A Remaining Useful Life Prediction approach for Li-ion batteries Based on Variational Mode Decomposition and SVM

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Abstract. This paper proposes a remaining useful life (RUL) prediction model for li-ion batteries which combines variational mode decomposition (VMD) and support vector machine (SVM). First, the battery capacity degradation data is decomposed into the trend degradation sequence and other fluctuation sequences through VMD. Then build SVM regression models for different modes. Finally, all the prediction results are added to get the final RUL prediction value. The experiment verifies the effectiveness of the method through NASA lithium-ion battery aging test data, and compared with the single SVM regression model and the Gaussian process regression model, the VMD-SVM method obtained more accurate prediction results.

1. Introduction
Li-ion batteries have been widely used in mobile devices, hybrid vehicles and other fields because of their light weight, high voltage, and long cycle life [1]. However, the performance of li-ion batteries will continue to deteriorate in the process of charge discharge cycle, and even lead to catastrophic accidents. Therefore, in order to ensure the safety of the system, it is necessary to accurately predict the remaining useful life (RUL) of the battery[2].

The decline of li-ion battery capacity is usually used as a health indicator of battery degradation to predict the battery’s RUL. However, many current models for RUL prediction do not take into account the local capacity regeneration phenomenon of li-ion batteries[3]. When a li-ion battery is in a static state, its capacity will rise slightly, resulting in a local peak in the capacity drop curve. Therefore, the universality of a single model is low and it is difficult to accurately predict.

Considering the impact of local capacity regeneration on prediction, this paper proposes a li-ion battery RUL prediction method based on variational mode decomposition (VMD) and support vector machine (SVM). Through VMD, the degradation component and capacity regeneration component are decomposed from the battery capacity degradation data, and the SVM regression model is constructed respectively, finally, the prediction results are superimposed to obtain the final RUL prediction result. It makes up for the defect that a single model is difficult to capture the capacity regeneration.

2. Variational Mode Decomposition
Variational mode decomposition is a new type of signal decomposition method, which decomposes a real-valued input signal into several finite bandwidths with center frequencies. The decomposition process mainly includes the establishment and solution of the variational model[4].

2.1 Establishment of Variational Model
The variational problem is described as, under the constraint that the sum of each mode is equal to the original input signal, find the minimum value of the sum of the estimated bandwidth of each mode, and
obtain each mode function $u_n(t)$. The specific steps are as follows:

- Use the Hilbert transform to obtain the analytic signal of each mode function $u_n(t)$, thereby obtaining the unilateral spectrum of $u_n(t)$;
- By analyzing the exponential aliasing of the center frequency corresponding to the signal, the frequency spectrum of the mode is modulated to the fundamental frequency band of the response;
- The bandwidth of each $u_n(t)$ can be calculated by the square $L^2$ norm of the gradient of the above modulation signal, and its solution can be expressed as a restricted variational problem.

2.2 Solution of Variational Model

The above variational problem is a constrained optimization problem. By introducing the balanced constraint parameter $\alpha$ and the Lagrangian operator $\lambda(t)$, the above equation can be transformed into the unconstrained optimization problem in the following formula.

$$L\{\{u_n\}, \{\omega_n\}, \lambda(t)\} = \alpha \sum_{n=1}^{N} \| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) \otimes u_n(t) \right] e^{-j\omega_n t} \|^2_2 +$$

$$\| y(t) - \sum_{n=1}^{N} u_n(t) \|^2_2 < \lambda(t), y(t) - \sum_{n=1}^{N} u_n(t) >$$

Through the alternate direction method of multiplication operator to alternately update $u_{n+1}, \omega_{n+1}, \lambda_{n+1}$, thus, N modes of the input sequence are obtained from the optimal solution in equation (1).

3. Support Vector Machine Regression Model

Support vector machine (SVM) was originally derived from the linearly separable optimal classification surface solution. Later, many researchers applied it to nonlinear function fitting, and used data mapping to non-linear problems are transformed into linear problems in high-dimensional space[5].

For a given set of training samples, we hope to learn a regression model:

$$f(x) = \omega^T \cdot \phi(x) + b$$

For all training data, the gap between the prediction and the actual is as small as possible. The final training result depends on the loss function[6], and its definition can be seen in the following formula:

$$|y - f(x)|_\varepsilon = \begin{cases} 0 & |y - f(x)| \leq \varepsilon \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases}$$

Considering that the constraints cannot be realized, a relaxation variable is introduced. After the introduction, the regression problem can be regarded as a quadratic programming problem, and the corresponding dual optimal problem is as follows:

$$\begin{align*}
Min & \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_i') \cdot K(x_i, x_j) - \cdots - \varepsilon \sum_{i=1}^{n} (\alpha_i - \alpha_i') + \sum_{i=1}^{n} y_i (\alpha_i - \alpha_i') \\
\text{s. t.} & \sum_{i=1}^{n} (\alpha_i - \alpha_i') = 0 \quad 0 \leq \alpha_i \leq C, 0 \leq \alpha_i' \leq C, i = 1,2 \ldots n
\end{align*}$$

Among them, $K(x_i, x_j)$ is the kernel function. The choice of kernel function determines whether a good prediction model can be obtained.

4. Experiment Analysis

4.1 Experimental Data

The experimental data in this article is derived from the Battery Data Set published by NASA[7]. The capacity degradation data is measured by charging and discharging 4 groups of 18650 li-ion batteries at room temperature. The battery failure threshold is set to 70% of the rated capacity. When the battery capacity is lower than the threshold, the battery can be judged function failure. This article takes two batteries B0005 and B0006 as examples to analyze and verify the method proposed in this article.

The battery capacity degradation curve is shown in Figure 1. With the increase of the cycle period, the overall capacity of the two batteries showed a downward trend, but due to the phenomenon of capacity regeneration in some cycles, the curve rebounded slightly.
4.2 Mode Selection

Variational mode decomposition need to set the number $K$ of VMD decomposition subsequences. Too small $K$ may cause signal aliasing, too large a value will lead to over-decomposition, part of the signal is intermittent after decomposition. There is currently no standard method for determining the $K$ value.

This paper refers to the selection method in [8], by comparing the correlation coefficients of each mode with different $K$ values and the original sequence and the center frequency of each mode, $K$ is finally determined to be 5, it is ensured that no modes with similar center frequencies will appear after decomposition. The results of two battery capacity degradation curves decomposed by VMD are shown in Figure 2.

IMF1 is the main trend degradation component. IMF2 can reflect capacity regeneration. IMF3~5 are random components, which can reflect random interference caused by battery degradation. The residual component has a small variation range, so the impact on battery capacity prediction can be ignored.
4.3 Construction of Support Vector Machine Regression Model

All three components have their own typical characteristics. Among them, the trend component shows an obvious monotonous decline, and the capacity regeneration component is similar to the random component, and has a certain periodicity. For the trend component IMF1, take the IMF1 data of the previous 100 cycles as the training set, the cyclic period as the training set input, and the capacity as the output training data. For the data at a certain time T (T>10) in IMF2~5, take the data of the first 10 cycles of that time as a feature to construct a training data, and also take the data of the first 100 cycles to construct a training set. Although this construction method will have accumulated errors, since the amplitudes of IMF2~5 are relatively small, this error can be ignored.

4.4 Evaluation Index

In order to verify the prediction performance of the prediction method proposed in this article, this article uses root mean square error (RMSE) and RUL absolute error as the evaluation indicators of the model:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y'_i)^2} \tag{5}
\]

\[
RUL_{ERROR} = |RUL_{True} - RUL_{pre}| \tag{6}
\]

In formula (5), \(y_i\) represents the true value of the capacity data, and \(y'_i\) represents the predicted value of the capacity. In formula (6), \(RUL_{True}\) represents the actual RUL, which is the number of cycles in which the capacity is lower than the failure threshold (1.38Ah). The actual RUL of two batteries are 113 and 126 cycles. \(RUL_{pre}\) is the predicted value of RUL. The smaller the value of the two evaluation indexes is, the more accurate the prediction model for RUL.

4.5 Experimental Results

This article uses two additional single prediction models to compare experiments with the models mentioned in this article. The first is GPR, which has also been used for RUL prediction in recent years[9]; the other is directly used SVM. Figure 3 shows the prediction results of two battery capacities.
under different models. Table 1 shows the evaluation index results of two different battery models.

From the comparison of the two single models, it can be found that they can roughly predict the future trend of battery capacity to a certain extent. GPR's prediction of B0005 is better than SVM, while B0006 is the opposite. Single model does not get good prediction results at the same time, and the fitted curve does not capture the battery capacity regeneration phenomenon.

Since VMD-SVM can predict the overall degradation trend of the battery and the capacity regeneration phenomenon at the same time, the prediction results of the two batteries are closest to the true capacity curve; at the same time, because the VMD-SVM is modeled according to the respective characteristics of different components, the fitting of the training set is also better than the other two single models, and the evaluation indicators of the two prediction performance are better than the other two methods. It is a more general prediction method for li-ion batteries.

![Figure 3. RUL prediction results of different models of li-ion batteries.](image-url)
Table 1. The prediction results of the three models.

| Battery | Model | RUL\textsubscript{pre} | RUL\textsubscript{Error} | RMSE |
|---------|-------|------------------------|-------------------------|-------|
| B0005   | SVM   | 111                    | 18                      | 0.2012|
|         | GPR   | 136                    | 7                       | 0.0946|
|         | VMD-SVM | 132               | 3                       | 0.0211|
| B0006   | SVM   | 107                    | 6                       | 0.0430|
|         | GPR   | 104                    | 9                       | 0.0907|
|         | VMD-SVM | 111               | 2                       | 0.0318|

5. Conclusion

This paper combines the signal decomposition method VMD with the SVM regression model to make up for the defect that it is difficult to capture the battery capacity regeneration phenomenon using a single SVM regression model. Through variational mode decomposition, the original battery capacity sequence is decomposed into a series of components with low complexity and good stability.

Taking the two sets of real capacity data of li-ion batteries from NASA Research Center as an example, the point prediction is carried out through the SVM model according to the respective characteristics of different components, which verifies the effectiveness of the prediction method proposed in this paper. The results show that VMD-SVM can fit a more real capacity drop curve compared with a single model, and improve the prediction accuracy of li-ion battery RUL.

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