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Cycle life estimation of lithium-ion polymer batteries using artificial neural network and support vector machine with time-resolved thermography

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ABSTRACT

A battery cycle life forecast method without requirements of contact measurement devices and long testing time would be beneficial for industrial applications. The combination of infrared thermography and supervised learning techniques provided the potential solution to this problem. This research investigates the application of machine learning techniques—artificial neural networks (ANNs) and support vector machines (SVMs)—in combination with thermography for cycle life estimation of lithium-ion polymer batteries. Infrared images were captured at 1 frame/min during 70 min of charging followed by 60 min of discharging for 410 cycles. The surface temperature profiles during either charging or discharging were used as the input nodes for ANN and SVM models. The results demonstrated that with thermal profiles as the input, ANN could estimate the current cycle life of studied cell with the error of < 10% under 10 min of testing time. While when compared to ANN, the accuracy of SVM-based forecast models was similar but generally required a longer amount of testing time.

1. Introduction

Lithium-ion batteries are the fastest growing and most promising candidates in the battery industry since the 1970s. They have a fast response to energy demand, high energy density and long life spans; lithium-ion batteries have been widely used in many small electronic devices and even battery powered electric vehicles. However, no matter how well a complex system is designed, the system will deteriorate over time or usage. In addition, the cost of lithium-ion battery failure is high. Any incident involving lithium-ion batteries could result in loss of market share and public trust. For example, Samsung's expected losses from the Galaxy Note 7 battery defects have soared above $3 billion [1]. To improve the safety and reliability of complex systems, condition-based maintenance and prognostics methods could be applied to battery management systems. The battery health information gathered from the prognostic system can be used to schedule maintenance ahead in time, prevent malfunction and catastrophic failures [2]. A critical function required for these applications is accurate prediction of cycle life to determine how long the battery can last and to evaluate battery health [3].

The cycle life of batteries, sometimes referred as remaining useful life (RUL), is defined as the remaining load cycles or time until the battery reaches its end of life (EoL). The establishment of a prediction method requires both knowledge of the battery aging process and advanced data processing techniques. In general, prediction methods for RUL of the battery can be categorized as model-based or data-driven. Model-based methods require accurate modeling of the electrochemical behavior of the battery under cycling conditions. These approaches commonly involve the establishment of a reliable mathematical model to describe the capacity of the battery cells and then estimate the remaining life. For example, Rong and Pedram [4] developed an analytical model for lithium-ion batteries capacity estimation based on online current and voltage measurements with an error of < 5%. Saha and Goebel [5] further explored how the RUL can be assessed for complex systems with internal state variables that are either inaccessible to sensors or hard to measure under operational conditions. The algorithm was based on indirect measurements, anticipated operational conditions, and Bayesian statistical analysis of historical data. Despite these studies, an accurate analytical model is usually difficult to develop for a complex and dynamic system, especially when the system operates under noisy and/or uncertain environments. Alternatively, data-driven approaches usually adopt the previous lifetime pattern of a similar system to predict the correlation between current performance data and remaining life. A typical data-driven procedure is described by Nuhic et al. [6]. The input and output vectors of the required support vector machine (SVM) learning dataset are generated by preprocessing

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Table 1
Evaluation of RUL estimation methods with respect to embedded devices and the required data length.

Method	Reference	Required data input	Required time length of the data	Prediction error
Coulomb counting	[17]	Voltage, current	One complete cycle	< 3%
Open circuit voltage (OCV)	[18]	Voltage	One charge cycle	< 3%
	[19]	Voltage	4% of one complete cycle	5% on average
Electrochemical impedance spectroscopy (EIS)	[11]	Impedance, temperature, voltage, current, state of charge variance	One complete cycle	2.1% on average
Kalman filter based (KF): EKF, DEKF, UKF, SPKF, CDKF	[20]	Capacity (integration of the time dependent current)	One complete cycle	< 4.08%
	[21]	Temperature, current, state of charge	One complete cycle	< 4%
Support vector machine (SVM)/relevance vector machine (RVM)	[22]	Capacity	One complete cycle	< 2.28%
Particle filtering: SIR, RBPF, Spherical Cubature Particle Filter	[23]	Capacity	One complete cycle	< 2.17%
	[24]	Capacity	One discharge cycle	~11% near the end of the life
State space modeling	[25]	Capacity	One discharge cycle	~13% near the end of the lift
Fuzzy logic	[26]	Voltage	One charge cycle	1.4%–9.2%
	[27]	Direct current resistance	One charge cycle	< 5%
Autoregressive integrated moving average model	[28]	Capacity	Previous cycles	5% on average
Gaussian process functional regression	[29]	Capacity	One charge/discharge cycle	1.5–6%
Bayesian approach	[30]	Capacity	Previous cycles	< 10% in three cases
Magnetic field probing	[12]	Stratification, electrode structure and current profile	N/A	N/A
Sample entropy	[31]	Sample entropy of the voltage response	One complete cycle	2% on average

the measured data through load collectives, preparing training data, and searching for optimal SVM parameters. Therefore, using data from previous years, the current states of charge and health can be estimated.

Extensive reviews of state of the art data-driven methods for predicting cycle life/RUL of lithium-ion battery states and parameters have been provided by previous scholars [7–9], where common prediction methods have been categorized and analyzed. These reviews focus on applications of the reviewed algorithms and the corresponding prediction errors. However, the requirements for testing times to generate accurate estimations have rarely been summarized. When testing batteries, reducing the testing time increases testing efficiency. For off-line battery testing, the setup time for the sensors is equally important. Consequently, the information from embedded sensors is also worth investigating.

The necessary information from the embedded devices and the required data length of several typical research papers have been summarized in Table 1, and they are organized following the categories established by Ungurean et al. [7]. From Table 1, several limitations of the current prognostic methods should be noted. Firstly, although the approaches vary, most methods require at least one full charge or discharge cycle (SOC from 100% to 0%, or vice versa) to be conducted to determine the current cycle/remaining life. With the charge/discharge current set as 1C, a minimum of 1 h of testing time would be needed, which could be too long for the practical application. Secondly, a number of reviewed battery RUL estimation methods use the battery capacity or internal resistance as health index. However, as pointed out by Liu et al. [10], it is difficult to take such measurements in online applications. Finally, the characteristics (maintenance costs and setup time) of the condition monitoring system need to be considered. Although advanced technologies, such as electrochemical impedance spectroscopy [11] and magnetic field probing [12], have been applied in previous research, only battery current, voltage, and temperature are accessible for a low-cost measurement system. Therefore, it is imperative to develop a low-cost method to estimate the cycle life of the batteries within a relatively short amount of time.

To reduce setup time and potential hazards when in contact with the electrical system, non-destructive/contact testing methods have recently received attention. Previous study [13] demonstrated that the cell temperature increases during charge and discharge, and such a temperature increment is correlated to the physical and electrochemical condition of the cells. Therefore, it is possible to correlate the thermal behavior of the cells during charge and discharge to the RUL. Currently, the temperature of the batteries is commonly measured by thermocouples adhered to the surfaces [14,15]; however, only a limited number of points on the surface can be sampled by such approaches. A promising idea is to use thermography to probe the changes of external and internal thermal properties during the battery cycling condition. Infrared thermography has already been demonstrated to be useful for measuring the internal temperature distribution of the battery by Robinson et al. [16]. They demonstrated that abnormal temperature increases during the cycling process might suggest the battery is under thermal runaway, potential thermal runaway, or other serious aging conditions. Therefore, in this paper, an infrared imaging technique was used to monitor the surface temperature change of battery under cycling conditions and data-driven methods were used to determine the current state of health of the battery cells using either thermal and electrical data as input. The research questions of this study are:

1) Can the battery cycle life be estimated from thermal profiles during the cycling process?
2) If the cycle life of batteries can be estimated with a certain accuracy, what is the minimum testing time?

This paper is organized as follows: Section 2 introduces the experimental methodology and design; Section 3 describes the two data-driven processing methods used in this paper; and Section 4 compares the performances of the models in forecasting of the cycle life before conclusions are drawn in Section 5.

2. Experimental design and methodology

2.1. Fundamentals of infrared thermal imaging

Infrared (IR) thermal imaging, also often briefly called thermography, is a technique that could capture the radiative energy emitted by objects and transform such energy into a temperature distribution by means of an infrared camera or sensor [32]. Thermography can be divided into two categories—active and passive thermography. If no