State of Health Estimation Framework of Li-on Battery Based on Improved Gaussian Process Regression for Real Car Data

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Abstract. With the diversification of power batteries in the market, the estimation and management of State of Health (SOH) become more and more important. The building of the models based on experimental data needs much time and many resources, and the models do not have strong versatility. In this paper, a data-driven on-line SOH estimation framework is built by using the measured data of vehicle operating process. In case that the charging data is incomplete and with low precision, an indirect feature (IF) extraction and combination scheme based on Incremental Capacity Analysis (ICA) is built, so as to realize the mapping between IF and SOH based on Gaussian Process Regression (GPR), and Multi-Colony Particle Swarm Optimization (MPSO) is adopted to solve the local optimum of GPR hyper-parameters. Finally, after the algorithm is verified and evaluated by applying NASA (National Aeronautics and Space Administration) dataset and real vehicle data, and when the training amount of operation data is enough, the error of SOH estimation can be controlled within 2%, which shows that the algorithm has good versatility and estimation precision.

1. Introduction

Power batteries of multiple brands, types and different quality are existing in the market at the same time, and the management of the State of Health (SOH) of power batteries will become an important research issue. SOH represents the difference between an aging battery and a new battery [1]. In recent years, scholars have built many estimation methods of SOH, including model-based methods and data-driven methods.

The building of battery model requires much time and resources, which does not have strong versatility, and it is difficult to build a reliable model with actual vehicle operating data. Compared with model-based methods, data-driven methods are more flexible without considering external disturbances. Existing data-driven SOH estimation methods include Autoregressive Model [2], Neural Network [3], Support Vector Machine [4] and Gaussian Process Regression (GPR) [5], etc. GPR is a non-parametric modeling process based on Bayesian learning, which has Bayesian essence and good robustness, can provide uncertainty of prediction, and is more adaptable to the requirements of changeable actual operating conditions and low data precision than other data-driven methods. In recent years, many scholars have studied battery degradation through signal processing methods, such as Incremental Capacity Analysis (ICA) and Differential Voltage Method [6]. These methods convert...
voltage platforms into observable peaks or valleys, and realize the analysis of aging degree and aging mechanism by observing the characteristic changes of curves during the aging process. Wang Z [7] realized the prediction of SOH by extracting the peak value of IC curve and peak voltage as indirect feature (IF) and training GPR model. However, most of the existing researches are based on high-precision and relatively complete experimental cycle, and the researches that are applicable to the actual operation data with poor accuracy and incomplete charging are still relatively rare.

Based on the above limitation, this paper designs a data-driven method for on-line estimation of SOH. In the following sections, the related algorithms are described briefly, the SOH Gaussian process regression model based on Multi-Colony Particle Swarm Optimization (MPSO) and ICA is built, the NASA (National Aeronautics and Space Administration) data set and the real vehicle data are analyzed respectively, and the feature extraction and combination method is constructed to realize the on-line estimation of SOH. Finally, the work of this paper is summarized and prospected.

2. Related Algorithms

2.1. Gaussian Process Regression

Gaussian Process Regression (GPR) is a statistical learning method based on Bayesian framework. The prior distribution is transformed into a posterior model by training of historical data, which gives confidence interval while outputting the mean value. The basic framework is shown in Figure 1.

![Gaussian process regression](image)

Figure 1. The basic framework of Gaussian process regression

GPR does not need to specify the specific form of the process \( f(x) \), but only assumes that it obeys the joint Gaussian distribution, then \( y \) is the observed value disturbed by noise, i.e.:

\[
y = f(x) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma_n^2)
\] (1)

\( \sigma_n^2 \) is the noise variance, and the set of finite observed values of \( y \) constitutes a Gaussian process that obeys the Gaussian distribution:

\[
y \sim \mathcal{N}(0, \text{Var}(x) + \sigma_n^2 I)
\] (2)

\( \text{Var}(x) \) is the covariance matrix of \( n \times n \), the \((i,j)\) element is the covariance function, i.e., the radial basis function (RBF):

\[
\text{Var}(x_i, x_j) = \sigma_f^2 \exp\left(-\frac{1}{2\lambda^2}|x_i - x_j|^2\right)
\] (3)

Wherein, \( \sigma_f \) and \( \lambda \) are constants. When a new test set, also obeys Gaussian distribution, the predicted \( \hat{y}^* \) and \( \text{Var}(\hat{y})^* \) are:

\[
\hat{y}^* = k^T(x^*)[\text{Var}(x) + \sigma_n^2 I]^{-1}
\] (4)

\[
\text{Var}(\hat{y})^* = \text{Var}(x^*, x^*) - k^T(X^*)[\text{Var}(x) + \sigma_n^2 I]^{-1}k(x^*)
\] (5)

Wherein, \( k(X^*) = [\text{Var}(x^*, x_1), ..., \text{Var}(x^*, x_n)]^T \)
The hyper-parameter \( \theta = (\sigma_n, \sigma_f, \lambda) \) is obtained by maximum marginal likelihood according to the equations (6), and whether the selection of \( \theta \) is accurate affects the prediction result. In this paper, the multi-colony particle swarm optimization is used to iteratively obtain the optimal hyper-parameter.

\[
L(\theta) = \frac{1}{(2\pi)^{0.5}|\text{Var}(x)+\sigma_I^2|^{0.5}} \times \exp \left\{ -\frac{1}{2}y^T[\text{Var}(x) + \sigma_n^2I]^{-1}y \right\}
\]  

(6)

2.2. Multi-Colony Particle Filter Algorithm

Many optimization algorithms are used for hyper parameter optimization of data-driven models, such as GA [6], linear programming [7], PSO[8], which greatly improves the accuracy of the model. In practical engineering applications, mature PSO is the most widely used. Particle swarm optimization (PSO) is a swarm intelligence algorithm, which has obvious premature convergence phenomenon and tends to fall into local optimum. In this paper, the particle swarm is divided into three sub-swarms evenly, which are evolved according to PSO, \( \omega \) Adjustment Particle Swarm Optimization (\( \omega \)APSO) [9] and Cloud Adaptive Particle Swarm Optimization [10] (CAPSO). And then MPSO is used by updating the three sub-swarms iteratively. The particle richness is increased, so that the computation speed is effectively increased, and the probability of falling into local optimum is reduced.

3. Model Building and Verification of Model

3.1. SOH GPR Model Based on MPSO and ICA

Gaussian Process Regression (GPR) model is obtained through training by using the existing charging data to extract IF sequence and SOH sequence. In the future, the SOH value of the battery during the charging is obtained merely by extracting the relevant features during the charging, rather than by a complete testing to get the residual capacity. There are 3 steps in the basic framework.

**Step1:**

![Diagram](image)

Figure 2. Get data set from historical records

As shown in Figure 2, extract the effective charging cycle of the experimental data or the real vehicle data, and obtain the IFs of the IC curve to form a combined feature, and calculate the SOH value of each cycle.

**Step2:**

The training set and the test set are divided, and the training data set is used to train the model. The hyper parameters of GPR are optimized by MPSO. Eventually, when the trained model can achieve satisfactory results on the test set, the training is over. As shown in Figure 3, the specific steps are as follows:

1. Divide the sample data into training samples \((x, y)\) and test samples \((x^*, y^*)\) a.
2. Calculate the marginal likelihood function and set the initial value of the hyper-parameter
3. Divided the particle swarm into three groups equally after initializing, and calculate the current fitness value.
4. Perform the iterative calculation according to the algorithm described in Section 2.2 to obtain the optimal hyper-parameter. If the fitness value meets a certain threshold twice in succession, it can be regarded as an iteration stop condition, but this may lead to premature convergence. Therefore, the number of iterations is selected as the stop condition.
(5) Take the test sample \( x^* \) as the input and bring it into the trained GPR model, and output the SOH mean value and variance corresponding to the charging cycle, with the variance covering a 95% confidence interval.

![Diagram](image)

Figure 3. Training process of data-driven model

**Step3:**

Get the latest charging data and extract IC curve features. As long as one or more features are obtained, the feature combination method can be used to obtain IFs.

### 3.2. Verification Based on NASA Lithium-ion Battery Data Set

#### 3.2.1. Data of NASA Lithium-ion Battery Aging Experiment

When performing the real vehicle data analysis, we did not find that multiple features exist in multiple cycles of vehicle charging data, so it is impossible to judge whether the combined method is correct. Firstly, the NASA experimental data set is used to verify the algorithm framework and optimize the feature combination method. Using 18650 lithium-ion batteries with a rated capacity of 2Ah, NASA Prognostics Center of Excellence conducted a large number of battery experiments under various conditions in Idaho National Laboratory [11]. In this paper, the experimental data of B5 and B7 battery is used for verification. A brief description of the battery test flow is as follows:

| Table 1. Test Flow of NASA Lithium-ion Battery Data Set |
|--------------------------------------------------------|
| **Experiment Procedure** | **Stage** | **Test Item** | **Cut-off Condition** | **Remarks** |
| Charging | Stage 1 | Constant-current charging | Reach the upper cut-off voltage | The upper cut-off voltage is 4.2 V. |
| | Stage 2 | Constant-voltage charging | The current drops to 0.01C | / |
| Discharging | / | Constant-current discharging | Reach the lower cut-off voltage | The lower cut-off voltage of B5 battery is 2.7 V; That of B7 battery is 2.5 V |
Repeat the charging and discharging to make the battery age. Stop the experiment when the actual capacity of the battery drops to 70% of the rated capacity. The capacity-based SOH [1] is defined as:

\[
\text{SOH} = \left( \frac{C_i}{C_0} \right) \times 100\%
\]  

Where \(C_i\) is the capacity measured in the \(i\)th cycle, and \(C_0\) is the initial capacity.

### 3.2.2. IC Curve Calculation and IF Extraction

Discharge voltage drop rate [12], the charging time under equal voltage rise [13], average voltage and temperature during charging [14] were extracted during the charging process as an indirect health factor and built its mapping relationship with SOH. But this kind of mapping relationship needs a relatively complete charge-discharge curve as the basis for extracting indirect health factors, which is not easy to achieve in the actual use of vehicles. Features of the IC curve, such as Peak Value, Peak Area, Peak Voltage, were also used to train the model because the incomplete charging curve can also be converted to an IC curve [15]. However, these methods are usually based on experimental data. In most cases during the actual operation of the vehicle, it is difficult to obtain the characteristics of the IC curve, or sometimes this feature is obtained, and sometimes another feature is obtained. Therefore, we make full use of each charging cycle and get combined feature training based on the grey correlation analysis, which effectively enriches the data set. The IC curve is calculated as:

\[
\frac{dQ}{dV} = \frac{\delta Q}{\delta V} = \frac{Q_t - Q_{t-1}}{V_t - V_{t-1}}
\]

Where \(Q\) is capacity, \(V\) is Voltage, and \(t\) is time point.

Here, the Savitzky-Golay [16] smoothing filter is used to process noise. The fitting result is shown in Figure 4. The point A corresponds to the Peak of the IC curve, the shaded area B is the Peak Area, and the point C corresponds to the V_peak.

![Figure 4. IC Curve Filtering Diagram of B5](image)

![Figure 5. Change of IC Curves of B5](image)

By selecting some cycles at equal intervals and plotting the IC curves on the same graph, Figure 5 shows that the I and II Peaks are significantly reduced, while the Areas are also reduced, and the V_peaks are increased. Peak, Area and 1/V_Peak of peak II are extracted as IF, and subject to normalization processing. The similarity is quantified by Grey Relation Analysis (GRA). GRA judges the correlation degree according to the similarity of geometric shapes between the sequence curves [16]. The grey correlation of SOH and Area and Peak are relatively high, as shown in Table 2. However, due to the error of the voltage sensor and the error introduced during the smooth filtering, it is difficult to obtain the accurate V_Peak, so the \(r\) of the 1/V_peak and SOH sequences is relatively low. In the real vehicle data analysis, the error is greater, so it is not used in subsequent calculations.

| Battery No. | IF Sequence | grey correlation |
|-------------|-------------|------------------|

Table 2. Grey Correlation between Indirect Features and SOH
3.2.3. Verification and Improvement of Algorithm

For the algorithm verification with single IF as input, taking the single IF test results of B5 battery as an example, the results are shown in Figure 6:

![Figure 6. Test Results with a Single Indirect Feature as Input of B5](image)

The left of the vertical dividing line is the training data, and the right is the results estimated by the trained GPR model. SOH\_real is the SOH measured by experiment, SOH\_Area is the SOH estimated with Area as IF, and SOH\_Peak is the SOH estimated with Peak as IF. The root mean square error (RMSE) analysis of the two groups of batteries is shown in Table 3:

| Battery No. | IF Sequence | RMSE   |
|-------------|-------------|--------|
| B5          | Area        | 0.003759 |
| B5          | Peak        | 0.003307 |
| B7          | Area        | 0.002614 |
| B7          | Peak        | 0.001690 |

It cannot ensure that IFs are extracted from each circle due to the limitation of SOC range when the vehicle is actually running. In this paper, therefore, IFs are reasonably combined. The combined IFs are used as input to train the GPR model, realizing SOH estimation. The combination is \( I_{new} = a \cdot \text{Peak} + b \cdot \text{Area} \), where, \( a + b = 1 \). The estimation results under the different values of the coefficients \( a \) and \( b \) are analyzed below.

| Battery No. | a:b          | RMSE   |
|-------------|--------------|--------|
| B5          | 1:1          | 0.003225 |
|             | \( r_{\text{Peak}}:r_{\text{Area}} \) | 0.003160 |
| B7          | 1:1          | 0.002200 |
|             | \( r_{\text{Peak}}:r_{\text{Area}} \) | 0.002162 |
As is shown in Table 4, by analyzing the estimation results under multiple combinations, the IF estimation result obtained by linear combination using the ratio of grey correlation is the best. The linear combination equation is:

\[ I_{F_{\text{new}}} = \frac{r_{\text{Peak}}}{r_{\text{Peak}} + r_{\text{Area}}} \cdot \text{Peak} + \frac{r_{\text{Area}}}{r_{\text{Peak}} + r_{\text{Area}}} \cdot \text{Area} \]  

(9)

3.3. Results Based on Real Vehicle Data and Discuss

3.3.1. Description of Actual Vehicle Operation Data

Currently, the monitoring center mostly collects the BMS data and the related data through vehicle-mounted terminals installed in the vehicle and uploads them to the cloud data center. The data used in the paper comes from the one-year operation data of a company's new energy minibus. Two vehicles (No. 2621 and 2672) are selected for data analysis in the paper. Table 5 gives a brief description of the actual vehicle data.

| Vehicle No. | Total data points | Missing/err or data points | Percentage of available data | Total charging cycles | Effective charging cycles |
|-------------|-------------------|---------------------------|-------------------------------|-----------------------|--------------------------|
| 2621        | 2956608           | 2324190                   | 78.61%                        | 198                   | 106                      |
| 2672        | 2935872           | 2389800                   | 81.40%                        | 182                   | 98                       |

At first, the pre-processing results of the original collected data were analyzed in Table 6. Although many charging cycles have been extracted, since the SOC range is not suitable for ICA, the number of cycles that can be effectively used for model training is relatively small.

Figure 7 shows a statistical chart for SOC range of the vehicle during operation, with 88.8% of the SOC range not exceeding 50%. Figure 8 shows a statistical chart for SOC range when the vehicle starts charging, with 87.2% of the SOC range being greater than 50% at the starting.
3.3.2. Data Preliminary Processing and Feature Extraction
Firstly, take the preliminary processing for the real vehicle data, including elimination of abnormal values, filling of missing values and so on. Secondly, extract all the charging cycles to identify the multiple segment data interrupted during the charging and connect them reasonably. And then, obtain the IC curve. As shown in Figure 9, A is the peak (Peak) and the shaded area B is the peak area (Area).

![Figure 9. IC Curve Filtering Diagram for Real Vehicle Data](image)

In actual vehicle operation data, Peak I and Peak II are rarely seen, so Peak III is selected. Table 7 shows the results of feature extraction for actual vehicles. It can be seen that the feature sequence is difficult to be completely obtained due to the data precision and under the impact of actual operation interval and the GRA between single feature and its corresponding SOH sequence is lower than the experimental data, so it is necessary to reconstruct the feature sequence. When only a single feature can be extracted, the feature is used as the IF of the current cycle. When both features can be extracted, IF is calculated according to equation (9).

Table 7. Feature Conditions Extracted from Real Vehicle Data

| Vehicle No. | effective cycles | Feature type | Available Features | Grey correlation |
|-------------|------------------|--------------|--------------------|------------------|
| 2621        | 106              | Area         | 73                 | 0.8378           |
|             |                  | Peak         | 85                 | 0.6435           |
|             |                  | Both         | 52                 | /                |
| 2672        | 98               | Area         | 89                 | 0.6274           |
|             |                  | Peak         | 52                 | 0.6106           |
|             |                  | Both         | 44                 | /                |

3.3.3. Verification Results
IF sequences and SOH sequences are used as real vehicle data samples, and different proportions of cycles are selected as training samples to carry out algorithm verification. Here, we chose Support Vector Regression (SVR) to replace GPR as a model comparison. MPSO is adopted to obtain the optimal hyper-parameter of SVR. Because the predicted results are graphically similar, only three verification results are given for each model of vehicles, as shown in Figure 11 and Figure 12.
The GPR model gives confidence interval while giving the predicted mean value to calculate the upper and lower limits. The SOH estimation results with 60 cycles as training of No.2621 are taken as an example, as shown in Fig. 10. The solid lines are the actual SOH sequences. It can be seen that in actual operation, the vehicle has obvious capacity recovery phenomenon and capacity degradation curve fluctuations due to much battery idle time, but overall shows a slow downward trend. The vehicle operation mileage is about 50,000 miles, and the capacity drop is less than 4%. The dotted lines are the SOH estimated based on the IF extracted from the current cycle of the trained GPR model. The first curve and the fourth curve are the upper and lower limits of the 95% confidence interval of the estimated values, respectively. It can be seen that basically all the real values are within the upper and lower limits of the confidence interval.

It can be seen from the above figures that both the GPR and SVR model under different proportions of training data can achieve the estimation of SOH in the future, and the larger the number of training is, the more accurate the model will be. Among them, GPR is better in most cases. Since GPR has a good confidence interval description ability, we conclude that GPR can show better performance in practical applications. However, the actual vehicle battery degradation is 3%-4% and the NASA experimental battery degradation is about 30%. When the degradation ratio difference of the two is not one order of magnitude, the RMSE is the same order of magnitude, as shown in Table 7. Although the maximum percentage error relative to the total capacity is small, the ratio of the maximum error value to the degradation at the cut-off time is above 10%, and the maximum error of No. 2621 is 30%. The computation accuracy of the actual data is far less than that of the experimental data.
Table 8. Error Analysis of Estimated SOH for Real Vehicle Data

| Vehicle No. | Number of cycles used for training | Proportion (%) of training data to sample data | Data-driven model | RMSE     | Maximum percentage error % |
|-------------|-----------------------------------|-----------------------------------------------|-------------------|----------|---------------------------|
| 2621        | 40                                | 37.74%                                        | GPR               | 0.002245 | 1.09%                     |
|             |                                   |                                               | SVR               | 0.002568 | 0.96%                     |
|             | 50                                | 47.17%                                        | GPR               | 0.002285 | 1.05%                     |
|             |                                   |                                               | SVR               | 0.001952 | 1.05%                     |
|             | 60                                | 56.60%                                        | GPR               | 0.001823 | 0.38%                     |
|             |                                   |                                               | SVR               | 0.001927 | 0.76%                     |
| 2672        | 40                                | 40.82%                                        | GPR               | 0.001938 | 0.52%                     |
|             |                                   |                                               | SVR               | 0.002648 | 0.98%                     |
|             | 50                                | 51.02%                                        | GPR               | 0.002016 | 0.74%                     |
|             |                                   |                                               | SVR               | 0.001713 | 0.45%                     |
|             | 60                                | 61.22%                                        | GPR               | 0.001976 | 0.72%                     |

From the above results we can see that an accurate model has been trained for each vehicle. Now, the electric vehicle service platform can use the charging data uploaded by the vehicle to extract IFs. Regardless of the depth and range of charging cycle, as long as one or more IC features can be extracted, the platform can feed back the current SOH for supporting other applications.

3.3.4. Error Analysis

Temperature fluctuation

Although the BMS has a thermal management function, the public charging stations may be placed outdoors, which can cause severe temperature fluctuations due to change of seasons. The temperature has a certain influence on the shape of the IC curve [12]. As the seasons change, it spans a wide temperature range.

Module inconsistency

In this paper, the total current and total voltage data are used to analyze the SOH at the module level. Affected by the aging degree and temperature difference between cells, the module inconsistency will obviously increase. Even for the battery module with the same capacity, if the cells have large inconsistency, the IC curve shape will be obviously different [17], which is beyond the scope of this paper.

Data quality and calculation error

Due to the limitation of the current hardware facilities and network transmission capability, errors are introduced in the processes of measurement, recording and transmission of the actual operation data, which leads to the poor accuracy of the original data. In the follow-up analysis process, additional calculation errors are inevitably introduced in the preparatory processing, preliminary processing, secondary calculation, the filtering process, etc.

Under the cumulative effect of the above errors, the IF combination method and GPR estimation model constructed in this paper have good performance, and the error is within the acceptable range.

4. Conclusions

In this paper, an online SOH estimation framework based on GPR is designed and verified by real vehicle charging data. The accuracy of SOH estimation can be controlled within 2% with enough data training. The contributions of this paper include:

1. For the incompleteness of charging curve in actual vehicle operation, the combination feature sequence is constructed by fully utilizing the extractable IC curve features, and the online estimation framework of SOH is realized based on GPR model, which can be used for partial charging curve data.
(2) The SOH estimation framework proposed in this paper can collect data synchronously to optimize the model in vehicle operation, which reduces the cost of experiment design and implementation.

(3) This method is suitable for all kinds of vehicles and batteries, and adaptable to the poor data accuracy condition to an extent.

Next, we will focus on the optimization of the algorithm framework in case of significant effects of temperature changes and inconsistencies in the battery modules.

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