State estimation based on least square support vector

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Abstract. As one of the important parameters of battery management system (BMS), accurate estimation of the state of charge (SOC) of lithium-ion battery (LIB) can ensure the safety of electric vehicles and improve the utilization rate of batteries. A new SOC estimation algorithm based LSSVM is applied. The battery parameters, including current and voltage, which are used as the inputs to estimate SOC. To promote the accuracy of SOC estimation, the SOC estimated at the previous time is taken as the feedback vector to estimate the SOC at the current time. The experimental results show that the proposed model can improve the estimation accuracy of SOC.

1. Introduction

Due to the advantages of high energy density, good stability, and high cycle life, LIB is widely used in energy storage devices of electric vehicles. However, due to the complex internal electrochemical properties and uncertain external working environment, it has great complexity in the use process [1-2]. SOC is one of the key parameters of LIB, its accuracy will directly affect the reliability and safety of electric vehicles. Therefore, accurate SOC estimation has always been the primary consideration [3].

At present, many scholars have used many methods to estimate SOC: ampere-hour (Ah) integration method [4], open-circuit-voltage method (OCV) [5], Kalman filter method [6] and neural network (NN) method [7]. The Ah method is widely used in industry, but the error of battery initial capacity will lead to the low accuracy of SOC estimation. SOC estimation by using OCV should stand a long standing time, which cannot be applied to on-line estimation. Kalman filter algorithm has been widely used in state estimation. By establishing the state-space equation of LIB, the recursive method is used to realize the minimum variance estimation of SOC. However, Kalman filter (KF) is suitable for linear system. Neural network (NN) is based the neural conduction process between inputs and outputs, which directly establishes the nonlinear relationship between SOC and voltage, current and other factors. However, it is easy to fall into local optimum, which affects the accuracy of SOC estimation. Support vector machine (SVM) [8], by seeking the minimum structural risk, the regularization coefficient and kernel function of the model are obtained. LSSVM replaces the inequality constraint in SVM with the equality constraint, which effectively avoids the continuous iteration and accuracy degradation.

2. The principle of LSSVM

LSSVM is an improved SVM algorithm, which uses quadratic loss function to replace the insensitive loss function in SVM. Suppose the input vectors is n-dimensional and the training set is D(\(x_i, y_i\)) , where \(x_i\) denotes inputs vector, \(y_i\) are the corresponding output vectors. The input space \(\mathbb{R}^d\) of the sample is mapped to the feature space by a nonlinear mapping \(\phi(\cdot)\):
\[ y = \omega^T \ast \varphi(x) + b \]  
\[ R = C * R_{emp} + \frac{1}{2} \|\omega\|^2 \]  
\[ \min R = C * \sum_{i=1}^{n} \xi_i^2 + \frac{1}{2} \|\omega\|^2 \]  
\[ y_i = \omega^T \ast \varphi(x_i) + b \]  
Where \( \omega \) is the weight vectors; \( b \) is the bias:

\[ \mathbf{C} \] is the normalization parameter; \( R_{emp} \) is the loss function. According to the principle of structural risk minimization, the decision function parameters \( \omega \) and \( b \) are determined.

\[ y_i = \omega^T \ast \varphi(x_i) + b \]  
\[ \frac{\partial L}{\partial \omega} = 0, \quad \frac{\partial L}{\partial b} = 0, \quad \frac{\partial L}{\partial \xi_i} = 0, \quad \frac{\partial L}{\partial \alpha_i} = 0 \]  

The parameters in Equation (4) can be obtained:

\[ \alpha_i = \sum_{i=1}^{n} \alpha_i \varphi(x_i) \]  
\[ \frac{\partial L}{\partial \alpha_i} = 0 \]  
\[ y_i = \omega^T \ast \varphi(x_i) + b + \xi_i \]  

If \( K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle \) is a kernel function satisfying Mercer’s condition, then Equation (4) and Equation (6) are combined to obtain the following equations.

\[ K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \]  

Finally, the regression equation based on LSSVM is obtained:

\[ y_i = \sum_{i=1}^{n} \alpha_i \ast K(x_i, x_i) + b \]  

Because of the strong anti-interference ability of radial basis function, which is selected as the kernel function of the LSSVM, where \( \sigma \) is the kernel function.

\[ K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}} \]  

This paper introduces an intuitive structure of SOC estimation based LSSVM.

**Figure 1.** Battery SOC estimation model based on LSSVM.

Figure 1 shows the LSSVM model of sampling \( k \) time. The inputs are the \( V(k), I(k) \) and \( T(k) \) of at sampling \( k \) time, and the outputs are the SOC(k) estimated at \( k \) time.

### 3. SOC estimation model

Due to the acquisition equipment, battery external environment and other conditions, which will lead to large measurement error. As the inputs vector of LSSVM model, large test error will decrease the estimation accuracy of SOC. However, in the instantaneous time interval, SOC will not suddenly change greatly. Therefore, this paper proposes a LSSVM model based on moving window method, which is shown in Figure 2.
According to the principle of LSSVM introduced in the first section, two important parameters of LSSVM model need to be identified: regularization coefficient $C$ and kernel parameter $\sigma$. Therefore, the parameter optimization algorithm of the proposed model is presented in Table 1.

**Table 1.** Algorithm flow.

1. **Step1.** In the experimental conditions of the battery, the corresponding data are collected: $V$, $I$, $T$ and SOC.
2. **Step2.** Select the training set $D (X, y)$, where $X$ are the $V(k)$, $I(k)$, $T(k)$ and SOC(k-1), $y$ is the SOC(k).
3. **Step3.** Normalize the selected data.
4. **Step4.** Two parameters of LSSVM-1 model are initialized, and the optimal parameters are obtained by using 10-fold cross validation method.

**4. Experimental verification of proposed model**

To prove the effectiveness of the proposed model, the NCM LIB is applied for testing: the rated capacity is 2.4Ah, the rated voltage is 3.7V, the maximum working voltage $U_{\text{max}} = 4.2 \pm 0.05V$, the minimum voltage $U_{\text{min}} = 3.0V$. At 25°C and 45°C, the NCM battery was tested under US06 conditions, and the Fluke is used to record the current and voltage at different temperatures. As shown in Figure 3.

\[
MSE = \frac{1}{2} \sum \left(y - \hat{y}\right)^2
\]

**Figure 3.** US06 conditions under different temperatures: (a) current, voltage and SOC measured at 25°C; (b) current, voltage and SOC measured at 45°C.

To verify the accuracy of the model, the MAE is used to evaluate the performance of each model, which is defined as Equation (10).

\[
MAE = \text{max}|y - \hat{y}|
\]
Figure 4. SOC estimation under different temperatures: (a) SOC estimation results under 25°C; (b) SOC estimation errors under 25°C; (c) SOC estimation results under 45°C; (d) SOC estimation errors under 45°C.

From Figure 4(a) and 4(b), the SOC estimation errors estimated by LSSVM, NN and GPR are [-4.72% ~ 3.81%], [-20% ~ 5.64%], [-4.23% ~ 4.51%] at 25°C, respectively. Compared with NN, the MAE based LSSVM estimation is reduced by 76.5%, while the estimation performance of LSSVM is higher than that of GPR. The experimental results show that the estimation performance of GPR is better than LSSVM and NN in SOC estimation. Compared with LSSVM, NN and GPR, the estimation accuracy of LSSVM-1 model is improved by 82.4%, 95.8% and 81.6% respectively.

Meanwhile, from Figure 4(c) and 4(d), the MAE of SOC based LSSVM-1 estimation is 0.48%. The estimation performance of the proposed algorithm is improved by 86.2%, 95.7% and 85.2% respectively compared with GPR, LSSVM and NN. From the Table 2, the estimation performance of the model is improved with the increase of temperature.

Table 2. MAE of SOC accuracy under the US06 conditions at different temperatures.

| Temperature | NN     | LSSVM  | GPR    | LSSVM-1 |
|-------------|--------|--------|--------|---------|
| 25°C        | 20.00% | 4.72%  | 4.51%  | 0.83%   |
| 45°C        | 11.21% | 3.43%  | 3.24%  | 0.48%   |

5. Conclusions

Accurate estimation of SOC is particularly important for electric vehicles. In this paper, LSSVM is applied to establish the nonlinear relationship between inputs and SOC. However, to improve the accuracy of SOC estimation, a new algorithm based LSSVM is applied. The SOC estimated at the previous time is taken as the feedback vector, together with battery parameters measured at the current time are used as the inputs to promote the estimation accuracy of SOC. Compared with LSSVM, GPR and NN, the estimation errors is controlled within 1%.
References

[1] Wang Y, Tian J, Sun Z, et al. 2020 A Comprehensive Review of Battery Modeling and State Estimation Approaches for Advanced Battery Management Systems[J]. Renewable and Sustainable Energy Reviews

[2] J Li, M Ye, S Jiao, et al. 2020 A Novel State Estimation Approach Based on Adaptive Unscented Kalman Filter for Electric Vehicles[J]. IEEE Access 2020(8) 185629-185637

[3] J Li, M Ye, M Wei, et al. 2020 A Novel State of Charge Approach of Lithium Ion Battery Using Least Squares Support Vector Machine[J]. IEEE Access 2020(8) 195398-195410

[4] Deng Y, Hu Y and Cao Y 2014 An Improved Algorithm of SOC Testing Based on Open-Circuit Voltage-Ampere Hour Method[C]. International Conference on Life System Modeling and Simulation and International Conference on Intelligent Computing for Sustainable Energy and Environment

[5] M A Roscher and D U Sauer 2011 Dynamic electric behavior and open-circuit-voltage modeling of LiFePO4-based lithium ion secondary batteries[J]. J. Power Sources 196(1) 331-336

[6] Wang Y and Chen Z 2020 A framework for state-of-charge and remaining discharge time prediction using unscented particle filter[J]. Applied Energy 260 114324

[7] Yao H, Zhang T, Huang J, et al. 2019 SOC estimation of battery based on improved momentum BP neural network[J]. Battery 49(04) 308-311

[8] Zhu J, Zhang W and Ma S 2019 SOC estimation of Li-ion battery based on online support vector regression[J]. Chinese Journal of Power Sources 43(10) 1611-1614