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# A novel health indicator for on-line lithium-ion batteries remaining useful life prediction

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## HIGHLIGHTS

- Finding a linear correlation between mean voltage falloff (MVF) and capacity.
- MVF is used as a novel HI for battery degradation modeling and RUL prediction.
- Box-Cox transformation is utilized to improve the HI performance.
- A regression equation between MVF and capacity is established.
- RUL prediction with statistical regression technique and optimized RVM.

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## ABSTRACT

Prediction of lithium-ion batteries remaining useful life (RUL) plays an important role in an intelligent battery management system. The capacity and internal resistance are often used as the batteries health indicator (HI) for quantifying degradation and predicting RUL. However, on-line measurement of capacity and internal resistance are hardly realizable due to the not fully charged and discharged condition and the extremely expensive cost, respectively. Therefore, there is a great need to find an optional way to deal with this plight. In this work, a novel HI is extracted from the operating parameters of lithium-ion batteries for degradation modeling and RUL prediction. Moreover, Box-Cox transformation is employed to improve HI performance. Then Pearson and Spearman correlation analyses are utilized to evaluate the similarity between real capacity and the estimated capacity derived from the HI. Next, both simple statistical regression technique and optimized relevance vector machine are employed to predict the RUL based on the presented HI. The correlation analyses and prediction results show the efficiency and effectiveness of the proposed HI for battery degradation modeling and RUL prediction.



## 1. Introduction

Equipped with the advantages of high energy density, high galvanic potential, excellent low-temperature performance, low self-discharge rate and long lifetime, lithium-ion battery has been widely applied to communication, aviation, aerospace and other industrial areas [1]. Consequently, lithium-ion battery gradually has become a key component in many important areas and industrial applications, such as in electric vehicles and plug-in hybrid electric vehicles. Nevertheless, lithium-ion battery functionality gradually deteriorates over time [2].

For electric vehicles and plug-in hybrid electric vehicles, prognostics and health management(PHM) plays an important role in battery management systems (BMS) since the performance failure of batteries may cause great inconvenience, expensive maintenance cost or even catastrophic failures. In order to evaluate the performance of a lithium-ion battery, state of charge (SOC) and state of health (SOH) estimation techniques are often implemented in BMS [3]. SOC is the percentage of the remaining charge to the battery's current maximum capacity. SOH describes the physical health condition of a battery compared to a fresh battery. The gradual decrease in the capacity of lithium-ion batteries is often used as a health indicator that tracks the degradation of lithium-ion batteries. Lithium-ion battery failure occurs when the capacity degradation data of the lithium-ion battery drops below some percentage of its nominal capacity [4]. Prognostics and RUL estimation entail the use of the current and previous system states of a

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battery to predict the future states of the battery system [5]. The reliable predicted information is of great importance for scheduling repairs and maintenance in advance and also providing an alarm before faults reach critical levels.

In recent years, extensive research work has been conducted on lithium-ion battery degradation modeling and RUL prediction. Saha et al. [6–8]studied the battery RUL prediction and the uncertainty representation and management with particle filter (PF) algorithm (using the empirical degradation model to build state transition equation). Moreover, the PF method as well as its extended versions has been widely adopted in prognostics [9–11]. For example, Miao.et al. [9] presented an unscented PF algorithm to improve the accuracy of lithium-ion battery RUL estimation.

As artificial intelligence and machine-learning techniques rapidly advance, research work on data-driven prognostics has been focused on the use of flexible models, such as various types of neural networks (NNs) [12], Support Vector Machine (SVM) [13], and Relevance Vector Machine (RVM) [14,15] for battery RUL forecasts. For example, He et al. [16] used wavelet analysis method to decouple global degradation, local regeneration and fluctuations in SOH time series, and then used a systematic multiscale Gaussian process regression (GPR) modeling method to tackle accurate SOH estimation problems. Liu et al. [17] also used the GPR, a data-driven approach, to perform SOH prediction with mean and variance values as the uncertainty representation of SOH.

While only one method cannot completely meet the very accurate prediction aim, complementing the capabilities of different approaches has been popular recently. The fusion prognostics method becomes a main research direction for improving the performance in battery RUL prediction. Li et al. [18] presented a novel integrated approach based on a mixture of Gaussian process model and PF for lithium-ion battery SOH estimation. Kozlowski et al. [19] proposed a data-driven RUL prediction approach by combining autoregressive and moving average (ARMA) model, neural networks, and fuzzy logic. Liu et al. [5] explored an ensemble echo state networks to realize satellite lithium battery RUL prediction with high prediction performance. Liu et al. [20] developed a fusion prognostic framework to increase the system long-term prediction performance. Xing et al. [21]proposed an ensemble model for predicting the RUL of a lithium-ion battery by combining a fused empirical exponential model, a polynomial regression model, and a PF algorithm. Liu et al. [22] presented a novel integrated approach based on a mixture of PF and optimized non-linear degradation autoregressive time series model for lithium-ion battery SOH estimation.

It should be noted that most of the recent research on lithium-ion battery RUL estimation is mainly focused on developing various algorithms to improve estimation accuracy and efficiency [23]. Almost all of these methods utilize either capacity [2,24] or internal resistance [8,25] as the battery HI for degradation modeling and RUL prediction. However, it is very difficult to perform on-line capacity and internal resistance measurement and monitoring on electric vehicles' dynamic battery due to the not fully charged and discharged condition and extremely expensive cost, respectively. Therefore, there is a great need to find an optional way, which can be readily employed on-line, to quantify the degradation of lithium-ion battery replacing the complex measurement and monitoring of capacity and the internal resistance.

By now, only a little work focused on other health indicators has been done to make prognostics of lithium-ion battery RUL. For example, the open circuit voltage (OCV) [26,27] is another appropriate HI for batteries' SOH. However, the measurement of OCV is time-consuming because the battery requires a long rest time to reach a steady state. Tseng et al. [28] observed that taking the voltage 60 s after full discharge to replace OCV in SOH modeling is more feasible and accurate enough to represent OCV. Liu et al. [5] observed that the time interval of equal discharging voltage difference in each discharge cycle can be used as an HI to measure the capacity degradation. Liu et al. [23] found that the discharging voltage difference of equal time interval can be used as an HI to measure the capacity degradation. Widodo et al. [29] proposed the use of sample entropy of discharging voltage under a prognostic framework for battery health assessment. This method provides a useful computational tool for assessing the predictability of a time series and can also quantify the regularity of a data sequence. However, this technique is time-consuming and also requires the capacity parameter in evaluating the sample entropy indicator. Differential voltage was also proposed to estimate the SOH [30,31], but the estimation process is quite complex.

As mentioned above, it is urgent to find an alternative on-line HI to quantify the battery degradation. In this work, we extract a novel HI from the operating parameters of lithium-ion batteries. The goal is to achieve a simple and reliable method for on-line battery degradation modeling and RUL estimation for electric vehicles and plug-in hybrid electric vehicles. Worried about the initially extracted HI not sufficiently meeting the aim to replace the capacity as the battery HI, we employ Box-Cox transformation to enhance the degree of linear correlation between the HI and the capacity. Then correlations analyses are utilized to quantitatively analyze the goodness of the regression between the capacity and HI. We use both simple statistical regression technique and optimized relevance vector machine [32] to predict the RUL of a lithium-ion battery based on the presented HI and we compare the prediction performance of the two approaches based on our presented evaluation criteria as well. What's more, the prediction result made by monotonic echo sate networks (MONESNs) [33] is also added to prove the novelty of the proposed method.

The rest sections of this paper are organized in the following order: The RVM algorithm and Box-Cox transformation are introduced in Section 2. Section 3 details the extraction and optimization of the proposed HI. Prognostics of lithium-ion batteries RUL is made based on the novel HI and prediction performance of different methods is compared in section 4. Finally, we make discussion and conclusion in section 5.

## 2. Related algorithms

### 2.1. Relevance vector machine

#### 2.1.1. Relevance vector regression

Given a data set $\{x_i, t_i\}_{i=1}^{N}$, ($x_i \in R^d$ and $t_i \in R$), considering scalar-valued target functions only, the general regression relationship between the target and input vectors can be described as follows:

$$\mathbf{t} = y(\mathbf{x}) + \boldsymbol{\varepsilon} \tag{1}$$

where $N$ is the number of data samples, $y(\cdot)$ is a non-linear function, $\varepsilon$ is the independent additive noise term subject to $\varepsilon \in N(0, \sigma^2)$. Thus $p(t_i|\mathbf{x}) \sim N(t_i|y(x_i), \sigma^2)$ where the notation specifies a Gaussian distribution over $t_i$ with mean $y(x_i)$ and variance $\sigma^2$. The goal of the regression model is to find an approximated function $\hat{y}$ based on the given data set. The output of the RVM model can be expressed as,

$$\mathbf{t} = \mathbf{\Phi w} + \boldsymbol{\varepsilon} \tag{2}$$

where $\mathbf{t} = (t_1, t_2, \ldots, t_N)^T$, $\mathbf{\Phi} = (\phi(x_1), \phi(x_2), \ldots \phi(x_N))^T$ is the $N \times (N+1)$ design matrix in which $\phi(x_i) = [1, K(x_i, x_1), K(x_i, x_2), \ldots K(x_i, x_N)]^T$, and $K(x, x_i)$ is the kernel function, $\mathbf{w} = (w_0, w_1, \ldots, w_N)^T$ is the corresponding weight vector.