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A novel Gaussian process regression model for state-of-health estimation of lithium-ion battery using charging curve

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HIGHLIGHTS

- A Gaussian process regression model is proposed for SOH estimation.
- Four features are extracted from charging curves as model inputs.
- Grey relational analysis is applied to analyze the relational degree of features.
- The method is proven to be accurate by the batteries from NASA dataset.
- A battery with dynamic profile is used to verify the robustness of this method.

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ABSTRACT

The state-of-health (SOH) estimation is always a crucial issue for lithium-ion batteries. In order to provide an accurate and reliable SOH estimation, a novel Gaussian process regression (GPR) model based on charging curve is proposed in this paper. Different from other researches where SOH is commonly estimated by cycle life, in this work four specific parameters extracted from charging curves are used as inputs of the GPR model instead of cycle numbers. These parameters can reflect the battery aging phenomenon from different angles. The grey relational analysis method is applied to analyze the relational grade between selected features and SOH. On the other hand, some adjustments are made in the proposed GPR model. Covariance function design and the similarity measurement of input variables are modified so as to improve the SOH estimate accuracy and adapt to the case of multidimensional input. Several aging data from NASA data repository are used for demonstrating the estimation effect by the proposed method. Results show that the proposed method has high SOH estimation accuracy. Besides, a battery with dynamic discharging profile is used to verify the robustness and reliability of this method.

1. Introduction

Electric vehicles (EVs) have been rapidly developed in recent years, which helps stave off energy crisis and environmental issues [1]. However, there are still problems in EVs that need to be solved for performance enhancement, such as the driving range, useful life of batteries, safety and so on [2]. Among these problems, how to estimate the battery state-of-health (SOH) is a vital and challenging issue in battery management system (BMS). An accurate SOH estimated value can help us make correct judgment about the aging level of the battery and how long the battery can still be used. What's more, the SOH estimation can provide driving guidance for reasonable battery use [3]. Lithium-ion batteries have been extensively applied as power sources of EVs due to their environmental friendliness, high energy density and long working life [4]- [5]. However they are also complex and nonlinear electrochemical systems. It is difficult to estimate the SOH accurately because of the complex electrochemical reactions and external performance changes during the battery aging process.

To address this problem, many methods have been proposed for battery SOH estimation in recent years. Estimation methods can be roughly divided into two categories: mechanism analysis method and data-driven method. The mechanism analysis method is based on the deep research of electrochemical mechanism and then builds mathematical models of battery degradation phenomenon [6]. The data-driven method has been popular for SOH estimation recently, mainly including adaptive state estimation methods [7]- [11], neural network [12]- [14], support vector machine (SVM) [15]- [17], Bayesian method [18]- [19], and so on. This kind of method is based on large number of

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data, where the deep understanding of electrochemical principles are not necessary [20]. Among data-driven method, the adaptive state estimation methods, such as particle filter (PF) algorithm and Kalman filter (KF) method [7] [8], have been frequently utilized for battery SOH and RUL prediction. Hu C et al. [9] proposed a Gauss–Hermite PF method to project the capacity fade to the end-of-service value for the RUL prediction and verified the effectiveness of the proposed method. In Ref. [10], a Verhulst model that reflects the capacity fade trends was proposed. The model parameters were identified by the particle swarm optimization algorithm. After that, the PF was used to update the model and made an accurate SOH prediction result. A joint estimation of battery state-of-charge (SOC) and capacity based on extended KF was proposed in Ref. [11], where the proposed method can estimate the battery capacity online. The PF and KF series methods provide a high estimate result in terms of battery SOH. However, one trait of these methods is the prior knowledge of a system state equation, which increases computation cost and is somewhat difficult to acquire for SOH estimation in some cases.

Machine learning method is one of the data-driven method, which has been widely proposed for battery SOH estimation. Wu J et al. [13] proposed a polynomial neural network to estimate SOH and a group method of data handling was employed to select the network input. In Ref. [14], a recurrent neural network was used to estimate the battery SOH and predict the deterioration in battery performance. The neural network method doesn't need the prior knowledge of battery behavior and it is considered as a black-box method with parameters of unclear physical meaning. The SVM has been a popular and effective way to estimate SOH [15]. For example, Dong H et al. [16] focused on both SOH and RUL. The support vector regression-particle filter approach was proposed for battery SOH monitoring and a RUL model was built to update the particle probability distribution to the end-of-life cycle. The relevance support machine was applied for battery RUL prediction by using a novel health indictor in Ref. [17]. Another common machine learning method is based on Bayesian theory. Ng SSY et al. [18] proposed a novel Bayes model for lifetime prediction under different conditions. Ref. [19] predicted lithium-ion battery residual lifetime evaluation based on functional principal component analysis and Bayesian approach.

The Gaussian process regression (GPR) is an emerging machine learning approach recently. It is applicable to complex regression problems such as high dimension, small sample and nonlinearity [21]. Compared to neural network and SVM, GPR has the advantages of hyper-parameter adaptive acquisition, moderately simple to implement and using without loss of performance. What's more, GPR is built in the Bayesian framework, so its predictive output can be explained in the probability-based form, which shows the reliability interpretation of the result [21]. Since the battery aging is a complex and nonlinear process, the GPR can be applied for SOH estimation of lithium-ion batteries. There have been a limited number of studies in this aspect. Liu D et al. [22] utilized the GPR method to perform SOH prediction and describe the uncertainty in evaluation and prediction. However, according to the experimental results presented in Ref. [22], the SOH prediction accuracy was not high. Ref. [23] analyzed the capacity estimate results with different covariance functions of GPR and multiple-output Gaussian processes effectively exploited correlations between data from different cells. Peikun S et al. [24] used a multi-island genetic algorithm-GPR (MIGA-GPR) model to study the relationship between battery charge performance and SOH. This method showed accurate SOH estimation results. However, the symbol chosen to represent the charge performance in Ref. [24] might not be suitable for other situations.

Based on the above discussion, a GPR model for an accurate SOH estimation is proposed in this paper. First, according to the characteristics of charging curves in different cycle numbers, four features are extracted as inputs of the GPR model for SOH estimation. These features can reflect battery aging phenomenon from different angles. This operation makes wider use compared with the model where cycle number is chosen as input, especially for the cases in which cycle number cannot be defined easily. Besides, the SOH estimation results show more similar decreasing tendency with real SOH changing curve. Second, the GPR model is improved in the aspects of the similarity measurement of input variables and covariance function design in order to improve the SOH estimation accuracy and adapt to the model with multi-dimensional excitation. What's more, grey relational analysis (GRA) is applied to analyze the relational grade between selected features and SOH. Several aging data from NASA data repository are used for demonstrating the estimation effect by the proposed method. Results show that the SOH estimation results have high accuracy of the batteries with static charge and discharge profiles. Besides, a battery with cyclic dynamic profiles is used to verify the robustness and reliability of this method.

The structure of this paper is listed as follows: first, in section 2, the battery aging phenomenon based on the lithium-ion battery data in NASA data repository is analyzed. Some features which can reflect battery SOH trend are selected and obtained from charging curves. The GPR method for an accurate SOH estimation are proposed in section 3. Some improvements are made to adapt the input data and battery degradation trend. Then the SOH estimation results are displayed and discussed in section 4. Finally, conclusions are discussed in section 5.

2. Selection of aging features based on charging curves

In this section, some parameters, which can reflect the charging curve changes during battery aging are selected for SOH estimation. First, the SOH definition is introduced in 2.1. Then based on the data of lithium-ion batteries in NASA data repository, the battery aging phenomenon and the changes of charging curve during battery usage are analyzed in 2.2. After that, four features from charging curve are selected to represent battery SOH variation in section 2.3. Then the features changing trend and relational degree with SOH are analyzed.

2.1. The definition of SOH

SOH is a key indicator of degradation degree of batteries. It can be used to show the health status of batteries and help reduce the probability of faults. There has been no uniform definition of SOH so far. Several indicators or notions are created to represent the SOH [25], such as capacity [26], internal resistance, cycle number and so on. The capacity ratio is commonly used to define the SOH [13], which is expressed as Eq. (1), where SOH_i means the SOH value in the ith cycle, C_i represents the capacity at the ith cycle, C_0 represents the initial capacity. With aging of the battery, the battery capacity shows a downward trend due to the change of internal electrochemical reaction.

$$SOH_i = \frac{C_i}{C_0} \tag{1}$$

2.2. Experiment data analysis

The cyclic aging data of lithium-ion batteries in this paper are obtained from the data repository of the NASA Ames Prognostics Center of Excellence [27] [28]. This data set was sampled from a battery prognostics test bed at NASA comprising commercially available lithium-ion 18650 battery cells. In order to show the SOH attenuation trend in different conditions, 4 batteries (labeled as No.5, 6, 7, and 33) were tested recurrently in different operating mode conditions. The tests were conducted at room temperature 24 °C. The experiments contain 3 operational profiles, which are constant current-constant voltage (CC-CV) charge, constant current (CC) discharge and impedance measurement. The charging process contains two modes: CC mode and CV mode. First battery is carried out in the CC mode at 1.5 A until the battery voltage reached 4.2 V and then continued in the CV mode until