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A novel prediction method based on the support vector regression for the remaining useful life of lithium-ion batteries

Qi Zhao, Xiaoli Qin, Hongbo Zhao*, Wenquan Feng

School of Electronic and Information Engineering, Beihang University, Beijing 100191, China,

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ABSTRACT

Traditional approaches to lithium-ion battery health management mostly focus on the state of charge (SOC) estimation issues, whereas the state of health (SOH) estimation is also critical to lithium-ion batteries for safe operation. For online battery prognostics, it is critical to make timely and accurate response to SOH. The loss of rated capacity of a battery is usually used to determine the battery SOH, whereas the measurement of the capacity of an operating battery is quite challenging. Normally, the rated capacity fading largely relies on laboratory measurements and offline analysis. In this paper, two real-time measurable health indicators (HI) - one is the time interval of an equal charging voltage difference (TIECVD), and the other is the time interval of an equal discharging voltage difference (TIEDVD) - are extracted. A novel method which combines feature vector selection (FVS) with SVR is utilized to model the relationship between these two HIs and capacity, then the online capacity can be evaluated, more accurate prognostics of SOH and remaining useful life (RUL) can be made. Besides, compared to standard SVR, the proposed method takes FVS to cut down the training data size, which improves the efficiency of model training and prediction. In the end, two datasets demonstrated this approach performs both well in accuracy and efficiency.

1. Introduction

Li-ion battery has characteristics of light weight, high power density and longer lifetime compared to other cells. The Li-ion battery is regarded as an optimal energy storage device for many applications [1–3]. Battery failure might not only affect the system normal operation but even result in catastrophic events [4], it is significant to make an effective and efficient state of health (SOH) evaluation and remaining useful life (RUL) estimation for online operating batteries. However, traditional approaches to battery health management mostly focused on the state of charge (SOC) problems. Attention to addressing the SOH is limited. Different RUL prediction approaches have been developed in recent years.

Existing models for battery RUL prediction roughly can be classified into three parts [5]: (1) electrochemical models, these models translated the degradation mechanisms related to the material properties into physical equations. But the internal electro-chemical reactions of a battery are usually complex, which causes the difficulty of obtaining a reliable model. (2) Equivalent circuit-based models, a kind of first order equivalent lumped parameters circuit-based model was reported in ref. [6]. Different estimation methods have been researched to identify the model parameters, such as particle filter (PF) [6–9], extended Kalman filter (EKF) [10]. Such models require large test datasets coming from battery degradation experiments. (3) Statistical models, the degradation models can be acquired by exploiting the data of ageing parameters without needing any prior knowledge on the battery ageing mechanisms. Such as the autoregressive moving average (ARMA) is the use of time series modeling. In addition to the ARMA model, lots of machine learning based methods have been applied to battery's SOH and RUL prognostic field. He et al. [11] took curve fitting to find an empirical battery capacity degradation model. DS theory was applied to initialize model parameters and PF was also used to optimize parameters iteratively. But this model is only fit for offline analysis. Ref [12] used the NN including four nodes in hidden layer to connect discharge current and the available capacity. The prediction performance of the model was good, but the size of the training set was small, an overfitting problem might occur.

Recently, some novel approaches were proposed, Lu et al. [13] presented a geometric approach extracting geometrical features that are sensitive to slight changes in the degradation process of a Li-ion battery. The geodesic on the manifold was used to estimate battery's capacity. This approach showed highly accurate prediction results. However, the curves of current charging and curves of voltage discharging throughout the entire battery life are needed for feature extraction,

* Corresponding author at: School of Electronic and Information Engineering, Beihang University, No 37, Xueyuan Rode, HaiDian District, Beijing 100191, China.
E-mail addresses: zhaoqi@buaa.edu.cn (Q. Zhao), bhzhb@buaa.edu.cn (H. Zhao), buaafwq@buaa.edu.cn (W. Feng).

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which is not feasible for online battery health estimation. Ref [14] proposed a new validation method for PSO-SVR model, which employed the particle swarm optimization (PSO) to obtain the SVR kernel parameters. Compared with eight published methods, [14] obtained more accurate prediction results. But it is merely applicable for offline capacity analysis.

Though the rated capacity is the most commonly used health indicator of a Li-ion battery, the measurement of maximum deliverable capacity for operating batteries is difficult. Because the cell is not likely to be fully charged or discharged during operation. In this paper, two online measurable parameters are analyzed, one is the time interval of an equal charging voltage difference (TIECVD), and the other is the time interval of an equal discharging voltage difference (TIEDVD). These two variables also fade with the battery ageing, so these monitoring variables might have connections with the capacity to some extent. If the relationship among them can be determined, the capacity of an online operating battery can be deduced. Then more accurate SOH prediction and RUL prognostic can be made compared to offline capacity analysis. SVR is a commonly used data-driven method, which performs well in prognostic [15], but the number of support vectors required grows linearly with the size of training dataset, in other words, the larger the data size is, the longer time for model training and capacity prediction is. Based on SVR, in order to quantify the relationship between the two online measurable variables and capacity, at the same time, improve the efficiency of model building and prediction, a novel data-driven prognostic approach named FVS-SVR is proposed.

The rest of this paper is organized as follows: Basic algorithms of SVR, FVS are introduced in Section 2. Section 3 is experimental data analysis. The proposed battery SOH and RUL prognostic method is discussed in Section 4. Two battery degradation datasets are investigated in Section 5 to validate the proposed approach. Conclusions are drawn in Section 6.

2. Related work

2.1. Support vector regression with ε-intensive loss function

This section explains the fundamental idea of support vector machines applied for solving regression problems. Support vector regression is a sort of data-driven method based on structural risk minimization (SRM). SVR is initially used to solve linear regression problems. After introducing the kernel trick, SVR also can deal with regression problems.

ε-SVR is a commonly used SVR model, given a training set$D = \{(\boldsymbol{x}_i, y_i) | i = 1, 2, \ldots N\}$, $\boldsymbol{x}_i \in R^m$, $y_i \in R$, for linear regression problems, the objection of ε-SVR is to find the best estimation function $f(x) = \boldsymbol{w}^T\boldsymbol{x} + b$, by solving the following quadratic optimization problem:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$
$$s.\ t.\ \begin{cases} y_i - (\boldsymbol{w}^T\boldsymbol{x}_i + b) \le \varepsilon + \xi_i \\ (\boldsymbol{w}^T\boldsymbol{x}_i + b) - y_i \le \varepsilon + \xi_i^* \\ \xi_i,\ \xi_i^* \ge 0 \end{cases} \tag{1}$$

where C ($C > 0$) is the penalty parameter, C determines the tradeoff between the flatness of function $f(x)$ and the upper bound of derivations larger than ε [16].Variable n represents the training set size. ξ_i and ξ_i^* are slack variables, when training error of the ith point is bigger than $\varepsilon(\varepsilon > 0)$, penalty error ξ_i is added to the ith point, otherwise, if the error is smaller than $(-\varepsilon)$, ξ_i^* is added.

The formation of the ε-intensive function is defined as:

$$|\xi|_\varepsilon = \begin{cases} |\xi| - \varepsilon,\ |\xi| \ge \varepsilon \\ 0,\ otherwise \end{cases} \tag{2}$$

Primal objective function and corresponding constraints can be transformed into a Lagrange function L_p:

$$L_p = \min_{w,b,\xi,\xi^*}(\max(L(\alpha,\eta)))$$
$$= \min_{w,b,\xi,\xi^*}\max\left(\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) - \sum_{i=1}^{n}\alpha_i(\xi_i + \varepsilon - y_i + \langle \boldsymbol{w}, \boldsymbol{x}_i\rangle + b) - \sum_{i=1}^{n}\alpha_i^*(\xi_i^* + \varepsilon - y_i - \langle \boldsymbol{w}, \boldsymbol{x}_i\rangle - b) - \sum_{i=1}^{n}(\eta_i\xi_i + \eta_i^*\xi_i^*)\right) \tag{3}$$

Constraints are given as:

$$s.\ t.\ \begin{cases} \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C \\ 0 \le \alpha_i^* \le C \end{cases} \tag{4}$$

The solution to the problem $f(x)$ can be expressed as:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle \boldsymbol{x}_i, \boldsymbol{x}\rangle + b \tag{5}$$

Only some points meet the condition$(\alpha_i - \alpha_i^*) \ne 0$, these data are support vectors (SVs). For nonlinear regression problems, we can employ kernel functions to convert nonlinear problems into linear ones. SVR model for nonlinear regression is as following:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle \boldsymbol{x}_i, \boldsymbol{x}\rangle + b \tag{6}$$

where $K(\boldsymbol{x}_i, \boldsymbol{x}) = \exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right)$ is the radial basis kernel function (RBF), σ is the width of the kernel function.

The SVR model includes C, σ, ε three hyper-parameters. Generally, grid search, pattern search and metaheuristic search are applied to obtain these hyper-parameters [17]. Although the computation cost of grid search is high, this method can guarantee finding a global optimum [18]. A grid search method proposed in [19] is used to determine values of these hyper-parameters.

2.2. Principle of feature vector selection

Define Γ as the input space, H represents the feature space named Hilbert space. Last section, the kernel trick was mentioned to map the input vector x in Γ to H through the functionϕ. For i, j = 1, 2, …, N, kernel function$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \langle\phi(\boldsymbol{x}_i), \phi(\boldsymbol{x}_j)\rangle$, here k_{ij} k_{ij} denotes $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ for simplification. Symbol N is the number of samples, the transformed data lie in a subspace H_s. In fact, the dimension of this subspace H_s is significantly lower than N and equals to the numerical rank of the kernel matrix$K = \{k_{ij} | 1 \le i \le N, 1 \le j \le N\}$. The FVS is proposed to select FVs, forming a set of basis vectors H_s in a feature space [20].

The original data are $\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$, corresponding points in the feature space are $\{\phi(\boldsymbol{x}_1), \phi(\boldsymbol{x}_2), \ldots, \phi(\boldsymbol{x}_N)\}$, noting $\phi(\boldsymbol{x}_1) = \phi_1$, $\phi(\boldsymbol{x}_2) = \phi_2$, …, $\phi(\boldsymbol{x}_N) = \phi_N$, the set of the selected vectors is marked as $S = (\boldsymbol{x}_{s_1}, \boldsymbol{x}_{s_2}, \ldots, \boldsymbol{x}_{s_l})$, these vectors are represented by$\boldsymbol{\Phi}_S = (\phi_{s1}, \phi_{s2}, \ldots \phi_{sl})$ in a feature space, l is the number of FVs. As any data can be projected on these bases in the feature space, thus the estimation value of any mapping vectorϕ_i can be approximated as the linear combination of the elements in $\boldsymbol{\Phi}_S$, the formulation is as following:

$\widehat{\phi}_i = \boldsymbol{\Phi}_S\boldsymbol{e}_i$, $\boldsymbol{e}_i = (e_{i1}, e_{i2}, \ldots, e_{il})^T$, where$\boldsymbol{e}_i$ is the coefficient vector. Given a point$\boldsymbol{x}_i$, the goal is to find the coefficient vector $\boldsymbol{e}_i$ that can make the estimated mapping $\widehat{\phi}_i$ is as close as possible to ϕ_i. Define the estimation error ratio γ_i as:

$$\gamma_i = \frac{\|\widehat{\phi}_i - \phi_i\|^2}{\|\phi_i\|^2} = \frac{\|\phi_i - \boldsymbol{\Phi}_S\boldsymbol{e}_i\|^2}{\|\phi_i\|^2} \tag{7}$$

$$\min_{\boldsymbol{e}_i}\gamma_i = 1 - \frac{\phi_i^T\widehat{\phi}_i}{\|\phi_i\|^2} \tag{8}$$