SOH and RUL Prediction of Lithium-Ion Batteries Based on LSTM with Ensemble Health Indicators

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***Abstract*—The reliable prediction of state of health (SOH) and remaining useful life (RUL) of lithium-ion batteries can prevent broken battery by monitoring capacity loss or increase of internal resistance as a health indicator. Considering that there is relation battery health with capacity loss and increase of internal resistance. In this paper, ensemble health indicators (EHIs) are extracted from current and voltage data which represent to the battery health degradation process. Then, SOH prediction is obtained by LSTM with considering capacity loss and increase of internal resistance. At the same time, RUL predictions are calculated by LSTM taking into account SOH prediction results. Several battery data set is used to verify accuracy of this framework. The result confirmed that high accuracy of SOH and RUL prediction can improve by this framework.**

***Index Terms*—State of health, remaining useful life, Long short-term memory , Ensemble Health Indicators, lithium-ion battery.**

I. Introduction

Health prognosis is important part of Lithium-ion batteries management system (BMS) since the battery health will degrade over time. Therefore, it is urgent to predict state of health (SOH) and remaining useful life (RUL) which represents battery health. Accurate SOH and RUL predictions can prevent failures caused by using a low battery continuously.

Battery SOH and RUL can be monitored as the increase of equivalent series resistance (ESR) or the ratio of current capacity to initial capacity [1]. In order to improve accuracy of SOH prediction some researcher used model based method to predict SOH such as the electrochemical model (EChM) and the equivalent circuit model [2], [3]. The model considers internal resistance and the chemical process inside the battery which causes the model have high prediction accuracy. However, measuring internal resistance by model based method and impedance meter is difficult to apply in real-time applications.

Many researchers also used data-driven methods to perform SOH and RUL prediction. Some papers have applied Feed-forward Neural Network (FNN) based on measured data [4]. The data-driven methods can capture the uncertainties of battery capacity degradation by their adaptability to nonlinear systems. The result in [4] shows the prospect of SOH and RUL prediction using a data-driven method. Long short-term memory (LSTM) is used to consider long-term memories of battery degradation behavior as in [5]. Although the model has several advantages the authors only considered the battery capacity as input LSTM to monitor battery health degradation which is difficult to obtain battery capacity in real-time applications.

In order to achieve simple implementation in real-time application, many papers proposed novel health indicators to substitute capacity data as input of data-driven methods. There are parameters that are easier to measure than capacity such voltage (V), current (C), and temperature (T) as in [6]. Authors of paper [6] extracted some parameters from charging curves and used them as input the Gaussian process regression (GPR). However, the paper only considered capacity degradation to monitor battery health which has high uncertainties.

This paper extracted ensamble health indicators (EHIs) to reflect both increasing internal resistance and capacity loss of lithium-ion batteries. EHIs extraxted from voltage curve to reflect incrasing ESR and used current curve to reflect capacity loss. Then, EHIs are used as input LSTM to predict battery SOH and RUL. The result based on aging test reveal the changes in both battery capacity and ESR.

II. Model Description

A. Ensemble Health Indicator

Many researchers measured internal resistance of battery to reflect the current capacity as in [7] since the internal resistance of the battery increases with the deprivation of battery capacity. However, internal resistance is not easy to apply in real-time application because it is time-consuming. Therefore, some papers predict the SOH and RUL of lithium-ion batteries by using other parameters which are easier to obtain in real-time applications.

In this paper, EHIs is divided into two categories: (i) EHIs representing the capacity loss extracted from the current curve and (ii) EHIs representing increasing ESR extracted voltage curve. The first category HIEs extraxted from the current curve to reflect battety capacity loss. The relation between capacity $C(t)$ and current time series $I(t)$ can be expressed by

$$C(t) = \int_{t_1}^{t_2} I\ (t)\ dt \tag{1}$$

where t_1 and t_2 are the starting and ending time of charging or discharge process. The current data which can measure

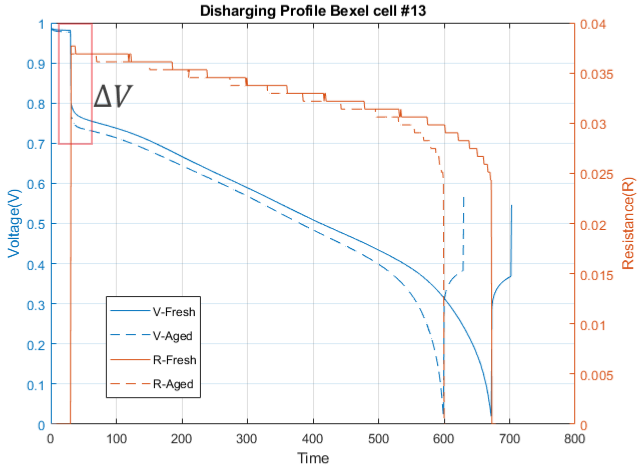

Fig. 1. Discharging profile.

using sensor in real-time applications is used to obtain battery capacity.

The second category HIEs, the instantaneous voltage drop at the start of discharge is shown in Fig. 1. The gap between highest charge point and start discharging point on fresh battery is smaller than aged battery. The voltage drop ΔV has been verified to obtain the ESR as in [8]. The Ohm's law is used to obtain ESR with a given current I and voltage drop ΔV. Therefore, the ESR can be calculated as

$$ESR = \frac{\Delta V}{I}. \tag{2}$$

In order to achieve real-time measurements the ESR value in this paper calculated using (2) instead of using the electro-chemical impedance spectroscopy (EIS) technique.

B. Overall Prediction Process

Lithium-ion battery performance will be degraded over time and usage. This process can be monitored by capacity loss or increasing resistance over time. Therefore, this paper considers monitoring both capacity loss and increasing ESR instead of only monitoring one of them to predict SOH and RUL.

In addition, SOH and RUL prediction is necessary to determine the end of life threshold. Study in [9] shown the end of life threshold is the loss of 20% of initial capacity or a 100% increase in ESR indicates these criteria. Then battery SOH and RUL were calculated based on both the capacity and ESR values predicted. The framework overall process of SOH and RUL prediction based on LSTM is shown in Fig. 2.

III. Conclusion and Future Work

A SOH and RUL prediction based on LSTM with EHIs has proposed in this paper. EHIs are utilized to realize SOH and RUL prediction in real-time applications. This paper considered both increasing ESR and capacity loss of battery as health indicators to improve accuracy. The proposed model can be further studied in several batteries and works condition. Future works include data analysis and algorithm optimization.

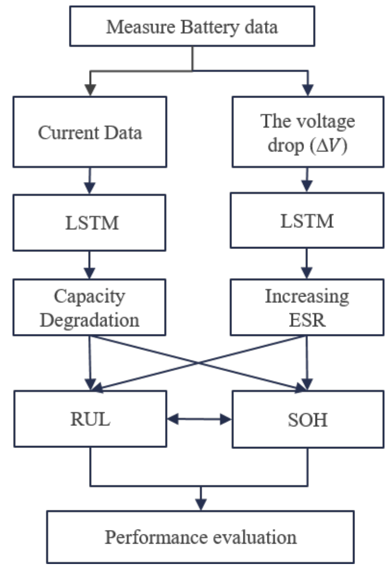

Fig. 2. Overall Prediction Process.

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