Research on residual life prediction method of lithium ion battery for pure electric vehicle

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Abstract: To overcome the complexity of the lithium-ion battery inside the chemical reaction resulting in a low battery life remaining prediction accuracy, the paper proposes a new electric vehicle lithium ion battery remaining life prediction method based on a correlation vector machine. According to the operating characteristics of lithium-ion batteries in electric vehicles, this method selects health factors that affect battery life, and selects related factors. According to the marginal likelihood function, the factor weights are integrated to obtain the health factor sequence target. Relevance vector machine is used to optimise and evaluate the characteristics of health factors, and complete the prediction of electric vehicle lithium-ion battery capacity and remaining battery life. Comparative experiments show that the prediction effect and stability of the method in this paper are better, and the minimum prediction error is only 0.013.

Keywords: correlation vector machine; lithium ion battery; pure electric vehicle; residual life; prediction effect.

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1 Introduction

Lithium ion battery plays a very important role in both industrial development and daily life. Compared with lead-acid battery, lithium-ion battery has the advantages of low cost and long life (Li et al., 2019b). Lithium ion batteries are used to provide power and control for devices ranging from small mobile phones, watches and other daily fields to large-scale equipment such as airplanes. When the lithium-ion battery is charged, the lithium ion generated by the positive electrode moves to the negative electrode through the electrolyte (Asadi et al., 2018). Compared with other batteries, lithium-ion batteries have been widely used because of their large specific energy, long cycle life and good safety performance. However, the lithium-ion battery still has low recovery rate, resulting in short life time due to overcharge and over discharge, resulting in the performance degradation of the whole system (Susilo et al., 2018; Salah et al., 2019). The remaining service life (RUL) prediction is an effective method to provide lithium-ion battery life information for manufacturers and users. The prediction of lithium-ion battery state and life is the key to affect the battery management system, and provides the prediction information for the system, and provides important research significance for future development (Li et al., 2019b).

Kellner et al. (2018) put forward the prediction method of residual life of lithium-ion battery for electric vehicles based on particle filter. The method uses genetic algorithm to map the battery degradation model to the particle degradation problem, extracts the battery life tuning prediction parameters, calculates the sensitivity of the parameters, and completes the life prediction of electric vehicle lithium-ion battery according to the sensitivity. However, the prediction accuracy of this method still needs to be further improved. Quiones et al. (2018) proposed a battery life prediction method for electric vehicles based on fusion technology. In order to reduce the amount of training data, the method uses Monte Carlo method to build the battery aging model, and trains the battery operation data through aging model training to obtain the battery life prediction results, but the prediction efficiency of this method is low. Wang et al. (2017a) proposes a battery life prediction method for electric vehicles based on improved particle filter. The battery capacity is used as the index to evaluate the battery life, and MCMC algorithm is used to improve the particle filter algorithm. The improved particle filter algorithm is used to collect the battery capacity data, build the empirical model of battery capacity decline, and complete the battery life prediction. However, the high cost of this method leads to the limitation of the application scope of this method.

None of the above-mentioned traditional methods are effective in evaluating the health status and life detection of lithium-ion batteries. Therefore, a relevance vector machine-based method for predicting the remaining life of lithium-ion batteries is proposed. The overall research plan of the method is as follows:

1. Based on the operation principle of lithium-ion battery for electric vehicles, the relevant parameters of battery operation were selected as the health factors of battery life, and the health factors were calculated with super prior distribution to verify the performance of health factors.
2. According to the results of the selected health factors, the health factors are selected by feature selection, and the weight of the factors is integrated by using the edge likelihood function to complete the ranking of health factors. The health factors are input into the correlation vector machine to complete the optimisation evaluation, and the lithium-ion battery capacity and remaining life prediction of electric vehicles are realised.
3. The experimental results show that the proposed method is compared with Kellner et al. (2018) and Quiones et al. (2018) with battery capacity prediction accuracy, root mean square error and battery life prediction error as the experimental comparison index.

2 Prediction of remaining life of lithium ion battery based on health factor

At present, more and more researchers have applied the data-driven method to the prediction of the remaining life of Vehicle Lithium-ion batteries. Compared with other methods, it does not need to study physical and chemical reactions (Yu et al., 2017; Li et al., 2019a; Zhang et al., 2019). Data driven method is to obtain the correlation of characteristic parameters between the data through experiments, and predict the motion trajectory of the equipment. In this study, firstly, the correlation vector machine algorithm was used to predict the trend of battery degradation, and the health factor sequence in the data was extracted to predict the remaining life of lithium-ion battery. The uncertainty of the prediction results was quantified and evaluated to verify its effectiveness (Gao and Huang, 2017; Wei et al., 2018; Wang et al., 2017b).

2.1 Battery life health factor selection

In order to predict the trend of battery degradation, this study selects the correlation vector machine (RVM) algorithm to predict. Although the function form of RVM algorithm is similar to that of vector machine (SVM) algorithm (Li et al., 2019b), its advantage is that it is not restricted by Macy's theorem and can establish multiple kernel functions. It is easy to calculate, fast and accurate, and can simultaneously carry out probability and binary output. RVM includes correlation vector (RV) and correlation vector regression (RVR) (Mohamed and Wilson, 2018; Wang and Mamo, 2018; Razavi-Far et al., 2019; Kontar et al., 2017).

In this study, the single dimension sequence is selected as the health factor sequence, and the one-dimensional prediction of battery RUL is as follows.

The health factor sequence can be input into the correlation vector regression algorithm to predict the aging of battery in the future. A set of health factor series datasets $\{x_i, t_i\}_{i=1}^{N}$ $x_i \in R^d$, $t_i \in R$, where n is the total number of input samples. The model is as follows:

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

In equation (1), $y(x)$ is a nonlinear function and ε is a factor coefficient. The expression of correlation vector regression is as follows:

$$t = \phi\omega + \varepsilon \tag{2}$$

In formula (2), $\omega = (\omega_0, \ldots, \omega_N)^T$, ω is the weights of RVR. It is $n + 1$ dimension column vector, Φ is kernel function matrix, and $\phi = [\phi_1, \phi_2, \ldots, \phi_N]^T$; $\phi i(xi) = [1,, K(x_i, x_1), \ldots, K(x_i, x_N)] = i = 1, 2, \ldots, N$; $K(\cdot)$is kernel function.

Given that the dataset $p(t|x)$ belongs to $N(t|y(x), \sigma^2)$ normal distribution, the maximum likelihood estimation of the sample dataset is as follows:

$$p\left(t \middle| \omega, \sigma^2\right) = \left(2\pi\sigma^2\right)^{-\frac{N}{2}} \exp\left\{-\frac{\|t - \phi\omega\|}{2\sigma^2}\right\}^2 \tag{3}$$

$$p(\omega|\alpha) = \prod_0^N N\left(\omega_i | 0, \alpha_i^{-1}\right) = \prod_0^N \frac{\alpha_i}{\sqrt{2\pi}} \exp\left\{\frac{\omega_i^2 \alpha_i}{2}\right\} \tag{4}$$

In order to ensure the appropriate fit of health factors, the Gauss type prior distribution is set up by using the super parameter pair to increase the constraint.

In formula (4), $\alpha = \{\alpha_0, \alpha_1, \ldots, \alpha_N\}$ is $N + 1$ super parameters, which are associated with the weight ω.

Under the sparsity ability of health factor algorithm, the super prior distribution of super parameter α and noise variance σ^2 is also called Gamma distribution.

$$p(\alpha) = \prod_{i=0}^{N} Gamma\left(\alpha_i \left| a, b\right.\right) \tag{5}$$

$$p\left(\sigma^2\right) = \prod Gamma(\beta | c, d) \tag{6}$$

In equation (5), $Gamma(\alpha_i|a, b) = \Gamma(\alpha)^{-1} b^a \alpha^{a-1} e^{-ba}$. In order to ensure its accuracy, gamma distribution assumes that the four parameters take very small values, such as $a = b = c = d = 10^{-4}$.

2.2 Battery life prediction based on correlation vector machine

The health factors of lithium-ion batteries are prone to over fitting, so it is necessary to optimise the algorithm

$$p\left(t_{N+1} \left| t\right.\right) = \int p\left(t_{N+1} \left| \omega, \alpha, \sigma^2\right.\right) p\left(\omega, \alpha, \sigma^2 \left| t\right.\right) d\omega d\alpha d\sigma^2 \tag{7}$$

In equation (7), T_{N+1} corresponds to the new observed value x_{N+1}. Equation (7) can not calculate the super parameter α, simplify the above formula and then approximate the calculation. It can be concluded that:

$$p\left(\omega, \alpha, \sigma^2 \left| t\right.\right) = p\left(\omega \left| t, \alpha, \sigma^2\right.\right) p\left(\alpha, \sigma^2 \left| t\right.\right) \tag{8}$$

After calculation, the posterior distribution and prior distribution of parameters are Gaussian distribution:

$$\begin{aligned} p\left(\omega \left| t, \alpha, \sigma^2\right.\right) &= \frac{p\left(t \left| \omega, \sigma^2\right.\right) p(\omega | \alpha)}{p\left(t \left| \alpha, \sigma^2\right.\right)} \\ &= \left(2\pi\right)^{-\frac{N+1}{2}} |\Sigma|^{-1/2} \exp\left\{-\frac{(\omega - \mu)^T \Sigma - 1(\omega - \mu)}{2}\right\} \end{aligned} \tag{9}$$

The posterior variance Σ and mean μ of the weights are obtained as follows:

$$\Sigma = \left(\sigma^{-2} \phi^T \phi + A\right)^{-1} \tag{10}$$

$$\mu = \sigma^{-2} \Sigma \phi^T t \tag{11}$$

In equation (10), $A = \text{diag}(\alpha_0, \alpha_1, \ldots, \alpha_N)$. In the above calculation process, if the super parameter α is regarded as infinity, the posteriori distribution is infinitely close to 0. The calculated correlation vector is the core feature of health factor series dataset. In order to process the health factor estimation data correctly, the algorithm should be optimised.

In equation (12), the health factor sequence objectives are obtained by integrating the weights with the edge likelihood function

$$p\left(t\middle|\alpha,\sigma^2\right)=\int p\left(t\middle|\omega,\sigma^2\right)p(\omega|\alpha)d\omega \tag{12}$$

The integral results of Gaussian distribution are as follows:

$$p\left(t\middle|\alpha,\sigma^2\right)=N(0,C) \tag{13}$$

In equation (13), $C = \sigma^2 I + \phi A^{-1}\phi^T$, super parameter α and variance σ^2 are represented by α_i^{new} and $(\sigma^2)^{new}$ respectively (Kontar et al., 2018; Jahani et al., 2020).

$$\alpha_i^{new}=\frac{\gamma_i}{\mu_i^2} \tag{14}$$

$$\left(\sigma^2\right)^{new}=\frac{\left\|y-\phi\mu\right\|}{N-\sum_i \gamma_i} \tag{15}$$

In equations (14) and (15), the super parameter and variance are an iterative form, and the iterative calculation is carried out until the convergence. The mean value of the i^{th} posterior weight of $\gamma_i = 1 - \alpha_i\sum ii$, μ_i, $\sum_{ii}$ is the I diagonal element of the posterior variance matrix $\sum$.

When the new health factors are input into x^*, the predicted distribution of t^* of the predicted output also follows the Gaussian distribution $p(t_*|t) \sim N(\mu^T\phi(x_*), \sigma_*^2)$, and satisfies the following conditions:

$$t_*=\mu^T\phi\left(x_*\right) \tag{16}$$

$$\sigma_*^2=\sigma^2{}_{MP}+\phi\left(x_*\right)T\Sigma\phi\left(x_*\right) \tag{17}$$

In traditional experiments, the line graph is usually used to represent the rul prediction results, which can only give the estimated value, and the accuracy of point estimation prediction is not high. Therefore, this study uses interval estimation to predict the remaining life of battery. Interval estimation (CI) is a fluctuation interval, which can accurately predict the accuracy of rul. Interval estimation can judge a certain range of intervals through the prediction value of health factors, and then get the upper and lower limits of prediction parameter estimation. It can better reflect the degree of assurance of the prediction results. The confidence interval of health factors is used to express the prediction results of health factors.

The overall parameters of CI are θ, θ_L and θ_U are the determined values of two health factors. Given α ($0 < \alpha < 1$), there are:

$$P\left(\theta_L<\alpha<\theta_U\right)=1-\alpha \tag{18}$$

(θ_L, θ_U) refers to the confidence interval of $1 - \alpha$; in formula (18), θ_U is the upper limit; θ_L is the lower limit; $1 - \alpha$ is the confidence level. The specific calculation steps are as follows (Liu et al., 2020): calculate the mean value (M) and standard deviation (ST) of the predicted value, then $\theta_L = M - n * ST$; $\theta_U = M + n * ST$. When the confidence level was

$1 - \alpha = 95\%$, $n = 1.96$. According to the correlation vector machine, the confidence interval of 95% confidence is selected, and the confidence interval of prediction results of B5, B6, B7 and B18 lithium batteries after the 80th cycle is calculated, and the satisfaction comparison is conducted to improve the applicability of the results and make the analysis method more perfect.

3 Experimental results and analysis

In this study, XGBoost was selected for experiment. Input battery cycle period N and temperature change rate, output capacity C after model training. Capacity prediction adopts random ideas for fusion. When training data, 70% of the training samples are randomly selected for model training. The number of cycles is set to 300, and the final result is obtained after averaging. Take no. 5 and no. 7 batteries as samples, and set the prediction starting point to 100 for the experiment.

The overall scheme of the experiment is as follows: taking the battery capacity prediction accuracy, root mean square error and battery life prediction error as the experimental indexes, the proposed method is compared with Kellner et al. (2018) and Quiones et al. (2018).

3.1 Prediction accuracy of battery capacity

The results of capacity prediction for no. 5 and no. 7 batteries at the starting point of 100 are shown in Figures 1 and 2. In the figure, the abscissa is the number of cycles and the ordinate is the battery capacity.

Figure 1 Prediction results of battery capacity at predicted starting point of no. 5 lithium ion battery 100

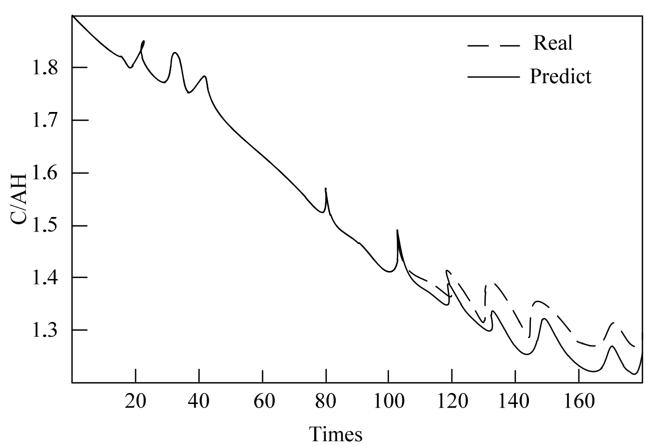
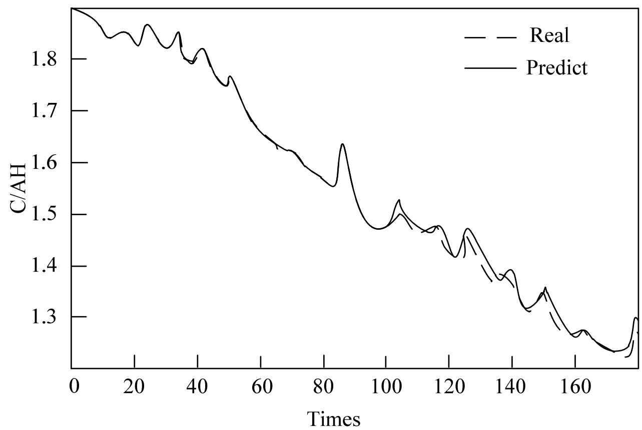


Figure 2 Prediction results of battery capacity at predicted starting point of no. 7 lithium ion battery 100



Analysing the battery capacity prediction results in Figures 1 and 2, it can be seen that the predicted results of the proposed method for the two battery models are relatively close to the actual results. As the number of battery cycles increases, the similarity can always be maintained.

3.2 Root mean square error of battery capacity prediction

The root mean square error results are shown in Figures 3 and 4. In the figure, the abscissa is the number of cycles, and the ordinate is the RMSE indicator.

Figure 3 RMSE of cell no. 5 at different prediction starting points (see online version for colours)

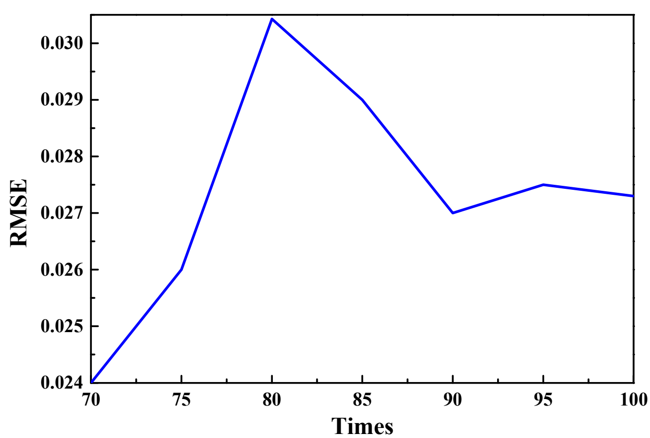
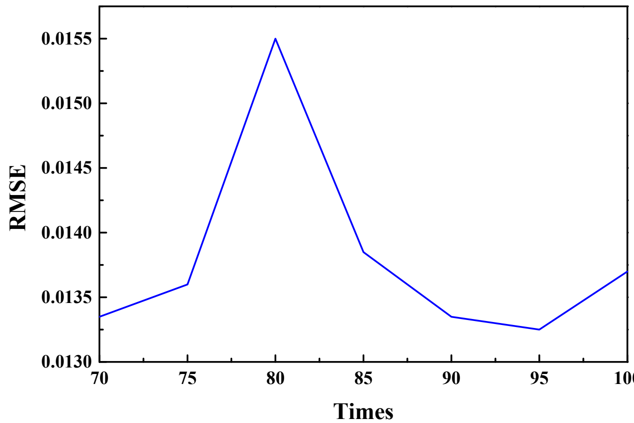


Figure 4 RMSE results of no. 7 lithium ion battery at different predicted starting points (see online version for colours)

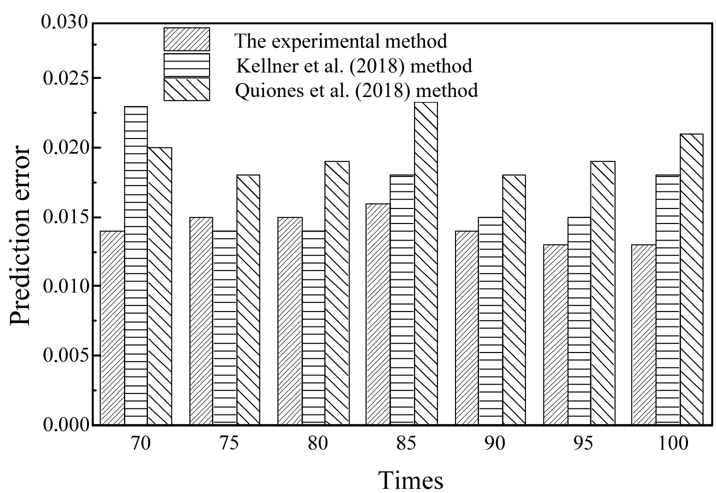


Analysis of the above pictures shows that the number of cycles of no. 5 battery fluctuates greatly at 75–85, which proves that the algorithm only fluctuates in a certain range and has good stability. The fluctuation of no. 7 battery is larger than that of no. 5 battery at about 80 cycles. Therefore, the stability of the proposed method for battery capacity prediction is high.

3.3 Battery life prediction error comparison

The proposed method is compared with the method in Kellner et al. (2018) and the method in Quiones et al. (2018), and the comparison result is shown in Figure 5.

Figure 5 Battery life error results of different methods



According to Figure 5, it can be seen from the prediction error results in Figure 5 that the prediction error of the proposed method is slightly lower than that of Kellner et al. (2018) and Quiones et al. (2018), and the minimum prediction error of the proposed method is only 0.013, while the minimum prediction error of Kellner et al. (2018) and Quiones et al. (2018) is 0.023 and 0.024 respectively.

4 Conclusions

A prediction method based on correlation vector machine is proposed. The performance of the method is verified from both theoretical and experimental aspects. The method has higher capacity prediction accuracy and lower life prediction error when predicting the residual life of lithium-ion battery in pure electric vehicles. Specifically, the battery capacity prediction results of the proposed method are very close to the actual results; compared with the methods based on particle filter and fusion technology, the prediction error of battery remaining life is lower, and the minimum error is only 0.013.

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