

A Novel Indirect Health Indicator Extraction Based on Charging Data for Lithium-Ion Batteries Remaining Useful Life Prognostics

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ABSTRACT

In order to solve the environmental pollution and energy crisis, Electric Vehicles (EVs) have been developed rapidly. Lithium-ion (Li-ion) battery is the key power supply equipment for EVs, and the scientific and accurate prediction of its Remaining Useful Life (RUL) has become a hot topic in the field of new energy research. The internal resistance and capacity are often used to characterize the Li-ion battery State of Health (SOH) from which RUL is obtained. However, in practical applications, it is difficult to obtain internal resistance and capacity information by using the non-intrusive measurement method. Therefore, it is necessary to extract the measurable parameters to characterize the degradation of Li-ion battery. At present, the methods of extracting health indicators based on measurable parameters have gained preliminary results, but most of them are derived from the Li-ion battery discharging data.

In this paper, a novel indirect Health Indicator (HI) is extracted from the charging data to quantify Li-ion battery fading. In particular, the Box-Cox transformation is adopted to improve the correlation between the extracted HI and the capacity, which is then quantified by the Pearson and Spearman correlation analysis. Furthermore, Extreme Learning Machine (ELM) is proposed to predict the Li-ion battery RUL based on the novel HI. The forecast results validate the effectiveness and efficiency of our presented method in Li-ion battery RUL prognostic and degradation modeling.

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INTRODUCTION

Because of using clean energy, which has no pollution to the environment, Electric Vehicles (EVs) have been developed by various countries, and will become the main means of transportation in the future. Lithium-ion (Li-ion) battery has been widely used as the main equipment for EVs because it has many advantages, such as high energy density, low self-discharge rate, high output voltage, long lifetime and so on [1], [2]. The performance of Li-ion battery deteriorates with the increase of charging and discharging cycles. The main factors of degradation are related to electrode corrosion and degradation of electrolyte. In order to prevent EVs from breaking down on the road because of Li-ion battery failure, it's of great importance to predict the Remaining Useful Life (RUL) of Li-ion battery. Therefore, the scientific and accurate prediction of the Li-ion battery RUL becomes the key technical problem of the EVs Battery Management System (BMS).

Extensive researches have been done on the prediction of the Li-ion battery RUL in recent years. In order to improve the prognostic accuracy of Li-ion battery RUL, various techniques and methods have been proposed. In general, these methods can be divided into two kinds, one is based on the model, and the other is based on data-driven method.

For model-based methods, the mathematical model is used to describe the complex electrochemical process of the Li-ion battery. For example, Zhang et al. [3] used a physics-based single particle model to study the cycling data of a Li-ion cell, which is constructed to describe the physical and chemical processes in the cell, and the influence of aging process on the state variables is obtained based on the laws of Physical Chemistry. A degradation model of Li-ion battery based on non-equilibrium thermodynamics, which takes into account the chemical potential and the Solid Electrolyte Interphase (SEI) film is proposed by Anil V. Virkar [4]. James L. Lee et al. [5] presented a one-dimensional physics based reduced-order model for the estimation of the battery state based on the discrete time estimation algorithm. Miao et al. [6] proposed an Unscented Particle Filter (UPF) algorithm to improve the accuracy of Li-ion battery RUL prognostic based on exponential empirical degradation model. Xing et al. [7] presented an integrated model of exponential degradation model and polynomial regression model, and the particle filter algorithm is used to improve the RUL prediction accuracy. Because the electrochemical characteristics of the Li-ion battery are very complex, and they are vulnerable to external factors such as temperature, it is very difficult to establish accurate mathematical and physical models.

For data-driven methods, we only need to predict the Li-ion battery RUL based on historical data by taking it as a black box without figuring out complex electrochemical process in the model. It's noted that the applied algorithms or related parameters are the main factor affecting the accuracy of RUL prediction. With the rapid development of machine learning and Artificial Intelligence (AI), more and more algorithms have been used to predict Li-ion battery RUL, such as Auto Regressive (AR) model [8], artificial neural network [9, 10, 11], support vector machine [12, 13, 14], Gauss process regression [15] and relevance vector machine [16,17].

At present, many methods have been developed based on improving the previous algorithm or combining with a variety of algorithms. For example, Zhou et al. [18] proposed a method which combines Empirical Mode Decomposition (EMD) and Auto Regressive Integrated Moving Aaverage (ARIMA) model for RUL prognostic. Zheng et al. [19] developed a data-driven method which joined Unscented Kalman Filter (UKF) and Relevance Vector Regression (RVR) for RUL and short-term capacity prediction of the Li-ion battery. Dong et al. [20] proposed a method for estimating the Li-ion battery SOH using health condition parameters by Support Vector Regression-Particle Filter (SVR-PF), which has provided a good foundation for multi-step ahead prediction. Compared with the model-based method, the data-driven approach is flexible and easy to use, so it has become the main method to predict the Li-ion battery RUL.

Extreme Learning Machine (ELM) theory has been widely used in time series prediction, power load forecasting and function approximation because of high precision, fast speed and simple parameters [21]. ELM is a new type of feed forward neural network, which is based on the Moore-Penrose generalized inverse matrix theory to transform the training iteration into linear equations. Compared with the traditional neural network, the output weights of the network must be determined by several iterations, thus ELM greatly improves the efficiency of network prediction modeling [22]. Therefore, ELM is used to predict the Li-ion battery RUL in this paper.

For data-driven approaches, in addition to the researches concentrated on algorithms, there are also some researches on Health Indicators (HIs), which represent the health state of Li-ion battery. Generally, the HIs of the Li-ion battery are divided into two kinds: direct HIs and indirect HIs.

The direct HIs are mainly the capacity [16, 23] and internal resistance [24, 25] of the Li-ion battery. The capacity is the amount of electricity that a battery can supply from the fully charged state to entirely discharged state, which can be calculated by integrating the current over time. However, the capacity and internal resistance belong to the internal parameters of the Li-ion battery, which can only be obtained in the laboratory or offline, so they are not suitable for practical application.

The indirect HIs, which have a strong correlation with the actual capacity or internal resistance, can reflect the health state of the Li-ion battery. At present, the works of predicting the Li-ion battery RUL based on indirect HIs have been carried out.

For example, Achmad Widodo et al. [26] proposed an intelligent prognostic for the Li-ion battery health based on Sample Entropy (SampEn) feature of discharge voltage, and used Support Vector Machine (SVM) and Relevance Vector Machine (RVM) to predict SOH. SampEn can provide computational means for assessing the predictability of a time series and also can quantify the regularity of a data sequence. Therefore, when it is applied to discharging voltage battery data, it could serve an indicator for battery health. Liu et al. [27] analyzed the changing trend of the discharging voltage in the Li-ion battery degradation process, and extracted the Time Interval of Equal Discharging Voltage Difference (TIEDVD) as a HI of the Li-ion battery. The TIEDVD parameter is defined as the time interval corresponding to a certain discharging voltage difference. The indicated degradation based on the TIEDVD parameter is similar to that of the Li-ion battery capacity as well as RUL. Zhou et al. [28] also analyzed the changing trend of the discharging voltage in the Li-ion battery degradation process, and chosen the Mean Voltage Falloff (MVF) as a HI to quantify the capacity fade. They used Box-Cox transformation to improve HI performance. And Pearson and Spearman correlation analyses are used to evaluate the similarity between real capacity and the estimated capacity derived from the HI. Yang et al. [29] proposed a new HI for SOH estimation and RUL prediction based on the changing rate of temperature, which is extracted from discharging data.

However, most of these indirect HIs are based on the data of the Li-ion battery discharging cycle, and few of them are based on charging data. The discharging process of the Li-ion battery in EVs will be affected by the external factors such as the fluctuation of road surface and temperature. So the data measured during the discharging period is not very accurate. However, the charging process of the Li-ion battery in EVs is static process, and the data measured during the charging period is relatively accurate. Therefore, this paper extracts a novel HI based on the Li-ion battery charging data. Then we use Pearson and Spearman correlation analysis to analyze the correlation between the extracted HI and the capacity. Finally, ELM is employed to predict the Li-ion battery RUL based on the extracted HI.

The remaining parts of this article are arranged as follows: Section 2 introduces related algorithms. The work of extracting the novel HI based on the NASA Li-ion battery charging data is carried out in Section 3. Section 4 uses ELM to predict Li-ion battery RUL based on the proposed HI and evaluates the prediction results. Finally, a summary of the full paper is given in Section 5.

RELATED ALGORITHMS

Extreme Learning Machine (ELM)

This part will introduce some basic theories of ELM. ELM is an algorithm for solving Single-hidden Layer neural network proposed by Huang [30, 31, 32]. ELM randomly generates the connection weights between the input layer and the hidden layer, and the threshold value of the hidden layer neuron. Moreover it only needs to set the number of hidden neurons, and the unique optimal solution can be obtained. Compared with the traditional training method, this method has the advantages of fast learning speed and high generalization performance.

The Single-hidden Layer Feedforward neural Network (SLFN) is shown in Figure 1. It is composed of input layer, hidden layer and output layer. The input layer consists of m neurons, corresponding to m input variables; the hidden layer consists of l neurons; the output layer is composed of n neurons, corresponding to n output variables. And μ_{ij} represents the connection weights between the i th neuron of the input layer and the j th neuron of the hidden layer.

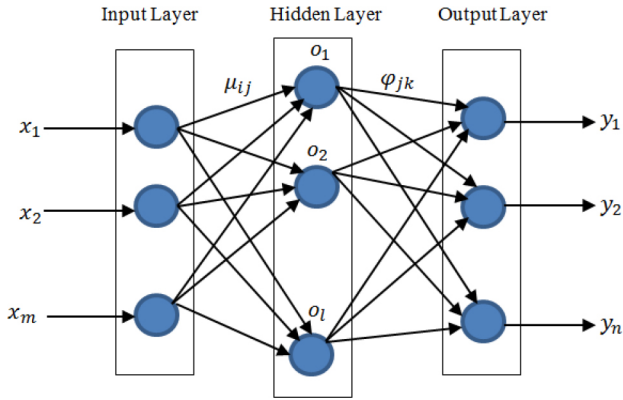


Figure 1. The Structure of SLFN

Supposed the connection weight between the input layer and the hidden layer is μ :

$$\mu = \begin{bmatrix} \mu_{11} & \cdots & \mu_{1m} \\ \vdots & \ddots & \vdots \\ \mu_{l1} & \cdots & \mu_{lm} \end{bmatrix}_{l \times m} \quad (1)$$

Supposed the connection weight between the input layer and the hidden layer is φ :

$$\varphi = \begin{bmatrix} \varphi_{11} & \cdots & \varphi_{1n} \\ \vdots & \ddots & \vdots \\ \varphi_{l1} & \cdots & \varphi_{ln} \end{bmatrix}_{l \times n} \quad (2)$$

Where φ_{jk} represents the connection weights between the j th neuron of the hidden layer and the k th neuron in the output layer.

Supposed the threshold of the hidden layer neuron is b :

$$b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_l \end{bmatrix}_{l \times 1} \quad (3)$$

Assuming that the training set input matrix $\mathbf{X}$ and the output matrix $\mathbf{Y}$ with Q samples are:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1Q} \\ x_{21} & x_{22} & \cdots & x_{2Q} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mQ} \end{bmatrix}_{m \times Q} \quad (4)$$

$$\mathbf{Y} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1Q} \\ y_{21} & y_{22} & \cdots & y_{2Q} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nQ} \end{bmatrix}_{n \times Q} \quad (5)$$

The activation function of the hidden layer neuron is $h(x)$, and then Figure 1 shows that the output $\mathbf{P}$ of the neural network is:

$$\mathbf{P} = [\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_Q]_{n \times Q} \quad (6)$$

$$\mathbf{p}_j = \begin{bmatrix} p_{1j} \\ p_{2j} \\ \vdots \\ p_{nj} \end{bmatrix}_{n \times 1} = \begin{bmatrix} \sum_{i=1}^l \varphi_{i1} h(\mu_i \mathbf{x}_j + b_i) \\ \sum_{i=1}^l \varphi_{i2} h(\mu_i \mathbf{x}_j + b_i) \\ \vdots \\ \sum_{i=1}^l \varphi_{in} h(\mu_i \mathbf{x}_j + b_i) \end{bmatrix}_{n \times 1} \quad (j = 1, 2, \dots, Q) \quad (7)$$

Where $\mu_i = [\mu_{i1}, \mu_{i2}, \dots, \mu_{im}]$; $\mathbf{x}_i = [x_{1j}, x_{2j}, \dots, x_{mj}]^T$

Formula (7) can be expressed as:

$$\mathbf{H}\varphi = \mathbf{P}' \quad (8)$$

Where $\mathbf{P}'$ is the transpose of matrix $\mathbf{P}$; $\mathbf{H}$ is the hidden layer output matrix of neural network, specific forms can be expressed as follows:

$$\mathbf{H}(\mu_1, \mu_2, \dots, \mu_l, b_1, b_2, \dots, b_l, \mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_Q) = \begin{bmatrix} h(\mathbf{x}_1) \\ h(\mathbf{x}_2) \\ \vdots \\ h(\mathbf{x}_Q) \end{bmatrix} = \begin{bmatrix} h(\mu_1 \cdot \mathbf{x}_1 + b_1) & h(\mu_2 \cdot \mathbf{x}_1 + b_2) & \cdots & h(\mu_l \cdot \mathbf{x}_1 + b_l) \\ h(\mu_1 \cdot \mathbf{x}_2 + b_1) & h(\mu_2 \cdot \mathbf{x}_2 + b_2) & \cdots & h(\mu_l \cdot \mathbf{x}_2 + b_l) \\ \vdots & \vdots & \ddots & \vdots \\ h(\mu_1 \cdot \mathbf{x}_Q + b_1) & h(\mu_2 \cdot \mathbf{x}_Q + b_2) & \cdots & h(\mu_l \cdot \mathbf{x}_Q + b_l) \end{bmatrix}_{Q \times l} \quad (9)$$

When the input weight μ and bias b are determined by random assignment, and the hidden matrix $\mathbf{H}$ is a definite matrix. Therefore, training SLFN is transformed into finding the least squares solution of equation $\mathbf{H}\varphi = \mathbf{P}'$:

$$\|\mathbf{H}\hat{\varphi} - \mathbf{P}'\| = \min_{\varphi} \|\mathbf{H}\varphi - \mathbf{P}'\| \quad (10)$$

$$\hat{\varphi} = \mathbf{H}^+ \mathbf{P}' \quad (11)$$

Where $\mathbf{H}^+$ is the Moore-Penrose generalized inverse of matrix $\mathbf{H}$. Based on the above analysis, Huang [30] proposed ELM whose framework can be stated as follows:

The basic process of the ELM algorithm:

- Step1. Determine the number of neurons in hidden layer, randomly set the connection weight μ between the input layer and the hidden layer, and the bias b of the hidden layer neuron;
- Step2. Choose an infinite differentiable function as the activation function of the hidden layer neuron, then calculate the output matrix H of hidden layer;
- Step3. Calculate output layer weight $\hat{\phi} = H^+ P'$;
- Step4. Compute the result decision function:

$$f(x) = h(x)\hat{\phi} = h(x)H^+ P'$$

Box-Cox Transformation

In the process of linear regression, the unobservable error may be related to the prediction variables, which will bring error to the result of the least squares estimation of linear regression. In order to solve the problem of homogeneity of variance, Box and Cox [33] proposed a transformation form in 1964. By choosing the transform parameter λ , the corresponding transformation form is obtained, so as to solve the difficult problem of determining the data transformation model. After the transformation, we can reduce the correlation between the unobserved error and the prediction variable to a certain extent. According to the characteristics of data, the parameter λ is determined by maximum likelihood or Bayesian estimation.

Box-Cox Transformation

Given dependent variable $y = (y_1, y_2, \dots, y_n)^T$, multivariate independent variable $x = (x_1, x_2, \dots, x_q)$, where q is the number of variables, $x_q = (x_{q1}, x_{q2}, \dots, x_{qn})^T$, n is sample size.

The linear model between the dependent variable and the independent variable can be described as follows [34]:

$$y_j = \beta_0 + \beta_1 x_{1j} + \beta_2 x_{2j} + \dots + \beta_q x_{qj} + \varepsilon_j \quad (12)$$

Where $\beta = (\beta_0, \beta_1, \dots, \beta_q)^T$ is a regression coefficient, ε_j is an unobservable random error, and $\varepsilon_j \sim N(0, \sigma^2)$.

Mathematically, the Box-Cox transform can be expressed as:

$$k(x, \lambda) = \begin{cases} \frac{x^\lambda - 1}{\lambda}, & \lambda \neq 0 \\ \ln x, & \lambda = 0 \end{cases} \quad (13)$$

The corresponding inverses transform is:

$$g(x, \lambda) = \begin{cases} (\lambda x + 1)^{1/\lambda}, & \lambda \neq 0 \\ \exp(x), & \lambda = 0 \end{cases} \quad (14)$$

Where λ is the transform parameter which needs to be determined.

Considering the purpose of this paper is to obtain a linear relationship between the HI and the capacity, so the exogenous variable Box-Cox transform model is used to transform the HI.

$$y_j = \beta_0 + \beta_1 x_{1j}^{(\lambda)} + \beta_2 x_{2j}^{(\lambda)} + \dots + \beta_q x_{qj}^{(\lambda)} + \varepsilon_j \quad (15)$$

Estimation Method of Box-Cox Transform Parameter λ

There are two methods to estimate the parameter λ of Box-Cox transform: Maximum likelihood estimation and Bayesian estimation. And the maximum likelihood estimation is a typical method.

Taking the formula (15) as an example and assuming $\varepsilon_j \sim N(0, \sigma^2)$, then the variable y_j satisfies the following distribution:

$$y_j \sim N(x_j^{(\lambda)} \beta, \sigma^2 I) \quad (16)$$

Where $x_j^{(\lambda)} = (1, x_{1j}^{(\lambda)}, x_{2j}^{(\lambda)}, \dots, x_{qj}^{(\lambda)})$.

So the joint probability density function of $y = (y_1, y_2, \dots, y_n)^T$ is:

$$(y) = \frac{\exp\left(-\frac{1}{2\sigma^2}(y - x^{(\lambda)}\beta)^T(y - x^{(\lambda)}\beta)\right)}{(2\pi\sigma^2)^{\frac{n}{2}}} \quad (17)$$

Where $x^{(\lambda)} = (J, x_1^{(\lambda)}, x_2^{(\lambda)}, \dots, x_q^{(\lambda)})$, $J = (1, \dots, 1)^T$ is an n -dimensional vector, $x_i^{(\lambda)} = (x_{i1}^{(\lambda)}, x_{i2}^{(\lambda)}, \dots, x_{in}^{(\lambda)})$, $i = 1, 2, \dots, q$.

The log-likelihood function of formula (16) can be expressed as:

$$L(\beta, \sigma^2, \lambda | y, x) = -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} (y - x^{(\lambda)}\beta)^T (y - x^{(\lambda)}\beta) \quad (18)$$

For different β and σ^2 , the formula (18) has different values.

Find the partial derivatives of β and σ^2 respectively, and make them zero. And the following results can be obtained by solving the normal equations:

$$\hat{\beta}(\lambda) = \left((x^{(\lambda)})^T (x^{(\lambda)}) \right)^{-1} (x^{(\lambda)})^T y \quad (19)$$

$$\hat{\sigma}^2(\lambda) = \frac{(y - x^{(\lambda)}\hat{\beta})^T (y - x^{(\lambda)}\hat{\beta})}{n} \quad (20)$$

According to the formula (18), formula (19) and formula (20), the log-likelihood function can be expressed as:

$$L^*(\beta, \lambda) = C - \frac{n}{2} \ln \left\{ \frac{(y - x^{(\lambda)}\hat{\beta})^T (y - x^{(\lambda)}\hat{\beta})}{n} \right\} \quad (21)$$

Where C is a constant independent of λ .