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An online method for lithium-ion battery remaining useful life estimation using importance sampling and neural networks

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HIGHLIGHTS

- An online RUL estimation method for lithium-ion battery is proposed.
- RUL is described by the difference among battery terminal voltage curves.
- A feed forward neural network is employed for RUL estimation.
- Importance sampling is utilized to select feed forward neural network inputs.

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ABSTRACT

An accurate battery remaining useful life (RUL) estimation can facilitate the design of a reliable battery system as well as the safety and reliability of actual operation. A reasonable definition and an effective prediction algorithm are indispensable for the achievement of an accurate RUL estimation result. In this paper, the analysis of battery terminal voltage curves under different cycle numbers during charge process is utilized for RUL definition. Moreover, the relationship between RUL and charge curve is simulated by feed forward neural network (FFNN) for its simplicity and effectiveness. Considering the nonlinearity of lithium-ion charge curve, importance sampling (IS) is employed for FFNN input selection. Based on these results, an online approach using FFNN and IS is presented to estimate lithium-ion battery RUL in this paper. Experiments and numerical comparisons are conducted to validate the proposed method. The results show that the FFNN with IS is an accurate estimation method for actual operation.

1. Introduction

Due to global energy crisis and environmental pollution, the past decade has witnessed the rapid development of new energy technologies such as Electric Vehicles (EVs), Hybrid Electric Vehicles (HEVs) and Microgrids. As a power source with high energy–density, low pollution and long service life, lithium-ion battery has been widely used in a large amount of new energy systems [1–4]. Throughout the life span of a battery, its electrical property would change with battery RUL which can be regarded as the length of time from present time to the end of useful life [5]. As shown in Refs. [6,7], the safety and stability alterations of the battery would occur as well when battery RUL changes. Therefore, an accurate RUL estimation for lithium-ion battery which can help predict the battery performance variance is necessary in order to get a more scientific battery management method, a longer battery service life and a safer battery system.

Batteries would have different electrical properties, such as battery charge/discharge performance, total available capacity, peak power and so on, under different RULs. In the past 5 years, several descriptions have been utilized to characterize battery RUL. Miao et al. [8] applied an exponential growth model to fit lithium-ion battery capacity degradation curves, because capacity could gradually decrease with various aging and failure process. A sum of two exponential functions of discharge cycles were applied to model the battery capacity fade as well by He et al. [9] based on the analysis of lithium-ion battery data. Furthermore, resistance can serve as a health indicator for describing the RUL of lithium-ion batteries. Eddahech et al. [10] used a single parameter identified from Electrochemical Impedance Spectroscopy (EIS) tests, which refer to the impedance real-part at a defined frequency, to identify the battery RUL. A battery RC model was built in Kim's work [11] where capacity fade and resistance deterioration were obtained by cell characterization test data and used for battery

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health condition indication. However, the definition of RUL using one or two battery parameter values may not be robust enough and may be lopsided. To address this issue, six influential factors were considered based on the evaluation of the battery performance characteristics, analyses on their disparities, and opinions of the experts to characterize RUL in Ref. [12]. A model fused an empirical exponential and a polynomial regression model to track the battery's degradation trend over its cycle life based on experimental data analysis is proposed in Ref. [13]. He et al. [14] described the battery aging state by several battery state of charges (SoCs) since battery with different aging states would have different SoC-OCV (open circuit voltage) curves. However, it is difficult to obtain precise OCVs in actual application. Accordingly, a reasonable definition for battery RUL is indispensable for practical operation.

On the basis of a rational battery RUL definition, a prediction algorithm is also quite necessary for RUL estimation. State estimation algorithms, like unscented Kalman filter (UKF), particle filter (PF), unscented particle filter (UPF), have been utilized for real-time prediction of battery RUL. Zheng et al. [15] employed a relevance vector regression method to simulate battery degradation. Then UKF was utilized to estimate the battery parameters for predicting RUL recursively. Similarly, PF was used for predicting RUL and time until end of discharge voltage of a lithium-ion battery in Ref. [16]. In their papers, PF was verified to have a more accurate prediction performance over UKF based on three lithium-ion battery models. Miao et al. [8] used UPF algorithm to obtain prediction results of lithium-ion batteries RUL based on a degradation model which can predict the actual RUL with an error less than 5%. RUL prediction based on machine learning tools has also been widely studied. Considering the impacts of different values of ambient temperature and discharge current, a naive Bayes (NB) model is proposed for the prediction of battery RULs under different operating conditions in Ref. [17]. A classification and regression model for RUL was built based on the critical features using Support Vector Machine (SVM) in Ref. [18] and the goal of accurate RUL prediction was achieved by using Support Vector Regression (SVR). An optimized relevance vector machine (RVM) algorithm to improve the accuracy and stability of RUL estimation and to provide an uncertainty representation for the resulting RUL estimates was presented by Liu et al. [19].

However, since (1) these advanced nonlinear filters and machine learning techniques, such as UPF in Ref. [8], SVM in Ref. [18] and RVM in Ref. [19], generally have high demands for hardware support, it is very hard to apply these algorithms in a micro controller unit (MCU) in actual battery management systems (BMS) for RUL estimation online. For example, as a binary classifier and also a non-parametric model, there may be large numbers of support vectors in SVM when it is applied to estimate RUL. This disadvantage is resulting in longer times for computation and makes SVM predominantly used as an offline tool [20]. (2) Some variables for RUL definition are hard to measure in actual operations, such as battery capacity [8,11], electrochemical impedance spectroscopy [10], and open circuit voltage [14]. The measurements of these variables require either specific equipment or particular charge/discharge schedule which make it hard to obtain the required variables. Thus the above methods may be inadequate for lithium-ion RUL estimation online.

In this paper, the RUL of lithium-ion battery is described by charge process and battery terminal voltage curve to make this characterization robust and reasonable. Batteries under different RULs would have different charge and discharge performance, which may lead to the variation of the shapes of charge and discharge curves. Afterward, FFNN with fixed hidden neurons is employed to simulate the relation between battery charge curves at constant current and battery RUL. A suitable number of hidden neurons helps to reduce hardware cost and makes the FFNN realizable to predict RUL for actual operation. In addition, IS is used for FFNN input selection to reduce the number of input neurons reasonably while also reconstitute the terminal voltage curve accurately. Then, the RUL can be estimated online by a set of weight and bias values which make up the FFNN and are stored in the MCU of BMS.

The rest of the paper is organized as follows. In Section 2, battery charge process in actual application is introduced. On the basis of this general routine, the description and definition for lithium-ion battery RUL is discussed. The FFNN and IS are introduced in Section 3. Afterward, FFNN with different hidden neuron numbers are compared in Section 4. Meanwhile, in order to evaluate the proposed FFNN with IS, comparison is accomplished as well.

2. Description and definition of RUL

Batteries would have different performance in different life states or ages. Based on this, a RUL definition is proposed in this paper.

2.1. Battery charge and discharge process in actual operation

There are three status of battery in actual practice: charge, discharge and rest. Under the influence of the rapidly changing current passing through batteries, the external and internal parameters are hard to measure or calculate accurately during the discharge process. In the stage of rest, battery parameters are generally constant or changing slowly, which would lead to a difficult estimation of internal battery parameters since they can't be calculated based on the amount of indistinctive data. However, batteries usually have a peaceable charge process in which the necessary external electrical performance can be easily measured because the charge process is controllable to battery management system. Hence, several internal battery parameters, such as battery direct current internal resistance and battery open circuit voltage, can be calculated or estimated during charging.

In this paper, the experimental IFP1865140-12Ah type lithium-ion battery which is widely used in EVs and Microgrids is developed by Hefei GuoXuan High-Tech Power Energy CO. LTD of China. Generally, charge process consists of two subprocesses in actual operation: constant current (CC) and constant voltage (CV). As shown in Fig. 1, the red[1] line is charge current curve which is constant $C/2$ (A rate of C/n is the equal of a full charge or discharge in n hours.) before battery terminal voltage reaches the cut-off voltage of 3.65 V. Afterward, battery is charged by a constant voltage of 3.65 V with a decreasing current and stops charging when the current became $C/100$. Battery terminal voltage of this IFP1865140 type lithium-ion battery that clearly indicates the severe nonlinearity is plotted in blue.

2.2. RUL description based on charge curve

It is known that the internal parameters of the battery are influenced by its RUL, and would be reflected by its external electrical performance. The battery should be replaced when it moves toward the end of its life due to the irreversible electrochemical degradation and poor discharge performance in practical operation. Obviously, internal electrochemical variation has effects on the external electrical performance and parameters. For example, battery impedance would impact battery terminal voltage, voltage drop and temperature rise. The terminal voltage is also affected by

[1] For interpretation of color in Figs. 1 and 4, the reader is referred to the web version of this article.