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A hybrid model based on support vector regression and differential evolution for remaining useful lifetime prediction of lithium-ion batteries

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HIGHLIGHTS

- A hybrid model based on SVR and DE is proposed for RUL prediction.
- The capacity, voltage, and current on discharge operation are considered.
- The proposed model has higher prediction accuracy than the other methods.
- Regeneration has insignificant influence on the prediction accuracy.

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ABSTRACT

Remaining useful life prediction plays an important role in battery management system. The fusion prognostics method has become a main research direction for improving the prediction performance. We present a hybrid model based on support vector regression and differential evolution to predict the remaining useful life of Li-ion battery, where differential evolution algorithm is used to obtain the support vector regression kernel parameters. The capacity, voltage, and current on discharge operation are considered in this study. Three Li-ion batteries from NASA Ames Prognostics Center of Excellence are used to illustrate the application. The results show that the proposed method has better prediction accuracy than the ten published methods. Regeneration factor has insignificant influence on the prediction accuracy of the proposed hybrid model.

1. Introduction

Due to the advantages of lightness of weight, high energy density, high efficiency, high galvanic potential, excellent low-temperature performance, low self-discharge rate and long lifetime, Li-ion battery has been widely used in various applications, such as spacecraft, aircraft, electric vehicles, trams, satellite, cell phones and laptops [1–3]. However, the performance of Li-ion batteries deteriorates over time. Prognostics and health management (PHM) is an enabling discipline that consists of methods and technologies to evaluate system reliability under real-life cycle conditions to diagnose incipient faults and prognosis probable failure [4]. Some possible strategies for the estimation of several battery parameters and/or health metrics, such as the state-of-health (SOH), state-of-charge (SOC), state-of-life (SOL), the end-of-discharge (EOD) time and remaining useful life (RUL) are recommended [5]. In particular, research on capacity degradation and RUL prediction of Li-ion batteries have become a challenging issue is reliability engineering and power sources. The predicted RUL is an important information for scheduling repairs and maintenance.

RUL is defined as the time when equipment performance degrades to the failure threshold for the first time or the first arrival time. RUL prediction methods for batteries can be divided into three categories: model-based methods, data-driven methods, and hybrid methods [6–8]. Model-based methods aim at relating observable quantities to the indicators of interest by building either electrochemical detailed model of the degradation processes affecting the battery life, or equivalent electrical circuits of the battery [6]. Data-driven methods aim at mapping the relationships between the accessible observations and the hidden indicators by some approximating, general model adaptively built on the basis of available data [7]. Hybrid methods aim at combining two or more model-based or data-driven methods to improve the prediction performance [8].

Model-based methods can be classified into two groups such as physical model and mathematical model. The physical model considers specific physical and chemical phenomena occurring during the utilization [9–11]. Mathematical model includes Grey model [12,13] and

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Gaussian process regression model [14–16]. Data-driven methods can be classified into four groups such as artificial intelligence (AI), statistical approach, stochastic process, and filtering process. AI approach includes neural network (NN) [4], support vector machine (SVM) [17,18] and relevance vector machine (RVM) [19]. The statistical approach includes autoregressive (AR) model [20]. Stochastic process approach includes Gaussian process (GP) [21], Wiener process (WP) [22], and hidden Markov model (HMM) [23]. Filtering approach includes particle filtering (PF) [24,25], Kalman filter (KF) [26], unscented particle filtering (UPF) [27,28], extended Kalman filter (EKF) [29], and unscented Kalman filter (UKF) [30]. Hybrid methods can be classified into two groups such as fusion of model-based and data-driven methods and integration of different data-driven methods [1,2,31–38].

It should be noted that most research on Li-ion battery RUL estimation consider only the capacity and focus on developing various algorithms to improve prediction performance. The degradation of the capacity is affected by the voltage and the current. In this study, we aim at developing a hybrid model based on SVR and DE for RUL prediction of Li-ion batteries with capacity, voltage, and current.

The rest of this study is organized as follows. Section 2 provides a hybrid model based on SVR-DE, Section 3 discusses an empirical comparison of a hybrid model based on SVR-DE with other models [13,14,32,37], and Section 4 presents a conclusion and future research direction.

2. A hybrid model based on SVR and DE

The SVM is a popular machine learning method which includes support vector classification (SVC), support vector regression (SVR), and other learning tasks [39]. SVR is suitable for prediction problem because it can map the non-linear relationship between input and output data. We consider a set of training points, $\{(x_1, y_1), ..., (x_i, y_i)\}$, where $x_i \in R^n$ is a feature vector and $y_i \in R$ is the target output. An SVR function is defined as:

$$f(x_i) = w^T\phi(x_i) + b \tag{1}$$

where $f(x_i)$ denotes the output value, $\phi(x)$ is a nonlinear mapping function, and the coefficients $w \in R^n$ and $b \in R$ are adjustable. Under the given parameters $C > 0$ and $\varepsilon > 0$, the standard form of SVR is rewritten as:

$$\min \frac{1}{2}w^T w + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{2}$$

with the constraints:

$$\begin{cases} w^T\phi(x_i) + b - y_i \le \varepsilon + \xi_i, \\ y_i - w^T\phi(x_i) - b \le \varepsilon + \xi_i^*, \\ \xi_i, \xi_i^* \ge 0, i = 1,2,...,n \end{cases} \tag{3}$$

where ξ_i^* denotes training errors above ε and ξ_i denotes training errors below ε. After the quadratic optimization with inequality constraints is solved, the parameter vector w in Eq. (1) is calculated as:

$$w = \sum_{i=1}^{l}(\beta_i^* - \beta_i)\Phi(x_i) \tag{4}$$

where β_i^* and β_i are obtained by solving a quadratic program and the Lagrange multipliers. Finally, the SVR function is calculated by:

$$f(x) = \sum_{i=1}^{l}(\beta_i^* - \beta_i)K(x_i, x_j) + b \tag{5}$$

where $K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2)$ is the Gaussian radial basis function (RBF) kernel function.

DE is a search heuristic which was first proposed by Storn and Price in 1996 [40]. It has been successfully applied in a wide variety of fields from computational physics to operations research. It has several advantages such as its simple structure, ease of use, speed, and robustness. Therefore, the DE algorithm is used to find the best hyper parameters for SVR.

The DE procedure is summarized as follows. The variable *NP* represents the number of parameter vectors in the population. At generation 0, *NP* guesses the optimal parameter value, and vectors are made using random values between the lower and upper bounds. Each generation involves the creation of a new population from the current population members $x_{i,g}$, where i indexes the vectors and g indexes the generation. This is accomplished using a differential mutation of the population members. A trial mutant parameter vector $v_{i,g}$ is created by choosing three members of the population (x_{r0}, x_{r1}, $andx_{r2}$) at random. $v_{i,g}$ is then derived by:

$$v_i = x_{r0} + F \times (x_{r1} - x_{r2}) \tag{6}$$

where $F \in (0,1)$ is a positive factor.

After the first mutation operation, the mutation is continued until either the mutation length has been made or *rand* > *CR*, where $CR \in [0,1]$ is a crossover probability. The choices of *NP*, *F*, and *CR* depend on the specific problem. It should be noted that $F = 0.8$ and $CR = 0.9$. DE are used in this study.

To improve the accuracy of RUL prediction of Li-ion batteries, we proposed a hybrid model based on SVR and DE (see Fig. 1). The procedure of the proposed method is given as follows.

Step 1: Normalize the capacity, voltage, and current.
Step 2: Define the fitness function as the mean absolute percentage error (MAPE), which is established as:

$$MAPE = \frac{\sum_{t=1}^{n}|(A_t - F_t)/A_t|}{n} \tag{7}$$

where A^t is the actual value at period t, F_t is the predicted value at period t, and n is the number of periods used in the calculation.

Step 3: Select a range for each parameter (C_i, γ_i, and ε_i). Perform an SVR model based on the formula of *capacity ~ cycle + voltage + current* and compute the MAPE value.
Step 4: Choose $NP = 30$, $CR = 0.5$, and $F = 0.8$ for the DE algorithm with the objection function of MAPE. If maximum iteration number (=100) is reached, then the estimated hyper parameters are determined.
Step 5: Perform a SVR model based on the formula of *capacity ~ cycle + voltage + current* under the estimated hyper parameters for prediction. If the termination criterion tolerance (0.0001) is attained, the predicted values are determined. Note that the inputs such as voltage and current for the testing data are obtained by an SVR model based on the formula of *voltage ~ cycle* or *current ~ cycle*.

3. Experiments and analysis

3.1. Raw data of Li-ion batteries

The degradation experiment data of Li-ion battery from NASA Ames Prognostics Center of Excellence (PCoE) were reanalyzed in this study [41]. The 18650 sized batteries (Nos. 5, 6 and 7) were run under three different operation condition (charge, discharge, and impedance) at constant temperature (24 °C). Charging current was constant with a level of 1.5 A until the battery voltage achieved 4.2 V and then, the batteries were continued in a constant voltage mode until the charge current fell to 20 mA. The discharge was run at a constant current level of 2 A until the battery voltage dropped to 2.7 V, 2.5 V and 2.2 V for batteries Nos. 5, 6, and 7, respectively.

Here, the capacity is used to describe Li-ion battery SOH which is defined as: