN model will be updated adaptively with evolving online measurements, the developed approach can not only capture the capacity fade over time effectively, but also make SoC and SoH estimation more robust considering the variability in battery materials and operating conditions. The rest of the paper is organized as follows. Section 2 introduces the definitions of SoC and SoH, and briefly reviews the DEKF method for SoC and SoH estimation. Section 3 explains approximation of battery terminal voltage using a structured ANN model, and presents the integration of an ANN model with the DEKF method for SoC and SoH estimation. Section 4 presents an experimental case study and the results. A brief conclusion and suggested future work will be provided in Section 5.

## 2. Related works

This section presents related work and terminology in battery health management. Section 2.1 discusses the definitions of SoC