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Research of the Relationship between Li-ion Battery Charge Performance and SOH based on MIGA-GPR Method

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Abstract

Owing to the problem that it is difficult to measure State of Health (SOH) of Li-ion battery online, a method to estimate SOH of Li-ion battery using the charge performance under different SOH is put forward. By Grey Incidence Analysis (GIA), the correlation degree between the charge performance and SOH is measured. Based on Multi-island Genetic Algorithm (MIGA) and Gauss Process Regression (GPR), with charge performance as input, SOH is estimates and variance of estimation is also calculated. The result shows that the above-mentioned method can evaluate SOH well.

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Keywords: Charge performance, SOH, Grey incidence analysis, Multi-island Genetic Algorithm, Gauss Process Regression

1. Introduction

The evaluation of life of a lithium-ion battery is an important issue for the development and expansion of the use of Electric Vehicles (EV) [1]. Capacity, which quantifies the available energy stored in a fully charged Li-ion battery cell is a important indicator of SOH [2]. SOH is usually defined as $SOH = (C_i / C_0) * 100\%$, where C_i is the *i*th capacity measured in time and C_0 is the initial value [3,4]. For the last several decades, many different models have been developed to estimate SOH, such as electrochemical model, empirical model and data-driven model [5-7]. Most of the models derive from the discharge process, however, the discharge process of EV is unstable and the charge process is stable. Therefore, it is of great significance to analyze the charge performance of Li-ion battery under different SOH.

NASA Prognostics Center of Excellence has conducted a lot of experiments of battery cycle life under

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different conditions and has also done a lot of researches to prognose SOH [8,9]. This paper uses the data of No.5 battery from NASA and the material is $LiCoO_2$.

Firstly, with GIA, this paper analyzes the correlation between charge performance and SOH. Secondly, the hyper-parameters are achieved using MIGA. Thirdly, with charge performance as input and SOH as output, mathematical model based on GPR is developed.

2. Paper structure

2.1. Grey incidence analysis

GIA is a branch of the grey system theory. The essence of GIA is to analyze the geometric similarity of factor list and data list. GIA provides a new scheme to analyze the series relationships, even if the given information is few [10,11].

Procedure of GIA is as followings:

(1) Collect raw data series and determine the comparison sequences X_i and reference sequence Y :

$$X_i = \{x_i(k) | k = 1,2,\cdots,n\} \tag{1}$$

$$Y = \{y(k) | k = 1,2,\cdots,n\} \tag{2}$$

where $i = 1,2,\cdots,m$. m is the number of comparison sequences, and n is the length of comparison sequences and reference sequence.

(2) Calculate the correlation coefficient $\xi_i(k)$ of $x_i(k)$ and $y(k)$

$$\xi_i(k) = \frac{\min_i \min_k |y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|}{|y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|} \tag{3}$$

Where, $\rho \in [0,1]$ is the distinguishing coefficient, usually, $\rho = 0.5$

(3) Calculate the correlation degree r_i between X_i and Y :

$$r_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \ , \ k = 1,2,\cdots,\mathrm{n} \tag{4}$$

Where, $r_i \in [0,1]$, the closer to 1 r_i is, the better correlation of X_i and Y is.

2.2. Gauss process regression

GPR is a type of modeling approach based on Bayesian learning. GPR has been demonstrated to give more reliable predictive performance. In addition, the Bayes origin of GPR automatically provides the uncertainty of prediction, which is indispensable to robust model-aided optimization [12-14].

Given a set of training data $D = \{(\boldsymbol{x}_i, y_i) | i = 1,2,\cdots,n\}$, a GPR is defined that the regression function $y(\boldsymbol{x})$ is the noisy realization of a latent variable f , that is:

$$y_i = f(\mathrm{x}_i) + \varepsilon_i, \ \ \varepsilon_i \sim N(0,\sigma_n^2) \tag{5}$$

where σ_n^2 is the variance of the noise. The relationship between x_i and $f(\mathrm{x}_i)$ is a random process, which is an Gaussian process model, given in a Gaussian Process prior with zero mean. Then,

$$\boldsymbol{y} \sim N(0, \boldsymbol{Var}(\boldsymbol{x}) + \sigma_n^2 \boldsymbol{I}) \tag{6}$$

where $\boldsymbol{Var}(\boldsymbol{x})$ is an $n \times n$ covariance matrix, whose *ij*th element is defined by a covariance function: $Var_{ij} = Var(\boldsymbol{x}_i, \boldsymbol{x}_j)$. A widely used covariance function is